Unraveling the impact of prolific: Exploring the presence of bias when studying psychological constructs related to the use of technology

Margherita Lanz[a], Rossella Caliciuri[a*], Alessia Spina[a], Anna Ongaro[a], Gaia Virginia De Sanctis[a], Gabriella Anna Vaughn[a], Marta Mastroni[a], Martina Barbieri[a], Martina Milani[a], Angela Sorgente[a]

[a] Department of Psychology,
Università Cattolica del Sacro Cuore, Milan
* *Corresponding author*, e-mail: rossella.caliciuri@unicatt.it

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Abstract

This study investigates potential biases in data collected through online paid platforms, specifically Prolific, compared to traditional snowball convenience sampling, when studying psychological constructs related to technology. The researchers analyzed data from a separate study examining ChatGPT adoption among Italian university students, using both Prolific and snowball sampling methods. Three technology-related constructs were examined: technology self-efficacy (SE), technology anxiety (AX), and social norms related to technology use (SN). Analysis of covariance revealed a significant difference between groups in technology self-efficacy (SE), with Prolific participants exhibiting higher scores. No significant differences were found in AX and SN. The findings highlight potential selection bias, suggesting Prolific may attract participants with higher technological confidence. It is important to stress that this difference may also reflect a combination of self-selection into the platform, the presence of financial compensation, and the inherent biases of convenience snowball samples. The study underscores the importance of considering such recruitment-related biases when generalizing research findings, particularly in technology-related studies, and emphasizes the need for transparency in reporting sampling methods.

Key words: bias, sampling, technology, Prolific, ChatGPT, data quality

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Introduction

In recent years, there has been a growing trend in utilizing online paid platforms for research recruitment (Buhrmester et al., 2018; Goodman & Paolacci, 2017; Palan & Schitter, 2018; Peer et al., 2014). These platforms offer a cost-effective means of collecting data from a large pool of individuals in a relatively short period of time (Peer et al., 2014).

There are several online paid platforms for research recruitment. The most commonly used are MTurk (also known as Amazon Mechanical Turk), CloudResearch, Prolific, and Qualtrics (Douglas et al., 2023). Specifically, MTurk recruits participants from its own pool of workers, where surveys are posted and appear on the dashboard of eligible workers who are compensated with Amazon credit; CloudResearch utilizes the MTurk Toolkit to collect data from MTurk, applying quality filters to ensure reliable data, with participants also being paid through Amazon credit; Prolific operates similarly to MTurk but uses its own pool of participants, who are paid by cash for completing surveys; finally, Qualtrics employs various recruitment methods, including direct emails to participants, who are compensated with cash, gift cards, air miles, or coupons based on their preferences (Douglas et al., 2023).

Palan & Schitter (2018) note that Prolific stands out as a platform specifically dedicated to online research recruitment, unlike general crowd working platforms such as MTurk. Prolific is designed to offer targeted recruitment standards and clearly inform participants that are taking part in research studies (Bock et al., 2014; Greiner, 2015; Palan & Schitter, 2018). Thanks to these characteristics, the platform effectively combines high data quality and reasonable costs, making it very popular among researchers in various fields, including economics (Marreiros et al., 2017) and psychology (Douglas et al., 2023).

The main concerns when using online platforms for data collection are issues related to data quality and sampling (Newman et al., 2021). Several studies have compared the quality of data obtained from online recruitment platforms with data from traditional sources, consistently demonstrating that online platforms can provide high-quality data. Participants recruited through these platforms tend to pass attention checks, perform well on tasks, and score high on measures of reliability (Hauser & Schwarz, 2016). For example, a meta-analysis by Walter et al. (2019) examined 90 independent samples involving 32.121 participants and found that data collected via online platforms showed psychometric properties and validity comparable to traditional sources. In particular, estimates derived from online panel data fall within the credible range (i.e., statistical intervals used to express the uncertainty around an estimate) of estimates obtained from traditional data sources. A more recent study by Douglas et al. (2023) evaluated data quality across different platforms, including MTurk, Prolific, CloudResearch, Qualtrics, and a system used at the University of Wisconsin-Madison to recruit undergraduate students for research participation. The study assessed various quality indicators such as attention checks, response times, scale reliabilities, and test-retest consistency. It also looked at open-ended responses, video content recall, and participant uniqueness. The results indicated that Prolific consistently provided the highest data quality, with participants excelling in attention checks, video recall tasks, and maintaining reliable and consistent data. Moreover, Prolific offered an excellent balance between quality and cost, with a cost per high-quality respondent that was considerably lower than MTurk and Qualtrics, and comparable to CloudResearch.

Albert and Smilek (2023) highlighted differences between Prolific and MTurk in terms of attentional engagement. Their study revealed that MTurk samples showed greater disengagement, higher rates of multitasking, and lower task performance. Also, Arechar and Rand (2021) found that Prolific participants exhibited higher engagement than those on MTurk. This difference is attributed to Prolific's compensation policy, which incentivizes higher data quality by allowing researchers to withhold payment for responses showing signs of disengagement or inattention.

In conclusion, the evidence indicates that Prolific is the leading online paid platform for research recruitment, providing the highest data quality in terms of participant engagement, reliability, validity, reproducibility, attentional bias, participant diversity, and overall response quality. Given these strengths, Prolific emerges as the superior choice for researchers seeking reliable and cost-effective data collection solutions.

In recent years, data collection practices in psychology have shifted from reliance on traditional convenience and snowball sampling toward the recruitment of participants through paid online platforms such as Prolific. Whereas snowballing was once among the most common sampling strategies, online platforms are now increasingly adopted for their efficiency and reach. Importantly, this shift raises the question of whether the change concerns only recruitment procedures or also reflects a substantive transformation of the sampling frame. In other words, the transition may be not only methodological but also demographic, as the populations accessible through Prolific may differ systematically from those typically reached via traditional recruitment methods.

Regarding sampling concerns, participant recruitment methods must always be taken into account – whether through online recruitment platforms like Prolific or MTurk, or through traditional methods – as it can introduce significant biases. Indeed, participants may choose to take part in particular research projects based on individual preferences, personal experiences, or other undisclosed factors, which could potentially influence the research findings (Cheung et al., 2017). All these factors related to participant selection and data collection procedures represent potential biases and could affect the outcomes of research, especially when investigating any psychological construct (Buchanan, 2018; Cheung et al., 2017).

Some researchers have raised concerns about the personality profiles of respondents who choose to participate in studies using online paid platforms for research recruitment, as the results may be skewed by the participants' personality traits, potentially affecting the generalizability of the findings. For instance, Buchanan's (2018) study found that participants recruited through online paid platforms tend to have higher levels of "Openness to Experience," one of the Big Five personality traits. This could have significant implications for the other constructs being studied.

We argue that the psychological profiles of respondents participating in studies using online paid platforms, compared to the ones of respondents selected through traditional sampling methods, may differ, not only in terms of personality but also in technology-related psychological constructs such as self-efficacy, anxiety, or perceived social norms regarding technology use. This is because people who choose to register on platforms like Prolific likely have a certain level of technological proficiency, making technology a particularly relevant domain for them.

We believe that the field would benefit from a greater focus on how much online paid platforms provide (un)biased data depending on the nature and content of the constructs being explored. In the current study we verified whether respondents collected through paid platforms are comparable to respondents collected through traditional sampling in the specific case the studies investigate technology-related psychological constructs. The decision to compare respondents collected through paid platforms with those gathered via traditional sampling methods, particularly snowball convenience sampling, is based on the fact that the aforementioned studies utilize this type of sampling as a traditional source (Hauser & Schwarz, 2016; Walter et al., 2019). We utilized data from a separate study investigating technology-related constructs. This study employed both Prolific and traditional recruitment methods to gather data. Specifically, the study examined ChatGPT adoption among 410 Italian students; 202 were recruited via snowball convenience sampling, and 208 via Prolific. The variables from this study relevant to our research are technology self-efficacy (SE), technology anxiety (AX), and social norms related to technology use (SN).

In particular, technology self-efficacy (SE) refers to an individual's confidence in their ability to effectively use technological tools to achieve specific goals (Ni & Cheung, 2023). Technology anxiety (AX) describes the negative emotions and discomfort that individuals may experience regarding the use of technology. This anxiety can negatively impact technology adoption, as anxious individuals tend to feel reluctant or hesitant to use technological tools, especially when they fear they may not be able to use them successfully (Ni & Cheung, 2023). Finally, social norms (SN) related to technology use indicate the perceived social pressure individuals feel when deciding whether or not to adopt a specific behavior, such as using technology. Social norms influence people's decisions by serving as a justifying factor and can determine the intention to engage in a particular action based on what others consider appropriate or desirable (Aburbeian et al., 2022).

The present study

The present study aims to examine whether data collected through Prolific differ from data collected through traditional snowball convenience sampling when investigating psychological constructs related to technology. Although previous research has consistently demonstrated that online paid platforms provide high-quality data (e.g., Douglas et al., 2023; Walter et al., 2019), less is known about whether these samples are comparable to those obtained through traditional recruitment methods when the constructs under study are closely tied to technology use. This gap is particularly relevant because individuals who choose to register on Prolific are likely to possess a certain level of technological proficiency, which may affect their responses on technology-related measures.

Based on this reasoning, the present study set out to examine whether participants recruited through Prolific differ from those recruited via snowball sampling with respect to technology-related psychological constructs. We focused on three dimensions that are particularly relevant when considering individuals' relationship with technology: technology self-efficacy (SE), technology anxiety (AX), and social norms related to technology use (SN). In line with the assumption that individuals registered on Prolific are typically more familiar and comfortable with digital tools, we hypothesized that Prolific participants would report higher scores on all three constructs.

Method

Participants

Among the 410 Italian university students who participated in the study, 202 were recruited through snowball convenience sampling and 208 via Prolific. Inclusion criteria for both groups included being Italian and being university students.

A total of 202 participants, aged between 19 and 36 years, were recruited using snowball convenience sampling. (M = 22.35; S.D. = 2.39). The majority of participants, (66.2%), identified as female and were enrolled in a psychology faculty (31.1%), followed by those in an engineering faculty (15.3%). More broadly, according to the MIUR classification (Ministry of Education, University, and Research [MIUR], 2019), 64.9% of these participants are enrolled in a humanities or social sciences, and 35.1% in a scientific or technological faculty.

The remaining 208 participants were recruited via Prolific and were aged between 20 and 32 years (M = 24.10; S.D. = 2.52). The majority, (51.0%), identified as female and were enrolled in an engineering faculty (18.8%), followed by those in foreign languages and literature faculties (13.9%). More broadly, according to the MIUR classification (2019), 47.6% of these participants were enrolled in humanities or social sciences, and 52.4% in a scientific or technological faculty.

To determine if the two samples – one collected through snowball convenience sampling and the other via Prolific – were equivalent in terms of gender, age, and field of study, we conducted two chi-square analyses (for the categorical variables, gender and faculty) and a binary logistic regression (for the continuous variable, age). As the two sub-groups were not equally balanced for gender [χ^2 (1) = 8.584; $p = .003$; Cramer's V = .146; n = 401], field of study [χ^2 (1) = 11.269; $p < .001$; Cramer's V = .174; n = 372], and age [OR = 1.375, $p < .001$; Nagelkerke $R^2 = .158$; n = 410], we included these three socio-demographic variables as control variables in the following analysis and we run to compare the two samples regarding their levels on technology-related psychological constructs.

Procedure

The study was approved by the Ethics Committee of Università Cattolica del Sacro Cuore, and all participants provided written informed consent before participating in the research. The study consisted of a survey administered online. Participation in the survey was voluntary, whereby participants were recruited in May 2023 using a combination of snowball convenience sampling and the Prolific platform. Participants recruited through snowball convenience sampling did not receive any compensation, while those recruited through Prolific were compensated according to the platform's guidelines. Email invitations were sent to university students aged 18 and older. All university students who received the email invitation were asked to share the survey with other Italian university student. Individuals who agreed to take part in the study received online informed consent in accordance with the Declaration of Helsinki and, if the consent form was signed, participants were given access to the survey. The online survey was administered through Qualtrics and took approximately 20 minutes to be completed.

Measures

Besides providing socio-demographic data, participants were asked to complete different questionnaires. The variables used for this study are technology self-efficacy (SE), social norms related to technology anxiety (AX), and technology use (SN). These variables were all composed by items evaluated on a Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). For each scale, Confirmatory Factor Analysis (CFA) was performed. For further details on the factor structures of the scales, please refer to the original paper (Caliciuri et al., under review).

Specifically, *technology self-efficacy* (SE) was measured through four items taken from the study by Ni and Cheung (2022), for example: "I am able to use a new technology even if there is no one to show me how"; internal consistency score was good (McDonald's ω = .887). *Technology anxiety* (AX) was evaluated through four items taken from Guner and Acarturk (2020), for example: "I hesitate to use new technologies for fear of making mistakes that I cannot correct"; internal consistency score was good (McDonald's ω = .830). Finally, *social norms related to technology use* (SN) were assessed through two items taken from the study by Aburbeian et al. (2022), for example: "Others' opinions about new technologies influence my intention to use them"; these two items are adequately correlated with each other (Spearman $\boldsymbol{\rho}$ = .452) suggesting that the score is reliable (Eisinga et al., 2013).

Data Analysis

We first estimated descriptive statistics for each variable of the study using SPSS (version 29; IBM Corp., 2023).

To investigate potential differences between the two samples in the three technology-related variables (SE, AX, SN), we conducted three ANCOVAs or Analysis of Covariance. ANCOVA is a statistical technique that allows us to examine whether there are significant differences between groups on a dependent variable while controlling for the effects of one or more covariates. In our analysis, the independent variable was the sample origin (Prolific vs. Snowball Convenience), while the technology-related variables (SE, AX, SN) were included individually as dependent variables in the model. Additionally, since the two samples were not equivalent in terms of gender, age, and field of study, the model controlled for these demographic variables as covariates. To this end, we examined the main effect not only of the sample origin but also of the three control variables: gender, age, and field of study. This approach allows us to claim that the main effect of the sample origin can be significant regardless of the main effects of the control variables (Jamieson, 2004; Stanley, 2022). Furthermore, we also included all the interaction effects involving the independent variable "sample origin" in order to verify how its effect interacted with the control variables (Jamieson, 2004; Stanley, 2022). All analyses were performed using SPSS version 29 (IBM Corp., 2023).

Results

Descriptive Statistics

In Table 1, we reported the mean and the standard deviation for each variable investigated in this study, divided by the two samples collected.

Tab. 1 - Descriptive Statistics

			Snowball convenience sample		Prolific sample	
	min	max	M	S.D.	M	S.D.
Technology self-efficacy (SE)	1	5	3.68	0.84	4.16	0.68
Technology anxiety (AX)	1	5	2.29	0.97	2.00	0.80
Social norms related to technology use (SN)	1	5	2.42	0.98	2.54	0.88

Note. Snowball convenience sample*, N = 202; Prolific sample, N = 208.*

ANCOVA

To investigate potential differences between the two samples in the three technology-related variables (SE, AX, SN), we conducted three ANCOVAs.

Regarding technology SE, the test of between-subjects effects indicates a significant effect of the sample origin, [F (1,291) = 8.924; p = .003; η^2 = .030; n = 365] controlling for control variables (gender, field of study, age). These findings indicate that the technology SE score, regardless of respondents' gender, age, and field of study, is always higher in the sample recruited through Prolific (M = 4.17; S.D. = .69) compared to the snowball convenience sample (M = 3.69; S.D. = .83). All the interaction effects involving sample origin are not significant: sample origin*gender [F (1,291) = .008; p = .927]; sample origin*age [F (1,291) = .514; p = .824]; sample origin*field of study [F (1,291) = .588; p = .444].

Regarding technology AX, the test of between-subject effects reveals a non-significant effect of sample origin, [F (1,291) = 1.491; p = 0.223; η^2 = .005; n = 365]. All the interaction effects involving sample origin are not significant: sample origin*gender [F (1,291) = .120; p = .730]; sample origin*age [F (1,291) = .593; p = .762]; sample origin*field of study [F (1,291) = 1.067; p = .302].

Regarding SN related to technology use, the test of between-subjects effects indicates a non-significant effect of the sample origin, [F (1,290) = 1.784; p = .183; η^2 = .006; n = 364]. All the interaction effects involving sample origin are not significant: sample origin*gender [F (1,290 = .065; p = .799]; sample origin*age [F (1,290) = .731; p = .646]; sample origin*field of study [F (1,290) = 2.320; p = .129].

Discussion

In recent years, there has been an increasing trend in the use of online paid platforms for research recruitment (Buhrmester et al., 2018; Goodman & Paolacci, 2017; Palan & Schitter, 2018; Peer et al., 2014). Among these platforms, Prolific stands out as one of the most widely used for research recruitment. Unlike general crowd working platforms such as MTurk, Prolific is specifically dedicated to online research recruitment (Palan & Schitter, 2018). This platform effectively balances high data quality with reasonable costs, making it highly popular among researchers across various fields (Douglas et al., 2023).

Key concerns in using online platforms for data collection revolve around data quality and sampling issues (Newman et al., 2021). Numerous studies have compared the quality of data obtained from online recruitment platforms with that from traditional sources, consistently demonstrating that online platforms can yield high-quality data. In this context, the studies we reviewed (Albert and Smilek, 2023; Arechar & Rand, 2021; Douglas et al., 2023; Walter et al., 2019) highlight that Prolific is the leading online paid platform for research recruitment, offering superior data quality in terms of participant engagement, reliability, validity, reproducibility, attentional bias, diversity among participants, and overall response quality. Regarding sampling concerns, it is crucial to consider participant recruitment methods, as these can introduce significant biases. Participants may choose to participate in specific research projects based on individual preferences, personal experiences, or other undisclosed factors, which could potentially impact the research findings (Buchanan, 2018; Cheung et al., 2017). Additionally, it is essential to consider whether the results obtained from individuals registered on Prolific (or similar platforms) can be generalized to those who are not registered, assuming that there are no differences between the two types of respondents.

In the current study, we aimed to determine whether respondents recruited through paid platforms (Prolific) are comparable to those gathered through traditional sampling methods, particularly in the context of studies investigating technology-related psychological constructs. We expected individuals who decided to register in a platform that implies the use of technology (e.g., online surveys) may be not fully comparable to individuals not registered to such platforms, particularly with respect to technology-related psychological constructs such as self-efficacy, anxiety, or perceived social norms regarding technology use. The choice to compare respondents collected via paid platforms with those obtained through traditional sampling methods, specifically snowball convenience sampling, was due to the fact that the previously mentioned studies utilized this sampling method as a traditional source (Hauser & Schwarz, 2016; Walter et al., 2019). To this end, we analyzed data from a separate study exploring technology-related constructs, which employed both Prolific and traditional recruitment approaches. This study specifically investigated ChatGPT adoption among 410 Italian students, with 202 participants recruited through snowball convenience sampling and 208 through Prolific. The relevant variables from this study include technology self-efficacy (SE), technology anxiety (AX), and social norms related to technology use (SN).

To investigate potential differences between the two samples in the three technology-related variables (SE, AX, SN), we conducted three ANCOVAs. The results reveal a significant effect of sample origin only when comparing the two groups in terms of technology self-efficacy. Specifically, participants from Prolific exhibited significantly higher technology SE scores compared to those recruited through snowball sampling, even after controlling for potential confounding variables such as gender, age, and field of study. This finding suggests that Prolific may attract individuals with a naturally higher level of technological confidence. Participants who choose to join studies through Prolific may, on average, possess higher technological self-efficacy than those recruited through snowball sampling. This difference raises questions about the generalizability of findings obtained using Prolific, particularly when examining constructs directly related to technological proficiency. The study's results might over-represent individuals with higher technological self-efficacy if generalized to the broader population. Instead, our analysis indicated that technology anxiety and social norms related to technology use did not exhibit significant differences based on the sampling origin. However, our results suggest that this advantage may not be uniform across all domains, since Prolific samples may also introduce specific biases when the constructs under investigation are closely tied to technology. Thus, while Prolific represents an efficient and generally reliable tool for data collection, caution is warranted in assuming that it is universally superior across research contexts.

Despite our promising findings, they should be interpreted with caution, considering that the two groups we compared (Prolific vs. Snowball Convenience) also differed substantially in their demographic composition, particularly in terms of field of study: 52.4% of Prolific participants were enrolled in scientific or technological faculties, compared to 35.1% of the snowball sample. Although this imbalance was statistically controlled for in the ANCOVA, such a marked difference suggests that the two samples may reflect distinct underlying populations. In this sense, statistical adjustment does not completely eliminate the impact of structural differences, and the interpretation of adjusted means should therefore be made with caution (Jamieson, 2004; Stanley, 2022). As highlighted in methodological discussions (Miller & Chapman, 2001), ANCOVA can be problematic when groups differ substantially on covariates, since the assumption of homogeneous regression slopes may not hold. This reinforces the need to interpret our findings as preliminary and exploratory, rather than definitive evidence of differences between Prolific and traditional samples.

Implications

The findings of this study have important implications for researchers who are selecting samples utilizing the Prolific or similar platforms.

First, the issue of selection bias is particularly noteworthy. Our research highlights the potential for a selection bias even when utilizing the Prolific platform. This platform may attract individuals with specific profiles, in particular those who exhibit higher levels of technological self-efficacy. This result aligns with the findings of Buchanan (2018), who demonstrated that participants recruited through online paid platforms tend to have higher levels of "Openness to Experience," one of the Big Five personality traits. These preliminary findings suggest that researchers should be aware of this potential bias generated by the use of Prolific or similar platforms and should consider the implications it has on the generalizability of their findings to broader populations. Recognizing this could help mitigate the skewing of results and lead to more accurate interpretations.

Second, transparency in recruitment methods is paramount. Researchers should explicitly report their sampling strategies and acknowledge any potential biases associated with specific techniques. This level of transparency will not only enhance the reproducibility of research findings, but also bolster their validity, allowing for a clearer interpretation of results within the broader context of psychological research.

The findings of the study underscore the complexities involved in generalizing data from online platforms, such as Prolific, to traditional research methods. While Prolific consistently provides high-quality data in many studies, our findings as well as Buchanan (2018)'s findings caution against assuming homogeneity in participant characteristics across psychological constructs. The results emphasize the need for careful consideration of participant selection methods and their potential impact on study findings, particularly in technology-related research, to avoid potentially biased interpretations.

A further implication of our findings concerns the importance of transparency in recruitment methods. Researchers should clearly describe how participants were recruited, whether participation was compensated, and what potential biases these procedures might introduce. Such transparency is essential for evaluating the reproducibility and interpretability of results and for ensuring the validity of psychological research in the digital age. Explicit reporting of recruitment strategies enables readers to critically assess the extent to which findings can be generalized beyond the specific sample studied.

Our findings also suggest that Prolific should not be regarded as a definitive solution to sampling bias, as it replaces one type of bias (e.g., homogeneity of snowball networks) with another (e.g., self-selection of online platform users).

Limitations and Future Directions

The findings of this study should be interpreted in light of several limitations. Firstly, our research was exploratory and utilized secondary data, derived from a study designed with a different objective. Second, our comparison involved a Prolific sample and a snowball convenience sample. By definition, snowball samples are prone to strong recruitment bias, as they tend to be homogeneous and reflective of the social networks through which they are disseminated. This structural non-equivalence makes it difficult to attribute observed differences exclusively to the nature of Prolific as a recruitment platform. Finally, the two samples differed in compensation: Prolific participants were paid, whereas those in the snowball sample were not. This introduces a fundamental confounding variable, since economic motivation may be associated with personality traits, socioeconomic status, or even higher confidence in technology. The gap in self-efficacy observed between the two groups could therefore reflect a combination of self-selection processes on Prolific, the presence versus absence of compensation, and the inherent biases of snowball sampling (e.g., the over-representation of humanities students). Because our design does not allow disentangling these effects, conclusions must be interpreted with caution. Future research should address these limitations by comparing Prolific with probabilistic or randomized online samples, and by contrasting paid versus unpaid recruitment strategies. Nonetheless, the results we obtained are promising and suggest that pursuing studies in this direction is worthwhile. Future research should aim to address our limitations, specifically: (1) ensuring the inclusion of balanced samples for sociodemographic variables, as our two samples were imbalanced in terms of gender, age, and field of study; and (2) incorporating a greater number of psychological constructs where differences between sampling methods are anticipated. Therefore, more targeted research is needed to compare sampling methods.

Conclusion

In conclusion, our study highlights the importance of recruitment platform choice in psychological research. Our findings indicate potential selection biases, notably that participants recruited through Prolific exhibit higher technology self-efficacy than those from traditional snowball convenience sampling methods. However, it is important to recognize that these differences cannot be attributed solely to the Prolific platform. They may instead result from a combination of factors, including self-selection processes on Prolific, the economic motivation associated with financial compensation, and the structural biases of snowball recruitment. These considerations underscore that no single sampling strategy is free from limitations, and that caution is warranted when generalizing results obtained through one specific method. Future research should further investigate how different recruitment strategies shape sample characteristics and study outcomes, as well as identify conditions under which each approach may be most appropriate for psychological research.

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