2024

Understanding the Concept of Platform Control in the Context of Content Creators: Initial Insights from Scale Development

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Understanding the Concept of Platform Control in the Context of Content Creators: Initial Insights from Scale Development

Research in Progress

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Abstract. In the digital era, platform work has become prevalent, with millions of individuals striving to become influencers on popular social media platforms, like YouTube and Instagram. However, despite its benefits, platform work exposes content creators to the pervasive influence of algorithms that exert control over their activities. With content creation rapidly developing into a booming industry, there is a pressing need to better understand content creators' perceptions of platform control, including its dimensionality and implications for creators' well-being, performance, and creativity. Developed as part of a larger research project, we present the initial steps of the scale development process for platform control in this research-in-progress paper. This initial step contributes to a better understanding of the evolving landscape of digital work and its broader implications for individuals and society.

Keywords: Platform control, algorithmic control, content creators, social media platforms, scale development

1 Introduction

The arrival of content platforms such as YouTube and Instagram has opened up new venues for monetizing individual creativity and skills, giving rise to the rapid proliferation of a new group of professionals known as content creators (Hödl & Myrach 2023; Leung et al. 2022). Importantly, this new approach to work comes with a unique twist: content creators no longer have human managers to interact with (Cram et al. 2022); instead, they engage with platform algorithms, guidelines, and policies (Caplan & Gillespie 2020) that, together with the feedback from the audience, direct activities they pursue on the platform (Cheng et al. 2014).

Indeed, platform providers go to great lengths to manage the behavior of content creators. For instance, content creators are constantly evaluated based on performance metrics such as the number of views, video ratings, and the number of subscribers (Qiu et al. 2015) that implicitly steer them towards achieving corporate objectives (Cram et al. 2022). This manifestation of platform control is not always benevolent. Often mistakenly referred to as neutral and unbiased (Mittelstadt et al. 2016), platform algorithms are opaque, leading to uncertainty and hindering sensemaking (Möhlmann et al. 2023). Reflecting on control as "a sense of pressure, a sense of having to engage in the actions" enticed by a platform provider (Gagné & Deci 2005 p. 334), perceptions of platform control are likely to have far-reaching consequences for content creators' performance and well-being. Indeed, whereas controlling environments have been shown to negatively affect employees' health and work outcomes, environments fostering employee autonomy have been associated with an array of positive consequences (Deci et al. 2001; Gagné & Deci 2005).

With over 50 million people considering "themselves to be influencers" and "investments into the creator space" reaching $5 billion in 2021 (Gagliese 2022), it is crucial to understand how content creators interpret, make sense of, deal with, and are influenced by the near-daily exposure to platform control. Indeed, as more people are expected to work on digital platforms in the coming years (European Commission 2018; Mäntymäki et al. 2019), discerning content creators' perceptions of platform control, including its dimensionality, as well as the implications in terms of its impact on creators (e.g., Spiekermann et al. 2022). In pursuit of this goal, we focus on the following research question: *What are the dimensions of platform control as content creators perceive it, and how can these dimensions be measured?* To answer this research question, we build on the previous work to conceptualize the construct of perceived platform control, including its underlying dimensions (e.g., Hödl & Myrach 2023) (Section 2). In the next step, we present the initial steps of scale development, specifically item generation, content validity assessment, and scale refinement (Section 3). To conclude, we summarize our study's theoretical and managerial implications (Section 4).

2 Conceptual Background

Self-determination theory suggests that individual motivation is a function of the satisfaction of psychological needs (Ryan and Deci 2000). Importantly, the satisfaction of these needs is contextual, with factors pertaining to the social environment playing a major role in these processes (c.f., Gagné & Deci 2005). Specifically, work environments that support employee autonomy have been consistently linked to workers' need satisfaction, which, in turn, positively contributes to employee performance, job satisfaction, and favorable attitudes (Deci et al. 1989; Gagné & Deci 2005). At the same time, controlling social environments have been shown to produce the opposite effect (Cram et al. 2022; Gagné & Deci 2005).

The arrival of platforms that connect workers with customers online has spurred major interest in the effects of this transformation (Möhlmann et al. 2021; Wiener et al. 2021). Making use of digital capabilities, these platforms employ algorithms to guide and align user behavior with corporate goals (Bonina et al. 2021; Cram et al. 2022), thereby exercising control over workers' decisions and behavior. For example, online labor platforms have been shown to use algorithms for monitoring, goal setting, performance measurement, scheduling, compensation, and even job termination (Parent-Rocheleau & Parker 2022). In doing so, algorithms restrict, recommend, record, rate, replace, and reward workers (Kellogg et al. 2020). So far, platform control has been predominantly examined in the context of online labor platforms, such as Uber (Möhlmann et al. 2021; Wiener et al. 2021). At the same time, social media platforms exhibit distinct characteristics (Bonina et al. 2021). While online labor platforms typically monitor workers during the execution of their tasks, social media platforms lack oversight over content creators during the process of content creation. This and other differences call for a differentiated view of the dynamics of platform control in the context of content creators on social media platforms.

In their recent study, Hödl & Myrach (2023) find that content creators distinguish between algorithmic control, algorithmic distribution, and monetary control. In this context, they demonstrate that platform control via algorithms and revenue sharing can create paradoxical tensions with content creators' autonomy, particularly in scheduling and decision-making. Building on these insights, we propose that platform control on social media platforms can manifest itself in five distinct ways (see Table 1). Specifically, distribution control, monetary control, and metrics control (previously referred to as "algorithmic control"), as specified by Hödl & Myrach's (2023), represent three viable ways of steering the behavior of content creators. Further, by exercising control over scheduling and content decision-making, platforms may also interfere with the autonomy of content creators in these areas (Hödl & Myrach 2023).

Table 1. Construct Overview

Construct Definition	Control Practices, Enablement, Goals
Distribution control refers to the influence platform providers exert over the distribution of content shared by content creators on the platform.	• Algorithmic matching of content to user preferences/ target audiences[1]. • Is exercised by steering the reach of content shared on the platform[2]. • Limiting content distribution when content creators are shadow-banned[3].
Metrics control refers to the influence of metrics that platform providers integrate to aggregate data on content performance/user engagement to steer the behavior of content creators.	• Aligns content with the specific objectives of the platform[4]. • Evaluation of content and content creators' performance in real-time[4]. • Metrics allow platform providers to observe, analyze, rate, and guide the activities of content creators[2].
Monetary control refers to the influence of monetary incentives by the platform provider to steer the behavior of content creators.	• The advertising revenue per video from platforms[5]. • Incentivizes "advertiser-friendly" content for maximal advertising revenue[6]. • Rewards or penalizes content creators for adhering to or violating guidelines[6].

Scheduling control refers to the degree of control platform providers exert over the planning and timing of content creation.	• Incentives for consistent content production and sharing[2]. • Affects ways content creators time, prioritize, and organize the process of content creation and sharing[2]. • Interferes with creators' ability to set schedules based on their personal preferences[2].
Content control refers to the degree of control platform providers exert over the content that is permitted to be shared on the platform.	• Demonetizes[6] or shadow bans[3] content creators for violating guidelines. • Incentivizes non-controversial content that attracts the maximum number of advertisers[6]. • Restrict the freedom of expression and topic selection[6].
References: [1] Bonina et al. (2021); [2] Hödl & Myrach (2023); [3] Cotter (2021); [4] Cram et al. (2022); [5] Tang et al. (2012); [6] Caplan & Gillespie (2020)	

3 Operationalizing Platform Control: Scale Development

To operationalize the construct of platform control, we followed well-established guidelines, such as Hinkin (1998), MacKenzie et al. (2011), and Moore & Benbasat (1991). The first step of scale development began with conceptualization, where we outlined the conceptual definitions for the constructs (see Section 2). Next, we will discuss the three steps in the development of measures: item generation, content validity assessment, and scale refinement (MacKenzie et al. 2011).

First, for item generation, items can originate from various sources. They are commonly derived deductively from reviewed literature and theory, or created inductively through empirical research such as interviews or focus groups with experts and representatives of the population (MacKenzie et al. 2011). We initially created items based on existing literature and empirical data gathered by the first author based on interviews with content creators. These interviews were part of a larger research project, the findings of which have already been published (Hödl & Myrach 2023). We drew inspiration from previously tested scales, all of which had been validated within the context of online labor platforms (c.f., Alizadeh et al. 2023; Cram et al. 2022; Parent-Rocheleau et al. 2023). However, due to the distinct nature of social media platforms, items from existing scales were not applicable to our context or had to be heavily adjusted. Hence, we adapted or newly developed the items. Due to the authors being non-native English speakers, the items were further refined in collaboration with the OpenAI (2024) tool, which was used to add to and refine the initial pool of items. Resulting improvements and suggestions have been carefully reviewed by the authors, resulting in a few rounds of iterations. The goal was to ensure the comprehensive coverage of construct dimensions while upholding simplicity and precision (MacKenzie et al. 2011). As a result, a final pool of items comprising 10 items per construct was developed.

Second, after item generation, the items need to be assessed for their content validity to ensure that the constructs are adequately represented and to eliminate any items found to be conceptually inconsistent or ambiguous (Hinkin 1998; MacKenzie et al.

2011; Moore & Benbasat 1991). Various techniques can be employed for this purpose, including card sorting (Hinkin 1998; Moore & Benbasat 1991), item rating (Hinkin 1998; MacKenzie et al. 2011), and expert interviews (Zhang et al. 2022). As a first step, we conducted a card-sorting procedure to eliminate any items that were unclear or did not adequately represent the constructs (Hinkin 1998; Zhang et al. 2022). The literature suggests a range of 10 to 20 participants as cost-effective and reliable for card sorting (Lantz et al. 2019; Pechlevanoudis et al. 2023). Therefore, we recruited 25 participants via the online panel tool Prolific (Palan & Schitter 2018). We recruited participants on Prolific because it was challenging to contact content creators in our previous research project (Hödl & Myrach 2023), and we wanted to reserve our contact list for the final survey. With this approach, we cannot assume that any of the respondents were actual content creators – a limitation of our study. The following pre-screening options were used: location: all countries available; first language: English; primary language: English; approval rate: 97–100; number of previous submissions: 10–10000; sex: male (50%), female (50%). Respondents received a reward of £4.42 GBP for their participation. We began by briefing participants on the study, including information about data protection regulations, and obtaining their consent. In the next step, participants were introduced to the task, asked to imagine themselves as content creators, and provided with extended definitions of the constructs, which were also refined for clarity and readability using OpenAI (2024). Next, 50 items capturing five platform control dimensions as well as 10 items capturing an additional construct of interest – algorithmic transparency - have been presented to the respondents in a randomized order. Respondents were asked to categorize the items according to the provided definitions. Upon the completion of card sorting, respondents were also asked to assess task difficulty, with the option to leave comments. We inquired about task difficulty to potentially adjust our next steps but did not exclude participants based on their responses. We did not include control questions to verify whether participants accurately understood the definitions of the constructs. However, we pretested the questionnaire with a student assistant who had an average knowledge of social media and readjusted the wording based on the feedback.

We calculated the *average agreement index* (AAI) for each item, which represents the percentage of participants correctly classifying an item. It is recommended that this index be higher than 75% (Hinkin 1998). Overall, our findings show positive results for monetary control and content control, with seven items scoring between 0.76 and 1.0. Scheduling control has four items ranging from 0.76 to 0.84. However, our analysis for items measuring metrics control, and distribution control rendered mixed results. The top four items measuring distribution control have agreement scores ranging from 0.64 to 0.72.

Although the AAI helps us filter out critical items at the item level, one of its biggest criticisms is that it does not account for the agreement by chance, which leads to inflated values (Hallgren 2012). Therefore, we have included two additional measures to assess inter-rater reliability: *Light's kappa* (Light 1971) and the *intraclass correlation coefficient* (ICC) (Shrout & Fleiss 1979). Our design is fully crossed, meaning that all 60 items are rated by all 25 participants (Hallgren 2012), who were selected from a larger population on Prolific. Light's kappa, a variation of Cohen's kappa, measures agreement among more than two raters, who are all the same, and computes the arithmetic mean of the kappa for all rater pairs (Hallgren 2012). The raters demonstrate a lower moderate agreement at 0.428 (Landis & Koch 1977). For the ICC, we used a two-way random-effects model with absolute agreement and multiple measurements (k=25, ICC(2, k)) for our design (Koo & Li 2016). ICC(2, k) indicates the expected reliability for groups of, in this case, 25 raters (Shrout & Fleiss 1979). We employed absolute agreement to determine whether raters consistently assigned the same construct to the same items (Koo & Li 2016; McGraw & Wong 1996). ICC(2, k) resulted in 0.92 ($p < 0.001$, 95% CI: 0.89, 0.95), suggesting excellent reliability for the average of groups of 25 raters (Koo & Li 2016).

Third, for scale refinement, the card sorting did not allow us to determine whether our generated items were inadequate or if the participants deviated too much from the target group. Therefore, as the next step, we conducted three unstructured online interviews (Zhang et al. 2022) with content creators and reviewed all 60 items with them. Based on these interviews, we refined the items. We then verified these changes with the help of a professor in the field of content creation and reduced the items to seven per construct. As the last step, we conducted an item rating task (MacKenzie et al. 2011) with researchers who have published on content creation. The experts were asked to rate the seven items per construct on a 7-point Likert scale ranging from "extremely inappropriate" to "extremely appropriate." In response to our request, we received feedback from five researchers (assistant professor, lecturer, senior lecturer, associate professor, professor). Together, the feedback guided the final revision, resulting in four items per construct (plus a fifth for monetary control, suggested by a survey participant). The following exemplary items[1] are reflective of the platform control dimensions we measured: distribution control: *YouTube has control over whom my video is shown to*; metrics control: *I feel pressure to perform well in terms of the YouTube analytics*; monetary control: *I fear that my videos can be demonetized for no reason*; scheduling control: *YouTube incentivizes me to share content regularly, no matter what*; content control: *YouTube limits my choice of topics I can cover as a content creator.*

4 Study Implications

The procedures described in this research-in-progress paper represent an initial step in scale development. Platform control enables platform providers with a cost-efficient way to align the behavior of content creators with business objectives. However, exerting control can also pose risks to the sustainability of the platforms since controlling environments have been associated with an array of detrimental outcomes (Deci et al. 2001; Gagné & Deci 2005). As more people pursue this novel career path, it is essential to understand the effect of various dimensions of platform control on content creators. While research in this area is still in its early stages, the development of scales provides a first step toward examining this phenomenon.

[1] All scales are available at this link or upon request from the authors.

References

Alizadeh, A., Hirsch, F., Benlian, A., Wiener, M., & Cram, W. A. (2023). Perceived Algorithmic Control: Conceptualization and Scale Development. In *ECIS 2023 Research Papers.*, Vol. 353. Retrieved from https://aisel.aisnet.org/ecis2023_rp/353

Bonina, C., Koskinen, K., Eaton, B., & Gawer, A. (2021). Digital platforms for development: Foundations and research agenda. *Information Systems Journal*, **31**(6), 869–902.

Caplan, R., & Gillespie, T. (2020). Tiered Governance and Demonetization: The Shifting Terms of Labor and Compensation in the Platform Economy. *Social Media + Society*, **6**(2), 1–13.

Cheng, J., Danescu-Niculescu-Mizil, C., & Leskovec, J. (2014). How Community Feedback Shapes User Behavior. *Proceedings of the International AAAI Conference on Web and Social Media*, **8**(1), 41–50.

Cotter, K. (2021). "Shadowbanning is not a thing": black box gaslighting and the power to independently know and credibly critique algorithms. *Information, Communication & Society*, 1–18.

Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2022). Examining the Impact of Algorithmic Control on Uber Drivers' Technostress. *Journal of Management Information Systems*, **39**(2), 426–453.

Deci, E. L., Connell, J. P., & Ryan, R. M. (1989). Self-determination in a work organization. *Journal of Applied Psychology*, **74**(4), 580–590.

Deci, E. L., & Ryan, R. M. (2000). The "What" and "Why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior. *Psychological Inquiry*, **11**(4), 227–268.

Deci, E. L., Ryan, R. M., Gagné, M., Leone, D. R., Usunov, J., & Kornazheva, B. P. (2001). Need Satisfaction, Motivation, and Well-Being in the Work Organizations of a Former Eastern Bloc Country: A Cross-Cultural Study of Self-Determination. *Personality and Social Psychology Bulletin*, **27**(8), 930–942.

European Commission. (2018). *New Report Shows that Digital Employment Platforms Are Gaining a Foothold in Europe's Labour Markets*, European Commission. Retrieved from https://ec.europa.eu/social/main.jsp?catId=89&furtherNews=yes&langId=en&newsId=9146

Gagliese, J. (2022, July 8). The Rise Of The Influencer: Predictions For Ways They'll Change The World. Retrieved from https://www.forbes.com/sites/theyec/2022/07/08/the-rise-of-the-influencer-predictions-for-ways-theyll-change-the-world/

Gagné, M., & Deci, E. L. (2005). Self-determination theory and work motivation. *Journal of Organizational Behavior*, **26**(4), 331–362.

Hallgren, K. A. (2012). Computing Inter-Rater Reliability for Observational Data: An Overview and Tutorial. *Tutorials in Quantitative Methods for Psychology*, **8**(1), 23–34.

Hinkin, T. R. (1998). A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires. *Organizational Research Methods*, **1**(1), 104–121.

Hödl, T., & Myrach, T. (2023). Content Creators Between Platform Control and User Autonomy: The Role of Algorithms and Revenue Sharing. *Business & Information Systems Engineering*, **65**(5), 497–519.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, **14**(1), 366–410.

Koo, T. K., & Li, M. Y. (2016). A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *Journal of Chiropractic Medicine*, **15**(2), 155–163.

Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics*, **33**(1), 159.

Lantz, E., Keeley, J. W., Roberts, M. C., Medina-Mora, M. E., Sharan, P., & Reed, G. M. (2019). Card Sorting Data Collection Methodology: How Many Participants Is Most Efficient? *Journal of Classification*, **36**(3), 649–658.

Leung, F. F., Gu, F. F., & Palmatier, R. W. (2022). Online influencer marketing. *Journal of the Academy of Marketing Science*, **50**(2), 226–251.

Light, R. J. (1971). Measures of response agreement for qualitative data: Some generalizations and alternatives. *Psychological Bulletin*, **76**(5), 365–377.

MacKenzie, Podsakoff, & Podsakoff. (2011). Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques. *MIS Quarterly*, **35**(2), 293.

Mäntymäki, M., Baiyere, A., & Islam, A. K. M. N. (2019). Digital platforms and the changing nature of physical work: Insights from ride-hailing. *International Journal of Information Management*, **49**, 452–460.

McGraw, K. O., & Wong, S. P. (1996). Forming inferences about some intraclass correlation coefficients. *Psychological Methods*, **1**(1), 30–46.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, **3**(2), 205395171667967.

Möhlmann, M., Salge, C. A. de L., & Marabelli, M. (2023). Algorithm Sensemaking: How Platform Workers Make Sense of Algorithmic Management. *Journal of the Association for Information Systems*, **24**(1), 35–64.

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). Algorithmic Management of Work on Online Labor Platforms: When Matching Meets Control. *MIS Quarterly*, **45**(4), 1999–2022.

Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, **2**(3), 192–222.

OpenAI. (2024). ChatGPT (4) [Large language model]. Retrieved from https://chat.openai.com

Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, **17**, 22–27.

Parent-Rocheleau, X., & Parker, S. K. (2022). Algorithms as work designers: How algorithmic management influences the design of jobs. *Human Resource Management Review*, **32**(3), 100838.

Parent-Rocheleau, X., Parker, S. K., Bujold, A., & Gaudet, M. (2023). Creation of the algorithmic management questionnaire: A six-phase scale development process. *Human Resource Management*, hrm.22185.

Pechlevanoudis, C., Zilidis, G., & Katsanos, C. (2023). How Many Participants Do You Need for an Open Card Sort? A Case Study of E-commerce Websites. In J. Abdelnour Nocera, M. Kristín Lárusdóttir, H. Petrie, A. Piccinno, & M. Winckler, eds., *Human-Computer Interaction – INTERACT 2023*, Vol. 14145, Cham: Springer Nature Switzerland, , pp. 80–89.

Qiu, L., Tang, Q., & Whinston, A. B. (2015). Two Formulas for Success in Social Media: Learning and Network Effects. *Journal of Management Information Systems*, **32**(4), 78–108.

Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, **86**(2), 420–428.

Spiekermann, S., Krasnova, H., Hinz, O., … Trenz, M. (2022). Values and Ethics in Information Systems: A State-of-the-Art Analysis and Avenues for Future Research. *Business & Information Systems Engineering*, **64**(2), 247–264.

Tang, Q., Gu, B., & Whinston, A. B. (2012). Content Contribution for Revenue Sharing and Reputation in Social Media: A Dynamic Structural Model. *Journal of Management Information Systems*, **29**(2), 41–75.

Wiener, M., Cram, W. A., & Benlian, A. (2021). Algorithmic control and gig workers: a legitimacy perspective of Uber drivers. *European Journal of Information Systems*, **32**(3), 485–507.

Zhang, N. (Andy), Wang, C. (Alex), Karahanna, E., & Xu, Y. (2022). Peer Privacy Concerns: Conceptualization and Measurement. *MIS Quarterly*, **46**(1), 491–530.