



Selected Papers of #AoIR2025:
The 26th Annual Conference of the
Association of Internet Researchers
Niterói, Brazil / 15 – 18 Oct 2025

TECHNICAL VS. SELF-PERCEIVED: EXAMINING CROWDSOURCING WORKERS' ALGORITHMIC KNOWLEDGE ON AMAZON MECHANICAL TURK

Leon Zhenglang Wang
The Chinese University of Hong Kong

Ruiwen Zhou
The Chinese University of Hong Kong

Introduction

As one of the leading crowdsourcing platforms (Chambers & Nimon, 2019), Amazon Mechanical Turk (MTurk) remains a crucial source of income for gig workers (Turkers) from the Global South—including those based in Brazil (Moreschi et al., 2020). Meanwhile, the platform also serves as an ideal case where algorithmic management plays a crucial role in making ends meet (Safran & Che, 2017), and where scholars are seeking to understand the precarious nature of gig work (McKenzie, 2024). Aligning with the scholarly discussion on digital labor in the previous AoIR conference panel (Raman et al., 2024), our study probes into gig workers' understanding of algorithms embedded in crowdsourcing platforms, namely their *Algorithmic Knowledge*. Specifically, we highlight an inconsistency between Turkers' personal understanding of algorithmic operations and Turkers' knowledge of the technical facts about algorithms. By distinguishing these two dimensions of algorithmic knowledge—self-perceived and technical algorithmic knowledge—we explore their distinct roles in shaping Turkers' perceptions of precarity, particularly regarding their job satisfaction, continued work intention, and perception of personal growth.

Although sharing similar research interest in studying algorithms, qualitative and quantitative scholars often conceptualise it differently based on diverged epistemological positions. To qualitative critical scholars, the algorithm and its relevant mechanisms are not understood merely as technological tools but as part of our everyday practice, flowing into the cultural shaping of social norms, values, and understanding of the environment (Seaver, 2017). In this sense, algorithms are understood through users' personal experiences and meaning-making, such as folk theories (Ytre-Arne & Moe, 2021), imaginaries (Bucher, 2019), or 'gossip' (Bishop,

Suggested Citation (APA): Wang, L., Zhou, R. (October 2025). *Technical VS. Self-perceived: Examining Crowdsourcing Worker' Algorithmic Knowledge on Amazon Mechanical Turk*. Paper presented at AoIR2025: The 26th Annual Conference of the Association of Internet Researchers. Niterói, Brazil: AoIR. Retrieved from <http://spir.aoir.org>

2019) under the metaphor of 'black box' (Pasquale, 2015). Quantitative studies, in contrast, often seek to quantify people's knowledge of algorithms through standardised surveys, operating under the assumption that such understanding can be neatly captured (e.g., Cotter & Reisdorf, 2020; Zarouali et al., 2021). In the existing quantitative literature, algorithmic knowledge has been well examined either from a self-perceived perspective to see how people believe their level of knowing algorithmic mechanisms (e.g., Rader & Gray, 2015; Bucher, 2019) or from a technical perspective to examine the extent of how people 'really' understand algorithmic operations, such as knowing the working effects in search engines (Cotter & Reisdorf, 2020). However, these two types of algorithmic knowledge often coexist in Turkers' everyday practice, together shaping how Turkers feel about and making sense of the platform and crowdsourcing work.

Having summarised above, it becomes apparent that two layers of 'rupture' exist within the current literature: one between the quantitative and qualitative inquiries and one between the measurement of self-perceived knowledge and objectively verified knowledge. To excavate the possibility of being situated somewhere in between, our work-in-progress study aims to bridge these 'ruptures' by adopting a mixed-methods approach, combining a quantitative survey with a follow-up qualitative investigation, to study Turker's platform-contingent Algorithmic Knowledge. Through this integration, we propose a *complementary analytical framework* for studying algorithms in the context of gig work: *one that acknowledges the value of quantification for depicting a broad picture of the contemporary crowdsourcing landscape, while recognising interpretive and contextual dimension of algorithmic knowledge through qualitative inquiry*. In the current phase of our study, we conducted a quantitative survey ($N = 190$) to investigate how the two distinct dimensions of algorithmic knowledge—self-perceived and technical knowledge—in the context of MTurk crowdsourcing work affect Turkers' satisfaction with the platform (i.e., continued work intention), the crowdsourcing work (i.e., job satisfaction), as well as their future expectations (i.e., perception of personal growth). By probing into the three cognitive variables, we aim to explicate possible roles that algorithmic knowledge plays in shaping Turkers' perception of precarity regarding job loss and an uncertain future (Gallie et al., 2017). [*Full rationale of why examining the three dependent variables will be explained in the final paper*]

Methods

To investigate the role of two types of algorithmic knowledge in the relationships between Turkers' job satisfaction, continued work intention, and perception of personal growth, an online survey was administered via Prolific—a third-party platform for recruiting research participants—in October 2024. Purposive sampling was adopted to target respondents with work experience on MTurk using the prescreen function provided on Prolific, yielding the final sample size of 168. The decision to use Prolific instead of directly recruiting respondents from MTurk is twofold: one is due to practical consideration regarding the surge in low-quality data on MTurk in recent years (Chmielewski & Kucker, 2020); the other is about data reliability, by asking respondents questions about MTurk outside of the platform, the study alleviates Turkers' concerns towards possible platform surveillance (Wood & Monahan, 2019), thereby reducing potential noises. Respondents' algorithmic knowledge was measured through eight

exam-style questions assessing their understanding of algorithms in a general sense and specific awareness and knowledge within the context of MTurk ($M = 4.28$, $SD = 1.64$). For their self-perceived algorithmic knowledge, respondents were asked to self-report how well they think they understand the algorithms embedded in MTurk using an 8-point scale ($M = 3.82$, $SD = 2.11$). Other variables, including the degree of their platform engagement ($M = 10.82$, $SD = 13.84$), community engagement ($M = 2.91$, $SD = 1.21$), job satisfaction ($M = 3.09$, $SD = 1.29$, $\alpha = .90$), perception of personal growth ($M = 2.96$, $SD = 1.16$, $\alpha = .79$), continued work intention ($M = 3.02$, $SD = 1.16$, $\alpha = .76$), and controlled variables (demographic variables including gender, age, education, income, employment status; total working time; other crowdsourcing platform usage; and use of extra 'tricks'), were also measured. [*Due to the word limitation, full measure details will be explained in the final paper*]

Findings and Discussion

After performing multiple regression analyses using SPSS (see Table 1), we found that self-perceived algorithmic knowledge could significantly impact on Turkers' job satisfaction, perception of personal growth, and continued work intention. Technical algorithmic knowledge, in contrast, does not appear to have any significant effects. The significance of self-perceived algorithmic knowledge and the irrelevance of technical algorithmic knowledge reveal that what matters is not how well the crowdsourcing workers know the algorithm functions, but how well they believe they know, in other words, their level of confidence. Based on this finding, the study then employed an explanatory sequential design to conduct online semi-structured interviews with survey participants (in progress, currently $N = 4$) to better understand how Turkers make sense of the two dimensions of algorithmic knowledge in their everyday work, particularly focusing on those who appear overconfident (self-perceived knowledge greater than technical knowledge). During the interviews, interviewees revealed a tendency to place greater emphasis on self-perceived knowledge than on technical knowledge and expressed that their self-perceived knowledge is shaped not only by platform-specific engagements but also by feelings and experiences derived from other contexts (e.g., their full-time job).

Importantly, interviewees from the U.S. and South Africa interpreted self-perceived knowledge differently: U.S. participants described it as a matter of self-belief, independent of technical competence, whereas South African participants often emphasized the foundational role of technical knowledge in shaping self-perception. This variation to some extent points to the need for a nuanced and context-contingent investigation of the construction of self-perceived algorithmic knowledge, echoing the call to "challenge Western universalism and diversify the geographies of theory" (Poell et al., 2025, p.5).

Taking together from both the quantitative and qualitative findings, we argue that in the context of crowdsourcing work, Turkers are "playing" with the algorithmic system (Cotter, 2018) as they believe they are able to, but in a safe way under the control of platform governance. Compared with direct platform regulations, this form of governance is more subtle, nudging Turkers into a state in which their precarious feelings are dismantled as they come to believe in their algorithmic knowledge, while

the platform’s algorithmic systems can be maintained with ease, with workers’ continuous work and the irrelevance of technical algorithmic knowledge. One possible way to achieve such subtle governance, as we observed, could be the deliberate level of transparency regarding its algorithmic applications, disclosed by the platform itself, such as through its FAQs or policies pages (e.g., MTurk, 2018). Transparency, in this sense, can be regarded as a way of controlling rather than resistance to that control: with massive quantities of MTurk platform regulations and policies, the important piece of information that contributes to forming technical algorithmic knowledge is hidden, making it more burdensome to identify useful information without being distracted by unimportant ones (Ananny & Crawford, 2018; Stohl et al., 2016).

Table 1. Results of Multiple Regression Analysis Predicting Turkers' Job Satisfaction, Perception of Personal Growth, and Intentions for Continued Use of MTurk From Self-perceived Algorithmic Knowledge and Technical Algorithmic Knowledge

	Job Satisfaction		Perception of Personal Growth		Continued Use Intention	
	B	SE	B	SE	B	SE
Gender (male = 1)	-.40*	(.17)	-.27	(.14)	-.25	(.16)
Age	-.07	(.08)	-.08	(.07)	-.02	(.08)
Education	.24*	(.12)	.09	(.10)	.11	(.11)
Household income	-.06	(.07)	-.06	(.06)	.04	(.07)
Employment status	-.10	(.12)	-.06	(.10)	-.17	(.11)
Total working time (by months)	.00	(.00)	.01	(.00)	.00	(.00)
Other crowdsourcing platform use	.08	(.06)	.03	(.05)	.02	(.06)
Extra ‘tricks’ use	-.07	(.07)	.02	(.06)	-.06	(.06)
Platform engagement	.02*	(.01)	.01	(.01)	.02*	(.01)
Community engagement	.17*	(.09)	.23**	(.08)	.15	(.08)
Self-perceived Algorithmic Knowledge	.18***	(.05)	.19***	(.05)	.19***	(.05)
Technical Algorithmic Knowledge	.04	(.05)	.01	(.04)	-.02	(.05)
(Constant)	1.13	(.73)	1.38*	(.64)	1.51*	(.70)
R^2	.43***		.45***		.39***	
N	168		168		168	

Note. Entries are unstandardized coefficients. * $p < .05$, ** $p < .01$, *** $p < .001$.

References

Ananny, M., & Crawford, K. (2018). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Society*, 20(3), 973–989. <https://doi.org/10.1177/1461444816676645>

- Bishop, S. (2019). Managing visibility on YouTube through algorithmic gossip. *New media & society*, 21(11-12), 2589-2606.
- Bucher, T. (2019). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. In *The social power of algorithms* (pp. 30-44). Routledge. <https://doi.org/10.1080/1369118X.2016.1154086>
- Chambers, S., & Nimon, K. (2019). Conducting survey research using MTurk. In S. Chambers, K. Nimon (Eds.) *Crowdsourcing: Concepts, methodologies, tools, and applications* (pp. 410 –439). IGI Global.
- Chmielewski, M., & Kucker, S. C. (2020). An MTurk crisis? Shifts in data quality and the impact on study results. *Social Psychological and Personality Science*, 11(4), 464-473.
- Cotter, K. (2018). Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New Media & Society*, 21(4), 895–913. <https://doi.org/10.1177/1461444818815684>
- Cotter, K., & Reisdorf, B. C. (2020). Algorithmic knowledge gaps: A new horizon of (digital) inequality. *International Journal of Communication*, 14, 21.
- Follmer, D. J., Sperling, R. A., & Suen, H. K. (2017). The role of MTurk in education research: Advantages, issues, and future directions. *Educational Researcher*, 46(6), 329-334.
- Gallie, D., Felstead, A., Green, F., & Inanc, H. (2017). The hidden face of job insecurity. *Work, employment and society*, 31(1), 36-53.
- Hunt, N. C., & Scheetz, A. M. (2019). Using MTurk to distribute a survey or experiment: Methodological considerations. *Journal of Information Systems*, 33(1), 43-65.
- McKenzie, M. D. J. (2024). Precarious Participants, online labour platforms and the academic mode of production: examining gigified research participation. *Critical Sociology*, 50(2), 241-254.
- Moreschi, B., Pereira, G., & Cozman, F. G. (2020). The Brazilian Workers in Amazon Mechanical Turk: dreams and realities of ghost workers. *Contracampo*, 39(1).
- MTurk. (2018, May 17). *Acceptable Use Policy*. <https://www.mturk.com/worker/acceptable-use-policy>

- Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press.
- Poell, T., Duffy, B. E., Nieborg, D., Mutsvauro, B., Tse, T., Arriagada, A., ... & Sun, P. (2025). Global perspectives on platforms and cultural production. *International Journal of Cultural Studies*, 28(1), 3-20. <https://doi.org/10.1177/13678779241292736>
- Rader, E., & Gray, R. (2015). Understanding user beliefs about algorithmic curation in the Facebook News Feed. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*(pp. 173–182). Association for Computing Machinery.
- Raman, U., Premika, A., Mehta, C., Rangaswamy, N., & Madapathi, M. (2024, October). *Constructing the digital: working from the Global South*. Panel presented at AoIR2024: The 25th Annual Conference of the Association of Internet Researchers. Sheffield, UK: AoIR. Retrieved from <http://spir.aoir.org>
- Safran, M., & Che, D. (2017). Real-time recommendation algorithms for crowdsourcing systems. *Applied Computing and Informatics*, 13(1), 47-56.
- Seaver, N. (2017). Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big Data & Society*, 4(2). <https://doi.org/10.1177/2053951717738104>
- Stohl, C., Stohl, M., & Leonardi, P. M. (2016). Digital age| managing opacity: Information visibility and the paradox of transparency in the digital age. *International journal of communication*, 10, 15.
- Wood, D. M., & Monahan, T. (2019). Platform surveillance. *Surveillance & society*, 17(1/2), 1-6.
- Ytre-Arne, B., & Moe, H. (2021). Folk theories of algorithms: Understanding digital irritation. *Media, Culture & Society*, 43(5), 807-824. <https://doi.org/10.1177/0163443720972314>
- Zarouali, B., Helberger, N., & De Vreese, C. H. (2021). Investigating algorithmic misconceptions in a media context: Source of a new digital divide?. *Media and Communication*, 9(4), 134–144. <https://doi.org/10.17645/mac.v9i4.4090>