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Gig crafting: conceptualization, scale development, and cross-country validation through a multi-study approach

Sari Mansour
School of Administrative Sciences, TÉLUQ University, Montreal, Canada

Abstract

Purpose – This study introduces the concept of gig crafting and develops and validates its scale. Gig crafting refers to proactive, self-directed strategies through which gig workers shape and optimize their work, including diversifying across platforms, adjusting working hours and pursuing income-enhancing opportunities under algorithmic management. The study also examines the nomological and predictive validity of the scale.

Design/methodology/approach – A six-stage, multi-study, cross-country process was conducted. Expert review and item generation (Study 1) were followed by exploratory factor analysis (Study 2, Turkish sample, $n = 141$) and confirmatory factor analysis with convergent and discriminant validity assessment (Study 3, a time-lagged sample from Pakistan, $n = 188$). The scale invariance across the four countries was tested and validated. Finally, a time-lagged sample from Australia and China ($n = 319$) was used to test cross-cultural measurement invariance and to examine nomological and predictive validity (Study 4).

Findings – The findings demonstrated that the gig crafting scale exhibited robust psychometric properties across four countries. The results also provided evidence of its nomological and predictive validity, showing that it is predicted by algorithmic management and positively associated with technostress and playful work design. Moreover, the scale was indirectly linked to the intention to continue working in gig economy settings through the serial mediation of technostress and playful work design.

Originality/value – This is the first study to conceptualize and measure gig crafting, providing a tool to examine how gig workers proactively adapt to algorithmically mediated work. The validated scale enables researchers and practitioners to assess proactive strategies in the gig economy, understand their outcomes and inform the design of supportive platform practices across diverse cultural contexts.

Keywords Algorithmic management, HRM, Gig crafting, Technostress, Playful work design, Job crafting, Multi-homing, Digital platforms, Gig economy

Paper type Research article

1. Introduction

The automation of core human resource management functions through algorithms has become a defining feature of the gig economy and digital labor platforms (Keegan and Meijerink, 2025). This evolution reflects the rise of algorithmic management (AM) through which platforms use data-driven systems and relies on self-learning algorithms to evaluate, allocate, and discipline gig workers (Kellogg *et al*., 2020). AM thereby reduces human oversight and replaces tasks typically performed by workers (Duggan *et al*., 2020). Platforms often combine autonomy-enhancing practices with tight control. This hybrid approach can align or misalign with strategic goals and worker expectations, shaping job design in mixed ways (Cropanzano *et al*., 2023). Despite growing interest in the consequences of AM, most

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previous studies have focused on negative outcomes (Parent-Rocheleau *et al.*, 2024) and have rarely examined gig workers' behavioral responses beyond attitudes and well-being. For instance, gig workers experience marginalization and career precarity (Caza *et al.*, 2022), yet responses vary: some withdraw or develop workarounds (Cram *et al.*, 2022) while others adopt proactive strategies such as job crafting.

Recent reviews on AM (Cropanzano *et al.*, 2023; Keegan and Meijerink, 2025; Wu and Huang, 2024) highlights the relevance of proactive behaviors to be successful in the gig economy. Because digital platforms restrict autonomy and render tasks monotonous (Parent-Rocheleau *et al.*, 2024), workers may engage in proactive behaviors to reclaim control, manage performance pressures, and make their work more meaningful. Simultaneously, opaque AM, algorithmic experimentation, and fluctuating pay schemes create uncertainty and income instability (Ashford *et al.*, 2018), requiring workers to continuously adapt to unpredictable conditions. In response, they engage in proactive, strategic behaviors to secure tasks, stabilize earnings, and navigate platform constraints. However, the literature lacks a conceptual framework that captures these agentic responses. Existing research often reduces such behaviors to multihoming—typically inferred from mobility or cross-platform data such as task logs, earnings records, or connection histories—to assess it (Guo *et al.*, 2023; Yu *et al.*, 2021). Such studies thereby overlook the intentional and strategic nature of these behaviors. To address this gap, we introduce Gig Crafting (GC) as a distinct form of crafting tailored to platform-mediated labor.

While GC may include multihoming, it extends beyond platform switching to encompass deliberate efforts to optimize schedules, target profitable tasks, position oneself in high-demand areas, and strategically pursue bonuses or surge incentives. Although rooted in the broader crafting tradition, GC differs from traditional job crafting, which typically unfolds within formal employment structures characterized by stable roles and organizational oversight (Mansour and Tremblay, 2020; Wrzesniewski and Dutton, 2001). In contrast, gig work is fluid, fragmented, and governed by AM, creating unique constraints and opportunities that existing crafting frameworks have struggled to capture (Caza *et al.*, 2022; Demerouti, 2025).

Despite numerous job crafting scales (e.g. Leana *et al.*, 2009; Tims *et al.*, 2012), none address income optimization or economic stabilization—central features of platform work. Moreover, studies examining multihoming rely primarily on transactional data (e.g. task logs, earnings records), which do not capture workers' perceptions or intentions, even though prior HRM research demonstrates that subjective interpretations often drive behavioral outcomes (Nishii *et al.*, 2008). Although GC is central to platform work, it remains underexplored in the crafting literature (Cropanzano *et al.*, 2023). To date, no psychometric scale measures either multihoming or the broader proactive strategies encompassed by GC. Developing and validating a GC Scale is therefore essential to systematically assess these behaviors and their implications for well-being, income stability, and platform engagement.

Based on Conservation of Resources (COR) theory (Hobfoll, 1989), we argue that GC functions as a resource investment strategy through which gig workers acquire, protect, and leverage psychological and material resources (Hobfoll *et al.*, 2018) in response to threats inherent in platform work, particularly those created by AM. COR theory posits that individuals engage in proactive behaviors to prevent resource loss and rebuild depleted resources, especially under conditions of scarcity and dependence. For instance, a recent study showed that in telework settings with limited resources, employees often engage in job crafting as a coping strategy to offset resource depletion and enhance performance (Mansour and Mohanna, 2024). In the gig economy, workers' economic reliance on platforms heightens the need to safeguard and optimize resources (Kuhn and Maleki, 2017). Under conditions of uncertainty and algorithmic opacity, GC enables workers to strategically stabilize earnings and restore a sense of control, thereby mitigating potential loss spirals. However, these proactive efforts require continuous interaction with digital interfaces and algorithmic systems, increasing exposure to technological demands. Such exposure may generate technostress—defined as strain arising when technological requirements exceed one's coping capacity (Tarafdar *et al.*, 2019).

According to the Transactional Model of Stress (Lazarus and Folkman, 1984), stressors prompt a secondary appraisal in which individuals evaluate coping resources and select strategies to manage strain. In this framework, GC represents a primary, proactive coping strategy addressing resource threats from AM, whereas playful work design (PWD) operates as a secondary coping mechanism that helps buffer or reinterpret technostress. PWD refers to employees "personal initiative to change the psychological experience of work by redesigning work activities to be more fun or more competitive" (Dishon-Berkovits *et al.*, 2024, p. 257). Together, these processes shape gig workers' intention to continue working, a key indicator of sustainability in platform labor (Cram *et al.*, 2022).

This study advances knowledge in three ways. First, it conceptualizes GC as a distinct, agentic construct capturing income-optimizing strategies within volatile, algorithmically mediated labor markets. Second, it develops and validates a psychometric GC Scale, enabling systematic and cross-contextual examination of these proactive behaviors. Importantly, the cross-country, multi-study design is not intended to compare national contexts, but to test the construct's robustness across diverse institutional and cultural environments. By establishing measurement equivalence prior to aggregation, we assess whether GC reflects a stable behavioral adaptation to platform work rather than a context-specific phenomenon, thereby strengthening its external validity. Third, the findings offer practical insights for platforms and policymakers seeking to enhance worker well-being, transparency, and long-term engagement in algorithmically managed environments. How gig workers engage in GC and PWD allows platforms to design algorithms, task allocation, and reward systems that support worker well-being and performance. Policymakers can leverage these insights to promote fair and transparent algorithmic management, while platforms of all sizes can enhance retention, engagement, and sustainable work practices.

The remainder of the paper presents the conceptual model and clarifies GC's distinction from related constructs. We then outline the six-stage scale development process, from construct emergence and item generation to exploratory and confirmatory validation, culminating in tests of nomological and predictive validity.

2. GC: conceptualization and measurement

Job crafting refers to bottom-up (re)design behaviors through which employees proactively modify aspects of their jobs by balancing demands and resources (Tims *et al.*, 2012), thereby enhancing meaning and engagement (Wrzesniewski and Dutton, 2001). Over the past decades, research has distinguished between approach and avoidance crafting, with evidence largely supporting the benefits of approach-oriented forms (Demerouti, 2025; Zhang and Parker, 2019). However, this literature has predominantly focused on stable organizational settings characterized by defined roles, structured supervision, and relatively predictable income streams.

Platform-based gig work differs fundamentally. It is governed by piece-rate pay, algorithmic management, and fluctuating compensation structures that create financial insecurity and limit workers' control (Wu and Huang, 2024; Keegan and Meijerink, 2025). Dynamic pricing, ratings, and temporary incentives further intensify volatility (Rahman, 2021). In contexts marked by weak institutional protections (Duggan *et al.*, 2020), gig workers must actively manage income instability. Despite these pressures, many persist in platform work (Wong *et al.*, 2021). This persistence despite structural volatility underscores the importance of examining how workers actively navigate algorithmic constraints (Cropanzano *et al.*, 2023).

In response, workers develop strategic behaviors to secure and optimize income—such as switching across platforms, adjusting work hours to peak demand, relocating to high-demand areas, and prioritizing high-paying tasks. While multihoming such as working across competing platforms (Evans and Schmalensee, 2016), captures one dimension of this behavior, it represents only part of a broader strategic repertoire. Multihoming typically refers to cross-platform participation (Yu *et al.*, 2021), and may be reactive or opportunistic. In contrast, Gig Crafting (GC) emphasizes deliberate, self-directed optimization across temporal, spatial, and economic dimensions. It captures intentional strategies through which workers construct, stabilize, and enhance their work under algorithmic governance.

We therefore define GC as:

> GC is the set of proactive, self-directed strategies through which platform workers intentionally construct, optimize, and stabilize their work by diversifying across platforms, adjusting temporal and spatial work patterns, and pursuing income-maximizing opportunities within algorithmically managed labor markets.

Although numerous job crafting scales exist, none address income optimization or economic stabilization—central features of gig work. Prior studies examining crafting among platform workers rely on instruments developed for traditional employment contexts (e.g. Wong *et al.*, 2021), which do not reflect algorithmically mediated decision-making and fragmented task structures. Similarly, research on multi-homing and task switching often relies on transactional or computational data (Guo *et al.*, 2023; Yu *et al.*, 2021). While informative, these approaches capture observable behavior but not workers' intentionality or subjective appraisal. Yet perceptions of control and optimization are likely more predictive of well-being, income stability, and continued engagement than objective switching patterns alone. To advance theory and enable systematic investigation of worker agency in platform labor, a validated GC Scale is therefore essential.

The process of creation and validation is presented in Figure 1.

3. Scale development

3.1 Stage 1: emergence of GC

Prior to formal scale development, the concept of GC emerged from several years of field engagement with gig workers across multiple countries, including ride-hailing, food delivery, and local micro-task platforms. Recurrent conversations revealed consistent strategic patterns, such as switching between applications, targeting bonuses, adjusting work hours to algorithmically defined peak periods, and relocating to high-demand zones. Similar strategies were widely discussed in online worker communities (e.g. Reddit), where gig workers exchanged tactics to maximize earnings under algorithmic systems. Collectively, these observations indicated a coherent behavioral domain that was theoretically distinct yet not captured by existing constructs.

3.1.1 Country selection. To cross-validate the scale, four countries—China, Pakistan, Turkey, and Australia—were selected to ensure meaningful variation in institutional regulation, platform maturity, and cultural orientations. Prior research suggests that gig workers interpret algorithmic management practices through locally embedded institutional and cultural frameworks (Kellogg *et al.*, 2020; Wood *et al.*, 2019). Examining diverse

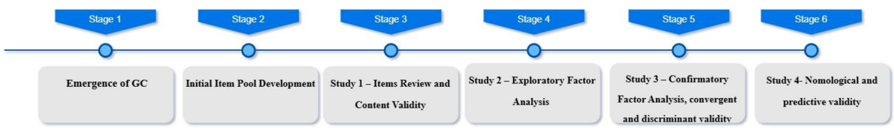

Figure 1. Gig crafting scale creation and validation process

environments therefore provides a stringent test of whether GC reflects a context-specific phenomenon or a generalizable behavioral adaptation.

These countries represent distinct labor market regimes, ranging from relatively regulated employment systems (e.g. Australia) to rapidly digitizing economies where platform governance continues to evolve (e.g. China and Pakistan), with Turkey occupying an intermediate position. In addition to institutional variation, cross-cultural HRM research highlights differences in cultural orientations such as power distance and long-term orientation (Farndale and Sanders, 2017; Sanders *et al*., 2021). The selected countries vary meaningfully along these dimensions (Hofstede, 1984), providing a theoretically grounded basis for assessing GC across heterogeneous environments. Importantly, the objective was not to compare countries, but to examine whether GC operates consistently across varied institutional and cultural contexts, thereby strengthening the construct's external validity.

3.2 Stage 2: initial item pool development

Following Stage 1, we adopted a deductive scale development approach (Hinkin, 1995) to generate the initial item pool. Drawing on prior research on job crafting, proactive behavior, algorithmic management, and multi-homing, as well as insights from Stage 1, we reviewed 125 peer-reviewed articles (2015–2025), including recent meta-reviews (e.g. Cropanzano *et al*., 2023; Deng *et al*., n.d.; Keegan and Meijerink, 2025; Wu and Huang, 2024), as well as qualitative studies with interview transcripts (e.g. Duggan *et al*., 2020; Franke and Pulignano, 2023). Items were developed to capture proactive strategies aimed at income optimization and opportunity management across platforms, including platform switching, schedule adjustment to peak demand, selective task choice, and spatial relocation to high-demand areas. While theory-driven, item wording was informed by field observations to ensure behavioral realism. This process resulted in an initial pool of 15 items, which were subjected to pilot testing in Stage 3 to assess clarity, relevance, and preliminary reliability. For example, one item assessing multi-platform management reads: "I manage different platforms simultaneously to avoid missing work."

3.3 Stage 3: Study 1 – items review and content validity

We conducted a pilot study with 40 active gig workers across multiple countries and task types (e.g. ride-hailing, food delivery, micro-tasks), consistent with recommendations for scale pretesting (e.g. Johanson and Brooks, 2010). Participants received a US$5 gift voucher compensation and evaluated each item for clarity, relevance, and importance, while providing qualitative feedback on comprehensibility. Ambiguous or overlapping items were revised or removed, and clarifying definitions were added where necessary. This refinement process reduced the pool from 15 to 7 theoretically grounded and clearly interpretable items, which were subsequently used in the exploratory factor analysis (Stage 4).

3.4 Stage 4: Study 2 – exploratory factor analysis (EFA)

3.4.1 Method. 3.4.1.1 Sample and procedure. To examine the dimensionality of the seven items shown in Table A1, we conducted an exploratory factor analysis (EFA) with gig workers in Turkey. The survey was translated using a back-translation procedure (Brislin, 1980) and pretested by an organizational behavior expert. Participants (minimum 20 h/week, multi-platform experience) received a US$5 gift voucher for completing a 5–10-min survey. Stage 3 respondents were excluded, and attention checks were applied. After removing incomplete or invalid responses, 141 usable surveys remained (58% response rate). Items were rated on a 7-point frequency scale (1 = never, 7 = everyday). Principal axis factoring with Promax rotation was conducted in SPSS 31. Items with loadings ≥0.35 were retained (Costello and Osborne, 2005).

3.4.1.2 Results. The Turkish sample included workers from multiple gig platforms: BiTaksi (57.4%), Yemeksepeti (31.2%), and Getir (10.6%). Most participants worked over 20 h per week (51.1%: 20–30 h; 48.9%: >30 h). Regarding work type, 60.3% were ride-hailing, 28.4% food delivery, and 9.9% freelance, with 58.2% reporting gig work as their main job. The sample was gender-diverse (62.4% female, 27.0% male, 10.6% undisclosed) and educationally varied (53.9% college diploma/certificate, 23.4% bachelor's degree, 22.7% high school or less).

EFA results indicated excellent sampling adequacy (KMO = 0.937; Bartlett's test $\chi^2(21) = 742.40$, $p < 0.001$). A single-factor solution (eigenvalue >1) explained 68.37% of the variance. Factor loadings ranged from 0.80 to 0.87, and internal consistency was high (Cronbach's $\alpha = 0.92$). These findings support a unidimensional GC construct and justify proceeding to confirmatory factor analysis in Stage 5.

3.5 Stage 5: Study 3 – confirmatory factor analysis, convergent and discriminant validity

To examine whether the one-factor GC structure was sample-specific, we conducted a confirmatory factor analysis (CFA) in a culturally distinct sample. This study also assessed convergent and discriminant validity by examining the relationship between GC and PWD. PWD is a proactive work design strategy in which individuals cognitively and behaviorally reframe work to enhance enjoyment and stimulation (Scharp *et al.*, 2021). It involves introducing self-imposed challenges, competition, or playful reframing without altering formal task boundaries. In contrast, traditional job crafting assumes control over tasks and responsibilities—conditions typically unavailable to gig workers operating under algorithmic management. This can include creating imaginative stories or transforming tasks into entertaining activities (Scharp *et al.*, 2023). PWD is conceptually closer to GC, as both reflect proactive behaviors enacted within existing structural constraints rather than through modifying task boundaries. However, they differ in focus: PWD enhances enjoyment and intrinsic motivation, whereas GC captures income-optimizing strategies in platform work (e.g. switching platforms, adjusting schedules, prioritizing higher-paying tasks). Given these conceptual distinctions (Scharp *et al.*, 2023), we expected small positive correlations between GC and PWD, supporting convergent validity while demonstrating discriminant validity between the constructs.

3.5.1 Methods. 3.5.1.1 Sample and procedure. Data were collected from 230 gig workers in Pakistan at Time 1, with 188 matched responses at Time 2 (71% final response rate). Participants received a US$5 gift voucher for completing a 10–15-min survey. Eligibility criteria mirrored Stage 4 (≥20 h/week, multi-platform experience, no prior participation in earlier stages). The survey was designed in English and translated into Urdu using the back-translation procedure (Brislin, 1980). Pretesting was conducted by a professor, a PhD student, and a postdoctoral researcher in organizational behavior. Responses with substantial missing data were excluded, resulting in a 71% final response rate.

Participants were distributed across platforms as follows: 43% FoodPanda, 17% Careem, 13% Fiverr, 8% Bykea, and 32% other platforms. Nearly all respondents (95%) worked over 30 h per week on their primary platform. Regarding occupational type, 44% engaged in other gig work, 25% in ride-hailing, 19% in food delivery, and 13% in freelance digital services. For most participants (93%), platform work was the main job. Education levels included college diploma (36%), bachelor's degree (33%), graduate degree (24%), and high school or less (7%).

3.5.1.2 Measures. GC was measured using our seven items developed in stage 1. For *PWD*, we measured it using the scale of Scharp *et al*. (2023), which consists of two factors: fun (6 items) and competition (6 items). Cronbach's alpha (α) was 0.90 for fun and 0.89 for competition, indicating high internal consistency.

3.5.1.3 Model fit, convergent and discriminant validity. Model fit was evaluated using χ^2/df, CFI, TLI, GFI, NFI, RMSEA, and SRMR. Following established guidelines, (Byrne, 2001; Hu and Bentler, 1999; Kline, 2005), CFI, TLI, GFI, and NFI ≥0.90 and RMSEA and SRMR <0.08 indicate acceptable fit, while χ^2/df < 3 reflects adequate model fit. Composite reliability

(CR) and average variance extracted (AVE) were calculated to assess reliability and convergent validity (CR > 0.70; AVE >0.50; Fornell and Larcker, 1981). Discriminant validity was examined through CFAs across constructs.

3.5.1.4 Results. *3.5.1.4.1 . CFA.* To test whether GC and PWD are distinct constructs, we compared three CFA models.

The one-factor model, with all items loading on a single latent factor, showed poor fit (χ^2/df = 6.27, RMSEA = 0.167, CFI = 0.656, TLI = 0.61, NFI = 0.62, GFI = 0.52, SRMR = 0.21), indicating that GC and PWD cannot be represented as a single construct.

The two-factor model, separating GC and PWD, demonstrated excellent fit (χ^2/df = 1.05, RMSEA = 0.01, CFI = 0.99, TLI = 0.99, NFI = 0.93, GFI = 0.92, SRMR = 0.04).

The three-factor model (GC, PWD Fun, PWD Competition) also showed excellent fit (χ^2/df = 1.04, RMSEA = 0.01, CFI = 0.99, TLI = 0.99, NFI = 0.93, GFI = 0.92, SRMR = 0.04). However, discriminant validity between the two PWD dimensions was not supported (HTMT = 0.85), indicating that Fun and Competition are not empirically distinct. Given the nearly identical fit indices, the more parsimonious two-factor solution was retained.

3.5.1.4.2. Reliability, convergent and discriminant validity. As shown in Table 1, both constructs demonstrated strong reliability (GC: α = 0.919, CR = 0.919; PWD: α = 0.948, CR = 0.948). Convergent validity was supported, as AVE values exceeded 0.50 (GC = 0.620; PWD = 0.603). Discriminant validity between GC and PWD was confirmed: HTMT = 0.131 (below 0.85), and the square roots of AVE (0.788 for GC; 0.776 for PWD) exceeded the inter-construct correlation (*r* = 0.124). The small positive correlation between GC and PWD reflects theoretical relatedness while supporting empirical distinctiveness.

3.5.2 Invariance test between Pakistan and Turkey. To examine whether the GC Scale functioned equivalently across culturally distinct contexts, we tested measurement invariance across the Turkish and Pakistani samples using SmartPLS 4.1.1.6. Nested models (configural, metric, scalar, strict, and strict with latent means) were estimated, which are appropriate for

Table 1. Factor loadings, reliability, convergent and discriminant validity (Pakistani sample)

Construct/ Item	Loading	Cronbach's α	ρc	AVE	$\sqrt{\text{AVE}}$/ Fornell–Larcker	Correlation	HTMT
GC		0.919	0.919	0.620	0.788	–	–
GC1	0.813						
GC2	0.761						
GC3	0.802						
GC4	0.796						
GC5	0.749						
GC6	0.809						
GC7	0.780						
PWD		0.948	0.948	0.603	0.776	0.124	0.131
PWD1	0.795						
PWD2	0.755						
PWD3	0.767						
PWD4	0.808						
PWD5	0.785						
PWD6	0.790						
PWD7	0.774						
PWD8	0.784						
PWD9	0.758						
PWD10	0.758						
PWD11	0.793						
PWD12	0.747						

Source(s): Author's own creation

relatively small samples (Hair *et al.*, 2021). Chi-square difference tests were non-significant across all comparisons (p = 0.579, 0.415, 0.842, 0.123, 0.578). Chi-square difference tests were non-significant across all comparisons (p = 0.579, 0.415, 0.842, 0.123, 0.578), indicating that constraining loadings, intercepts, and residuals did not reduce model fit. These results support configural, metric, scalar, and strict invariance, demonstrating cross-cultural equivalence of the GC measure.

3.5.3 Conclusion of study 3. Stage 5 confirmed a robust one-factor structure for the GC Scale, along with high reliability and strong convergent and discriminant validity relative to PWD. Measurement invariance further demonstrated that the scale operates equivalently across culturally distinct samples.

Together, these findings establish GC as a distinct proactive behavior in gig work while suggesting potential connections with other platform-based strategies (e.g. algorithmic adaptation, social crafting, and self-regulation), offering directions for future research.

3.6 Stage 6: Study 4- nomological and predictive validity

The final validation stage assessed the nomological and predictive validity of the GC Scale. We examined its position within a broader construct network, focusing on algorithmic management (AM) as a predictor and technostress, PWD, and intention to continue working in the gig economy as outcomes.

3.6.1 Research hypotheses. 3.6.1.1 GC as a resource-investing mechanism linking AM to technostress. In gig work, digital platforms use AM to monitor performance, allocate tasks, set goals, and determine compensation through ratings, nudges, and dynamic pricing. Although gig workers are formally autonomous, these mechanisms structure work opportunities and pressures (Duggan *et al.*, 2020). Features of AM—such as opaque monitoring, performance ratings, rigid scheduling, and income volatility—can threaten key resources, including income stability, time, effort, and psychological well-being (Ashford *et al.*, 2018). In line with the COR theory (Hobfoll *et al.*, 2018), when individuals perceive resource loss or threat, they invest existing resources to protect and replenish their resource pool. We argue that gig workers engage in GC as a proactive resource-investment strategy to regain control, stabilize earnings, and cope with AM-induced uncertainty. In this sense, GC functions as a coping mechanism within an algorithmically constrained environment. We therefore hypothesized:

H1. GC would be positively predicted by AM.

The effects of AM on worker well-being are complex and sometimes ambivalent (Cropanzano *et al.*, 2023; Keegan and Meijerink, 2025; Meijerink and Bondarouk, 2023). Although certain features (e.g. monitoring or ratings) may enhance perceived fairness (Deng *et al.*, n.d.). AM also intensifies technology-related demands. We focus on technostress, defined as stress arising from intensive technology use, including overload, complexity, uncertainty, invasion, and insecurity (Tarafdar *et al.*, 2007). While the precarious nature of gig work could be demoralizing, it could also motivate workers to cope with adverse conditions (Wu and Huang, 2024). In gig work, continuous adaptation to algorithmic systems, platform volatility, and performance optimization requires sustained cognitive and emotional investment. From a COR perspective (Hobfoll *et al.*, 2018), persistent resource investment without guaranteed returns may lead to resource depletion and stress. As gig workers engage in GC to cope with AM pressures—managing multiple platforms, adjusting strategies, and responding to algorithmic shifts—they may experience increased techno-overload, techno-uncertainty, and techno-insecurity. We therefore proposed:

H2. GC would be positively associated with technostress.

Because AM compels workers to invest time, effort, and cognitive resources to maintain performance and income, GC may function as the mechanism through which AM translates into technostress. Accordingly, we proposed:

H3. GC would mediate the relationship between AM and technostress.

3.6.1.2 GC: a pathway to PWD and continuance intention through technostress. Job stressors—such as workload and task complexity—can elicit strain but also be appraised as growth opportunities, motivating adaptive coping (Lepine *et al.*, 2005). Following the transactional model of stress, individuals first evaluate technological demands (primary appraisal), then assess coping resources (secondary appraisal), and select strategies to manage demands (Tarafdar *et al.*, 2019). Consistent with the transactional model of stress, the same stressor could be appraised simultaneously as both challenging and threatening (Lazarus and Folkman, 1984). For instance, Cram *et al.* (2022) found that Uber drivers experienced both techno-eustress and technostress in response to algorithmic control.

We propose that GC-induced technostress is interpreted as a challenge, motivating proactive coping through PWD. PWD comprises fun-oriented behaviors, which humanize and enrich tasks, and competition-oriented strategies, which involve self-imposed performance challenges (Scharp *et al.*, 2023). Fun-oriented behaviors (e.g. listening to music, seeking humor) humanized and enriched work experiences, while competition-oriented strategies (e.g. personal performance goals) helped cope with agency-related demands (Scharp *et al.*, 2021). These strategies allow gig workers to transform GC-related strain into engagement, expanding their resource pool. PWD thus functions as a secondary, resource-focused coping mechanism consistent with COR theory, which posits that individuals invest remaining resources to protect and potentially build new ones (Hobfoll *et al.*, 2018).

Accordingly, we hypothesize:

H4. GC would be indirectly associated with PWD through its impact on technostress.

By engaging in PWD, workers mitigate GC-induced technostress and replenish resources, reinforcing motivation and platform engagement. Resource-rich individuals cope better and acquire additional resources, enhancing well-being and performance, especially in resource-constrained environments (e.g. Mansour and Mohanna, 2024; Mansour *et al.*, 2026). Therefore, GC is expected to influence continuance intention indirectly via a serial pathway through technostress and PWD:

H5. GC would be indirectly associated with intention to continue through the serial mediation of technostress and PWD.

Our conceptual model is presented in Figure 2.

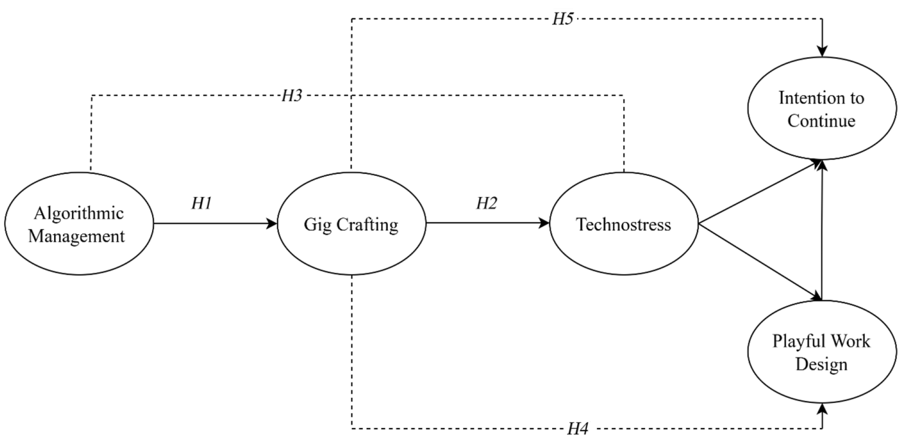

Figure 2. Conceptual model

3.6.2 Methods. 3.6.2.1 Sample and procedure. We conducted a time-lagged study among gig workers across multiple platforms in China and Australia, with university ethics approval. Data were collected via online surveys (Google Forms, Questionnaire Star) with support from research assistants and local students. Participants worked at least 20 h per week, had multi-platform experience, and provided informed consent. Surveys were administered in English and translated into Chinese using back-translation (Brislin, 1980) with pretesting by local experts. Participants received a US$5 gift voucher. Data collection occurred between December 2024 and January 2025.

The Time 1 survey included demographic information, AM, and GC. One month later, participants were invited to complete the Time 2 survey, which assessed technostress and PWD. Respondents provided the last four digits of their phone number to match responses across waves. After removing incomplete entries, 420 valid responses were obtained at Time 1 (China: 270, 69.8%; Australia: 150, 68.8%). At Time 2, 319 participants completed the follow-up survey, yielding response rates of 76.3% in China and 75.3% in Australia.

Participants worked predominantly 20–30 h per week, with gig types evenly distributed across food delivery, freelancing, ride-hailing, and other work. Most held a full-time job alongside gig work (84%). The sample was gender-diverse (45.5% men, 28.8% women, 25.7% undisclosed) and educationally varied (college/certificate: 37.3%, bachelor: 35.4%, graduate: 14.7%, high school or less: 12.5%).

3.6.2.2 Measures. *AM* was measured using the validated scale by Parent-Rocheleau *et al.* (2024), modeled as a second-order construct comprising five dimensions: monitoring, goal setting, task scheduling, performance rating, and compensation ($\alpha = 0.96$; example item: *"My platform tracks my performance through regular ratings"*). GC was assessed with the seven-item scale developed in this study ($\alpha = 0.93$; example item: *"I actively prioritize high-paying gigs, even if they are less convenient"*). Technostress was measured using a shortened version of the Tarafdar *et al.* (2007) scale. Retaining 15 items across five dimensions ($\alpha = 0.95$; example item: *"I must work faster than I can handle due to the platform"*). *PWD* was measured using Scharp *et al.* (2023) scale, comprising two dimensions: fun (6 items; $\alpha = 0.90$; example item: *"I approach my gig work in a playful way"*) and competition (6 items; $\alpha = 0.89$; example item: *"I try to set time records in my gigs"*). Intention to continue as a gig worker was measured using a three-item scale from Goldbach *et al.* (2018). One example item: *"I plan to work as a gig worker in the future"*. AM and GC were measured at Time 1, while technostress, PWD, and intention to continue were assessed at Time 2. Items were slightly rewarded to reflect gig work and platform contexts. GC items are provided in Appendix.

3.6.3 Analytical approach. 3.6.3.1 Common method bias. To reduce CMB, data were collected in two waves: AM and GC at Time 1, and technostress, PWD, and intention to continue as a gig workers at Time 2, minimizing priming and consistency bias. Additional procedural controls included anonymity, validated and pilot-tested scales, and careful translation/back-translation. Post-hoc tests confirmed minimal CMB: Harman's Single-Factor Test indicated a single factor explained only 25.76% of variance (<50%), VIFs were below thresholds, and construct correlations were <0.90 (Hair *et al.*, 2021). Together, these results confirm that CMB does not compromise our findings.

3.6.3.2 Measurement invariance and construct validity across Australia and China. We applied covariance-based structural equation modeling (CB-SEM) using SmartPLS v4.1.1.6 to test the measurement and structural models simultaneously. This approach enabled assessment of latent constructs, mediation, and cross-country invariance (Australia vs. China). Fit indices (χ^2/df, CFI, TLI, GFI, NFI, RMSEA and SRMR) were evaluated against standard thresholds (Byrne, 2001; Hu and Bentler, 1999). Reliability (CR) and convergent validity (AVE) were calculated (Fornell and Larcker, 1981), and CFA confirmed discriminant validity across constructs.

3.6.3.3 Hypothesis testing and mediation. All hypotheses were tested within a full CB-SEM model. Mediation effects were assessed using bias-corrected percentile bootstrapping with 10,000 resamples and 95% confidence intervals.

This rigorous procedure improves statistical power and reduces Type I error while ensuring robust estimation of direct, indirect, and serial effects (Preacher and Hayes, 2008).

3.6.4 Results. 3.6.4.1 Measurement model in each sample. The measurement model was first assessed separately in China and Australia. High correlations among the five AM dimensions, the two PWD dimensions, and the five technostress dimensions confirmed their internal structure. To simplify the structural model, PWD and technostress were treated as single latent factors. Fit indices were acceptable in both samples (χ^2/df < 1.3; RMSEA/SRMR ≤0.05; CFI/TLI ≥0.91), with high internal consistency (CR > 0.83; AVE >0.50). Discriminant validity was supported by the Fornell–Larcker criterion and HTMT ratios (<0.85), and all standardized loadings exceeded 0.70. No meaningful differences emerged between the two samples, justifying pooling for further analyses. These findings indicate that the measurement properties of the constructs are stable across the two cultural contexts. Detailed results are presented in Tables 2 and 3.

3.6.4.2 Measurement invariance between Australia and China. Nested invariance tests (configural, metric, scalar, strict, and strict with latent means) indicated good fit across all models (CFI = 0.91; RMSEA = 0.033–0.035), with non-significant chi-square differences (p > 0.54). This confirms that constructs—including GC, AM, technostress, PWD, and intention to continue as a gig worker—are interpreted consistently across cultures, supporting pooled analyses.

3.6.4.3 Measurement model (pooled samples). A CFA on the pooled data specified a five-factor model: AM (second-order, five first-order dimensions), GC, technostress (single factor), PWD (single factor), and intention to continue. The model fit excellently (χ^2/df = 1.15; RMSEA = 0.02; SRMR = 0.02; TLI/CFI = 0.98; NFI = 0.91) and outperformed

Table 2. Reliability and validity (China vs Australia)

Construct	China (α/AVE)	Australia (α/AVE)
Algorithmic management	0.95/0.51	0.96/0.53
Intention to continue	0.87/0.70	0.87/0.70
Gig crafting	0.93/0.66	0.93/0.66
PWD	0.94/0.59	0.94/0.58
Technostress	0.94/0.51	1.95/0.58

Note(s): Sample sizes: China (N = 206), Australia (N = 113)
Source(s): Author's own creation

Table 3. Discriminant validity (China vs Australia)

Construct	AM	Intention to continue	GC	PWD	Technostress
AM	*0.72/0.73*	0.10/0.15	0.83/0.84	0.10/0.18	0.13/0.12
Intention to continue	0.10/0.15	*0.83/0.83*	0.07/0.10	0.57/0.59	0.45/0.49
GC	0.83/0.84	0.07/0.10	*0.81/0.81*	0.08/0.09	0.15/0.12
PWD	0.10/0.18	0.57/0.59	0.08/0.09	*0.76/0.76*	0.62/0.53
Technostress	0.13/0.12	0.45/0.49	0.15/0.12	0.62/0.53	*0.72/0.76*

Note(s): Values are shown as China/Australia. Diagonal values in italic = square root of AVE (Fornell-Larcker criterion). Off-diagonal values = HTMT ratios. All HTMT values < 0.85, supporting discriminant validity. Sample sizes: China (N = 206), Australia (N = 113)
Source(s): Author's own creation

alternative models collapsing constructs (four-, three-, and one-factor models). As shown in Tables 4 and 5, all constructs demonstrated strong reliability (CR > 0.87) and convergent validity (AVE >0.50). Discriminant validity was confirmed via Fornell–Larcker and HTMT (<0.85), and all standardized loadings were >0.70.

3.6.4.4 Structural model and hypothesis testing. The structural model showed excellent fit (χ^2/df = 1.36; RMSEA = 0.02; SRMR = 0.04; TLI = 0.97; CFI = 0.97; NFI = 0.91), indicating strong alignment between the proposed relationships and the data.

3.6.4.5 Direct and indirect effects. Regarding direct effects, presented in Table 6, H1 predicted that AM would be positively associated with GC, and results strongly supported this hypothesis: AM had a positive and significant effect on GC (β = 0.83, $p < 0.001$), showing that higher levels of algorithmic management encourage gig workers to invest more intensively in GC. H2 proposed that GC would increase technostress, and consistent with this expectation, GC exhibited a positive and significant effect on technostress (β = 0.33, $p < 0.05$). These findings suggest that while GC is a proactive coping strategy, it also contributes to elevated levels of technostress as workers continuously adapt to algorithmic demands.

Indirect effects, presented in Table 6, provide support for H3, H4, and H5. Consistent with H3, GC significantly mediates the relationship between AM and technostress (β = 0.28, $p < 0.01$, 95% CI [0.08, 0.48]), indicating that AM-related pressures increase technostress partly by prompting workers to engage in proactive, resource-focused behaviors such as GC.

Table 4. Reliability and validity (pooled samples, Australia and China)

	Cronbach's alpha	Average variance extracted (AVE)
AM	0.955	0.518
Intention to continue	0.874	0.698
GC	0.931	0.659
PWD	0.944	0.584
Technostress	0.946	0.538

Note(s): N = 319 (Australian = 113 and Chinese = 206)
Source(s): Author's own creation

Table 5. Discriminant validity: Fornell-Larcker criteria (pooled samples, Australia and China)

	AM	CONT	GC	PWD	Technostress
AM					
Intention to continue	0.067				
GC	0.838	0.056			
PWD	0.094	0.576	0.054		
Technostress	0.075	0.465	0.130	0.583	
Heterotrait–Monotrait ratio (HTMT)					
AM	0.720				
Intention to continue	−0.010	0.835			
GC	0.832	0.051	0.812		
PWD	−0.082	0.575	−0.006	0.764	
Technostress	0.042	0.467	0.130	0.585	0.734

Note(s): N = 319 (Australian = 113 and Chinese = 206)
Source(s): Author's own creation

Table 6. Direct and indirect effects (pooled samples, Australia and China)

Path/Variable	GC (T1)	Technostress (T2)	PWD (T2)	Intention to continue (T2)
Controls				
Country	−0.07 ns	0.03 ns	−0.02 ns	0.01 ns
Number of hours	−0.02 ns	0.12*	−0.05 ns	−0.04 ns
Gig type	−0.00 ns	−0.03 ns	−0.05 ns	0.01 ns
Sex	−0.03 ns	0.00 ns	−0.04 ns	−0.04 ns
Education	0.00 ns	0.01 ns	0.02 ns	0.03 ns
Direct effects				
AM (T1)	0.83***	0.25*	−0.11 ns	0.003 ns
GC (T1)	–	0.33**	0.09 ns	0.06 ns
Technostress (T2)	–	–	0.60***	0.20**
PWD (T2)	–	–	–	0.58***
R^2	0.70***	0.05**	0.37***	0.35***

Indirect effects (bootstrapping, 95% CI)	β	*p*-value	Lower	Upper
AM → GC → Technostress	0.28**	0.006	0.08	0.479
GC → Technostress → PWD	0.20**	0.006	0.061	0.345
GC → Technostress → PWD → Intention	0.12**	0.007	0.036	0.206

Note(s): $N = 319$ (Australia and China samples); ns = non-significant; $^*p < 0.05$; $^{***}p < 0.001$
Source(s): Author's own creation

Supporting H4, GC indirectly predicts PWD through its effect on technostress ($\beta = 0.20$, $p < 0.01$, 95% CI [0.06, 0.35]), showing that GC-induced technostress motivates gig workers to adopt playful work design behaviors, such as adding elements of fun or competition, to cope with technological demands. Finally, consistent with H5, the serial mediation pathway GC → technostress → PWD → intention to continue is significant ($\beta = 0.12$, $p < 0.01$, 95% CI [0.04, 0.21]), demonstrating that GC indirectly enhances workers' intention to continue on the platform by first generating technostress and then triggering PWD as a secondary coping strategy, ultimately supporting engagement and retention.

All control variables were non-significant and did not influence the outcomes. Together, these findings highlight the dual role of GC as a proactive mechanism: although it may initially increase strain through technostress, it simultaneously activates adaptive coping behaviors (PWD) that foster positive outcomes, including sustained engagement and platform continuance, demonstrating its importance as a strategic behavior in algorithmically mediated gig work contexts.

3.6.5 Discussion. The study aimed to introduce GC and develop a reliable measure. GC is defined as a set of proactive, self-directed strategies through which platform workers intentionally shape and optimize their work—diversifying across platforms, adjusting hours, and pursuing income-enhancing opportunities within algorithmically managed labor markets. Following a six-stage process, we conceptualized the construct, generated an initial item pool, conducted expert review (Study 1), performed exploratory factor analysis (Study 2), confirmed factor structure and validity (Study 3), and assessed nomological and predictive validity (Study 4).

To ensure robustness and cross-cultural applicability, data were collected from four independent samples in Turkey ($n = 141$), Pakistan ($n = 188$), Australia, and China ($n = 319$). The Turkish sample explored the GC factor structure, the Pakistani sample confirmed it and tested convergent, discriminant, and measurement invariance, and the Australian and Chinese samples assessed nomological and predictive validity across culturally diverse contexts. Together, these samples provide strong evidence that the GC construct and its measurement are reliable, stable, and generalizable internationally.

3.6.5.1 Theoretical contribution. This study contributes to the literature in several ways. First, by introducing GC, we extend job crafting research to the gig economy and algorithmically mediated work. While GC shares the proactive logic of job crafting, it differs in three respects. Unlike job crafting, which occurs in stable organizations with defined roles (Mansour and Mohanna, 2024; Wrzesniewski and Dutton, 2001), GC unfolds in fragmented, market-driven platform environments where algorithmic management dictates task allocation, pay fluctuations, and performance monitoring. GC unfolds in fragmented, market-driven platforms where algorithmic management dictates tasks, pay, and monitoring. Second, whereas job crafting targets engagement or well-being, GC focuses on stabilizing and optimizing income, reducing economic risk, and securing opportunities under volatile conditions. Third, GC requires responding to externally imposed and opaque factors such as dynamic pricing, unpredictable demand, spatial and temporal adjustments, task selection, and income-maximizing strategies.

Second, GC addresses limitations in prior research on multi-homing. Unlike transactional measures capturing only observable behaviors (Yu *et al*., 2021). GC encompasses multi-homing along with temporal adjustments, spatial mobility, selective task choice, and income-maximizing strategies, highlighting intentionality and strategic motivation. This agentic perspective allows linking proactive behaviors to outcomes such as well-being, income stability, career sustainability, and platform engagement. For instance, Cropanzano *et al*. (2023, p. 9) noted that “to adapt in the gig economy, workers may respond to the new psychological contract by collecting small, standardized work tasks into diversified portfolios and thus crafting a unique ‘job’ that fits their individual needs and skills”. Third, the GC Scale provides a reliable tool to measure these strategies. Existing measures from traditional contexts fail to capture the economic optimization and intentionality central to platform work. The GC Scale allows reproducible research, cross-context comparisons, and longitudinal studies on how gig workers navigate algorithmically mediated labor.

Fourth, the GC Scale enables exploration of its nomological network. Our findings show that GC can generate positive outcomes such as PWD and intention to continue as a gig worker, while also increasing technostress. Measuring GC allows investigation of its role as a mechanism, consistent with COR theory (Hobfoll *et al*., 2018) and transactional model of stress (Lazarus and Folkman, 1984), linking proactive strategies to both resource gains and drains. Overinvestment in GC may deplete personal resources, increasing techno-overload, uncertainty, privacy concerns, and job insecurity, highlighting its dual effects. GC-induced technostress motivates PWD behaviors, transforming algorithmic stressors into proactive coping strategies that enhance engagement and continuance intentions. This approach responds to calls for more research on the duality of AM (e.g. Keegan and Meijerink, 2025) and the underlying processes through which AM generates both positive and negative responses (Cram *et al*., 2022). In line with COR theory, in resource-scarce and high-pressure environments, GC represents deliberate resource investments to protect existing resources and potentially acquire new ones. Yet, GC may also have a potential dark side. Overinvestment in GC can deplete personal resources—time, effort, and cognitive capacity—especially when supportive resources are limited or platform algorithms are rigid. This overinvestment may increase techno-overload, interaction complexity, uncertainty, privacy concerns, and perceived job insecurity, echoing recent findings on approach crafting and burnout (e.g. Harju *et al*., 2021). Measuring GC extends both COR theory and the transactional model of stress by linking proactive behaviors to resource gains and drains, providing a framework to understand how gig workers navigate algorithmically mediated work. Based on the transactional model of stress, gig workers may cope proactively and playfully with technostress through PWD, a behavior aimed at making work more enjoyable (Dishon-Berkovits *et al*., 2024). Our study shows that technostress directly enhances PWD. Because technostress can be perceived as both a challenge and a threat, it elicits adaptive and maladaptive responses (Cram *et al*., 2022; Tarafdar *et al*., 2019). PWD thus serves as an emotional and motivational coping strategy for gig workers facing technostress.

Finally, conceptualizing and measuring GC contributes to work design, HRM, organizational behavior, and algorithmic management research, addressing an interdisciplinary gap (Keegan and Meijerink, 2025). While AM represents a top-down design, GC illustrates bottom-up strategies in the gig economy, highlighting mechanisms for worker involvement and agency in algorithmically mediated work. These findings advance theory in gig work, inform HRM transformation, and provide insight into evolving employment relationships (Cropanzano *et al*., 2023).

3.6.5.2 Practical implication. This study offers several practical implications. First, the GC Scale provides platforms with a diagnostic tool to understand how gig workers proactively navigate algorithmic systems. This insight allows firms to adjust reward structures, simplify algorithmic complexity, and design features that reduce technostress. By aligning algorithmic practices with workers' needs, platforms can enhance well-being, strengthen retention, and sustain performance in competitive markets. Policymakers can also use these findings to promote fair and transparent algorithmic management, encouraging platforms to incorporate structured channels for worker feedback and suggestions.

Second, recognizing bottom-up behaviors such as GC and PWD is critical. While these behaviors can boost engagement and performance (Cropanzano *et al*., 2023; Dishon-Berkovits *et al*., 2024), excessive investment in GC may deplete workers' resources, raising technostress and turnover risks. Platforms should therefore adjust rigid algorithmic features—especially reward and penalty systems—to better accommodate workers' preferences and well-being. Providing training can equip gig workers to navigate complex, evolving technological demands (Kellogg *et al*., 2020). Finally, encouraging PWD behaviors can help workers manage stress and sustain engagement in demanding platform-based work (Scharp *et al*., 2021).

3.6.5.3 Limitations. This study has several limitations, offering opportunities for future research. First, we relied on self-reported data, which may raise concerns such as common method bias. However, the use of a time-lagged design mitigates this issue. Although GC and AM were measured simultaneously in Study 4, this is unlikely to pose a major concern, as gig assignments are often automatic and completed within seconds (Duggan *et al*., 2020). Diary studies (Ohly *et al*., 2010) could provide a more fine-grained understanding of the dynamic interplay between AM, GC, and PWD.

Second, while we treated AM as a single construct in line with previous research (e.g. Parent-Rocheleau *et al*., 2024), individual practices may have distinct effects on GC and technostress. For example, monitoring, compensation, and performance ratings may be perceived as exploitative, whereas task scheduling and goal setting could help workers organize gigs and maximize earnings (Franke and Pulignano, 2023). Future studies should examine the separate impact of each AM dimension. Third, contextual factors may shape how gig workers respond to AM—some may resist algorithmic controls, while others leverage them strategically (Keegan and Meijerink, 2025).

Finally, while sample sizes were moderate, they were sufficient for CFA, measurement invariance, and structural analyses. Replicating the study with larger, country-specific samples could further test the external validity of GC and explore contextual moderators. The cross-country invariance tests support the scale's robustness, but future research could extend findings to traditional organizational contexts where algorithmic management is increasingly applied.

3.6.5.4 Conclusion. This study introduces GC and provides a validated scale to measure it in algorithmically mediated work. Gig workers actively engage in proactive strategies to navigate and optimize their work. GC increases technostress, triggering adaptive behaviors such as PWD and enhancing intention to continue as a gig worker. Findings highlight the dual nature of proactive strategies in the gig economy—supporting positive outcomes while creating new sources of strain—and contribute to a nuanced understanding of how workers cope with and shape experiences under AM.

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Appendix

Table A1. GC items

Gig crafting
I actively switch between different gig platforms to maximize opportunities
I handle multiple tasks at the same time across different platforms to increase productivity
I actively adjust my working hours based on peak demand times
I actively prioritize high-paying gigs, even if they are less convenient
I actively look for bonus opportunities to increase my income
I selectively choose gigs that offer the highest pay
I move between locations to maximize my chances of getting more tasks

Source(s): Author’s own creation

References

Ashford, S.J., Caza, B.B. and Reid, E.M. (2018), “From surviving to thriving in the gig economy: a research agenda for individuals in the new world of work”, *Research in Organizational Behavior*, Vol. 38, pp. 23-41, doi: 10.1016/j.riob.2018.11.001.

Brislin, R.W. (1980), “Translation and content analysis of oral and written material”, in Triandis, H.C. and Berry, J.W. (Eds), *Handbook of Cross-Cultural Psychology: Methodology*, Allyn and Bacon, Boston, MA, pp. 389-444.

Byrne, B.M. (2001), “Structural equation modeling with AMOS, EQS, and LISREL: comparative approaches to testing for the factorial validity of a measuring instrument”, *International Journal of Testing*, Vol. 1 No. 1, pp. 55-86.

Caza, B.B., Reid, E.M., Ashford, S.J. and Granger, S. (2022), “Working on my own: measuring the challenges of gig work”, *Human Relations*, Vol. 75 No. 11, pp. 2122-2159, doi: 10.1177/00187267211030098.

Costello, A.B. and Osborne, J. (2005), “Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis”, *Practical Assessment, Research and Evaluation*, Vol. 10, doi: 10.7275/jyj1-4868.

Cram, W.A., Wiener, M., Tarafdar, M. and Benlian, A. (2022), “Examining the impact of algorithmic control on Uber drivers’ technostress”, *Journal of Management Information Systems*, Vol. 39 No. 2, pp. 426-453, doi: 10.1080/07421222.2022.2063556.

Cropanzano, R., Keplinger, K., Lambert, B.K., Caza, B. and Ashford, S.J. (2023), “The organizational psychology of gig work: an integrative conceptual review”, *Journal of Applied Psychology*, Vol. 108 No. 3, pp. 492-519, doi: 10.1037/apl0001029.

Demerouti, E. (2025), “Job crafting revisited: current insights, emerging challenges, and future directions”, Vol. 13 No. 1, pp. 195-220, doi: 10.1146/annurev-orgpsych-020924-064242.

Deng, H., Lu, Y., Fan, D., Liu, W. and Xia, Y. (n.d.), “The power of precision: how algorithmic monitoring and performance management enhances employee workplace well-being”, *New Technology, Work and Employment*, Vol. 40 No. 3, pp. 390-403, doi: 10.1111/ntwe.12328.

Dishon-Berkovits, M., Bakker, A.B. and Peters, P. (2024), "Playful work design, engagement and performance: the moderating roles of boredom and conscientiousness", *International Journal of Human Resources Management*, Vol. 35 No. 2, pp. 256-283, doi: 10.1080/09585192.2023.2227920.

Duggan, J., Sherman, U., Carbery, R. and McDonnell, A. (2020), "Algorithmic management and app-work in the gig economy: a research agenda for employment relations and HRM", *Human Resource Management Journal*, Vol. 30 No. 1, pp. 114-132, doi: 10.1111/1748-8583.12258.

Evans, D.S. and Schmalensee, R. (2016), "The new economics of multi-sided platforms: a guide to the vocabulary", *SSRN Electronic Journal*. doi: 10.2139/ssrn.2793021.

Farndale, E. and Sanders, K. (2017), "Conceptualizing HRM system strength through a cross-cultural lens", *International Journal of Human Resources Management*, Vol. 28 No. 1, pp. 132-148, doi: 10.1080/09585192.2016.1239124.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.

Franke, M. and Pulignano, V. (2023), "Connecting at the edge: cycles of commodification and labour control within food delivery platform work in Belgium", *New Technology, Work and Employment*, Vol. 38 No. 2, pp. 371-390, doi: 10.1111/ntwe.12218.

Goldbach, T., Benlian, A. and Buxmann, P. (2018), "Differential effects of formal and self-control in mobile platform ecosystems: multi-method findings on third-party developers' continuance intentions and application quality", *Information & Management*, Vol. 55 No. 3, pp. 271-284.

Guo, X., Haupt, A., Wang, H., Qadri, R. and Zhao, J. (2023), "Understanding multi-homing and switching by platform drivers", *Transportation Research Part C: Emerging Technologies*, Vol. 154, 104233, doi: 10.1016/j.trc.2023.104233.

Hair, J.F., Jr, Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P. and Ray, S. (2021), *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: a Workbook*, Springer Nature, Cham. doi: 10.1007/978-3-030-80519-7.

Harju, L.K., Kaltiainen, J. and Hakanen, J.J. (2021), "The double-edged sword of job crafting: the effects of job crafting on changes in job demands and employee well-being", *Human Resource Management*, Vol. 60 No. 6, pp. 953-968, doi: 10.1002/hrm.22054.

Hinkin, T.R. (1995), "A review of scale development practices in the study of organizations", *Journal of Management*, Vol. 21 No. 5, pp. 967-988, doi: 10.1016/0149-2063(95)90050-0.

Hobfoll, S.E. (1989), "Conservation of resources. A new attempt at conceptualizing stress", *American Psychologist*, Vol. 44 No. 3, pp. 513-524, doi: 10.1037//0003-066x.44.3.513.

Hobfoll, S.E., Halbesleben, J., Neveu, J.-P. and Westman, M. (2018), "Conservation of resources in the organizational context: the reality of resources and their consequences", *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 5 No. 1, pp. 103-128, doi: 10.1146/annurev-orgpsych-032117-104640.

Hofstede, G. (1984), *Culture's Consequences: International Differences in Work-Related Values*, SAGE, Beverly Hills, CA.

Hu, L.T. and Bentler, P.M. (1999), "Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 6 No. 1, pp. 1-55.

Johanson, G.A. and Brooks, G.P. (2010), "Initial scale development: sample size for pilot studies", *Educational and Psychological Measurement*, Vol. 70 No. 3, pp. 394-400, doi: 10.1177/0013164409355692.

Keegan, A. and Meijerink, J. (2025), "Algorithmic management in organizations? From edge case to center stage", *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 12 No. 1, pp. 395-422, doi: 10.1146/annurev-orgpsych-110622-070928.

Kellogg, K.C., Valentine, M.A. and Christin, A. (2020), "Algorithms at work: the new contested terrain of control", *The Academy of Management Annals*, Vol. 14 No. 1, pp. 366-410, doi: 10.5465/annals.2018.0174.

Kline, T.J.B. (2005), *Psychological Testing: A Practical Approach to Design and Evaluation*, SAGE Publications, Thousand Oaks, CA.

Kuhn, K.M. and Maleki, A. (2017), "Micro-entrepreneurs, dependent contractors, and instaserfs: understanding online labor platform workforces", *Academy of Management Perspectives*, Vol. 31 No. 3, pp. 183-200, doi: 10.5465/amp.2015.0111.

Lazarus, R.S. and Folkman, S. (1984), *Stress, Appraisal, and Coping*, Springer Publishing Company, New York, NY.

Leana, C., Appelbaum, E. and Shevchuk, I. (2009), "Work process and quality of care in early childhood education: the role of job crafting", *Academy of Management Journal*, Vol. 52 No. 6, pp. 1169-1192, doi: 10.5465/amj.2009.47084651.

Lepine, J.A., Podsakoff, N.P. and Lepine, M.A. (2005), "A meta-analytic test of the challenge stressor–hindrance stressor framework: an explanation for inconsistent relationships among stressors and performance", *Academy of Management Journal*, Vol. 48 No. 5, pp. 764-775, doi: 10.5465/amj.2005.18803921.

Mansour, S. and Mohanna, D. (2024), "How does organizational support for innovation influence job crafting and knowledge sharing behaviors? A comparison between teleworkers and office workers", *International Journal of Manpower*, Vol. 45 No. 9, pp. 1673-1700, doi: 10.1108/IJM-02-2024-0106.

Mansour, S., Mohanna, D., Tremblay, D.-G., Vandenberghe, C. and Nogues, S. (2026), "Does perceived organizational support for strength use enhance employee well-being and task performance? The role of investment in job crafting", *Journal of Organizational Effectiveness. People and Performance*, Vol. 13 No. 3, pp. 1-18, doi: 10.1108/JOEPP-02-2025-0097.

Mansour, S. and Tremblay, D.-G. (2020), "How can organizations foster job crafting behaviors and thriving at work?", *Journal of Management and Organization*, Vol. 27 No. 4, pp. 768-785, doi: 10.1017/jmo.2020.31.

Meijerink, J. and Bondarouk, T. (2023), "The duality of algorithmic management: toward a research agenda on HRM algorithms, autonomy and value creation", *Human Resource Management Review*, Vol. 33, pp. 1-14, doi: 10.1016/j.hrmr.2021.100876.

Nishii, L.H., Lepak, D.P. and Schneider, B. (2008), "Employee attributions of the 'why' of HR practices: their effects on employee attitudes and behaviors, and customer satisfaction", *Personnel Psychology*, Vol. 61 No. 3, pp. 503-545, doi: 10.1111/j.1744-6570.2008.00121.x.

Ohly, S., Sonnentag, S., Niessen, C. and Zapf, D. (2010), "Diary studies in organizational research: an introduction and some practical recommendations", *Journal of Personnel Psychology*, Vol. 9 No. 2, pp. 79-93, doi: 10.1027/1866-5888/a000009.

Parent-Rocheleau, X., Parker, S.K., Bujold, A. and Gaudet, M.-C. (2024), "Creation of the algorithmic management questionnaire: a six-phase scale development process", *Human Resource Management*, Vol. 63 No. 1, pp. 25-44, doi: 10.1002/hrm.22185.

Preacher, K.J. and Hayes, A.F. (2008), "Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models", *Behavior Research Methods*, Vol. 40 No. 3, pp. 879-891, doi: 10.3758/BRM.40.3.879.

Rahman, H.A. (2021), "The invisible cage: Workers' reactivity to opaque algorithmic evaluations", *Administrative Science Quarterly*, Vol. 66 No. 4, pp. 945-988.

Sanders, K., Yang, H. and Li, X. (2021), "Quality enhancement or cost reduction? The influence of high-performance work systems and power distance orientation on employee human resource attributions", *International Journal of Human Resources Management*, Vol. 32 No. 21, pp. 4463-4490, doi: 10.1080/09585192.2019.1675740.

Scharp, Y.S., Breevaart, K. and Bakker, A.B. (2021), "Using playful work design to deal with hindrance job demands: a quantitative diary study", *Journal of Occupational Health Psychology*, Vol. 26 No. 3, pp. 175-188, doi: 10.1037/ocp0000277.

Scharp, Y.S., Bakker, A.B., Breevaart, K., Kruup, K. and Uusberg, A. (2023), "Playful work design: conceptualization, measurement, and validity", *Human Relations*, Vol. 76 No. 4, pp. 509-550, doi: 10.1177/00187267211070996.

Tarafdar, M., Tu, Q., Ragu-Nathan, B.S. and Ragu-Nathan, T.S. (2007), "The impact of technostress on role stress and productivity", *Journal of Management Information Systems*, Vol. 24 No. 1, pp. 301-328, doi: 10.2753/MIS0742-1222240109.

Tarafdar, M., Cooper, C.L. and Stich, J.-F. (2019), "The technostress trifecta - techno eustress, techno distress and design: theoretical directions and an agenda for research", *Information Systems Journal*, Vol. 29 No. 1, pp. 6-42, doi: 10.1111/isj.12169.

Tims, M., Bakker, A.B. and Derks, D. (2012), "Development and validation of the job crafting scale", *Journal of Vocational Behavior*, Vol. 80 No. 1, pp. 173-186, doi: 10.1016/j.jvb.2011.05.009.

Wong, S.I., Kost, D. and Fieseler, C. (2021), "From crafting what you do to building resilience for career commitment in the gig economy", *Human Resource Management Journal*, Vol. 31 No. 4, pp. 918-935, doi: 10.1111/1748-8583.12342.

Wood, A.J., Graham, M., Lehdonvirta, V. and Hjorth, I. (2019), "Good gig, bad gig: autonomy and algorithmic control in the global gig economy. Work employ", *Society*, Vol. 33 No. 1, pp. 56-75, doi: 10.1177/0950017018785616.

Wrzesniewski, A. and Dutton, J.E. (2001), "Crafting a job: revisioning employees as active crafters of their work", *Academy of Management Review*, Vol. 26 No. 2, p. 179, doi: 10.2307/259118.

Wu, D. and Huang, J.L. (2024), "Gig work and gig workers: an integrative review and agenda for future research", *Journal of Organizational Behavior*, Vol. 45 No. 2, pp. 183-208, doi: 10.1002/job.2775.

Yu, J., Mo, D., Xie, N., Hu, S. and Chen, X.M. (2021), "Exploring multi-homing behavior of ride-sourcing drivers via real-world multiple platforms data", *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 80, pp. 61-78, doi: 10.1016/j.trf.2021.03.017.

Zhang, F. and Parker, S.K. (2019), "Reorienting job crafting research: a hierarchical structure of job crafting concepts and integrative review", *Journal of Organizational Behavior*, Vol. 40 No. 2, pp. 126-146, doi: 10.1002/job.2332.

Corresponding author
Sari Mansour can be contacted at: sari.mansour@teluq.ca