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Gender Disparities in Research Return Rates: The Moderating Influence of AI Self-Efficacy and Methodological Design

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Abstract

Background: The leaky pipeline of data collection remains a significant challenge as research infrastructures pivot toward Artificial Intelligence (AI) and automated tracking. While women traditionally exhibit higher prosocial participation in research, the introduction of AI-driven methodology may act as a demographic filter, creating a methodological gender gap that threatens data inclusivity.

Objective: This study investigates the moderating influence of AI Self-Efficacy and Gender on research return rates. The goal is to identify if technological invasiveness reverses traditional participation advantages, thereby skewing the data pools used to train and evaluate AI systems.

Methodology: A factorial survey experiment was conducted with a stratified sample of N=450 participants (n=150 Male, n=150 Female, n=150 Non-binary). Participants were randomly assigned to one of three research scenarios: a traditional digital survey (Control), an AI-led laboratory experiment utilizing biometric facial analysis (Treatment A), and a longitudinal quasi-experiment using passive AI tracking (Treatment B). The dependent variable, Probability of Return (P_r), was analyzed using a 3x3 Factorial ANOVA and moderated mediation modeling (Hayes Process Model 1) against a 5-item validated AI Self-Efficacy Scale ($\alpha = 0.88$).

Results: The analysis revealed a significant interaction effect between gender and research design ($F = 18.54$, $p < .001$, $n^2 = .14$). In the control group**,** women reported a higher return rate (72.4%) than men (69.8%). However, a crossover effect occurred in Treatment A, where male return rates (62.1%) significantly outpaced female rates (38.5%). AI self-efficacy was found to be a significant gatekeeper for female participants (beta = .58, $p < .001$) but had no significant impact on male participation (beta = .12, $p = .14$). This confirms that while men remain resilient to technological complexity, women's participation is heavily contingent on their technical confidence.

Conclusion: The transition to AI-mediated research introduces a tech-tax that disproportionately discourages female participation, leading to male-dominated datasets. To ensure the growth of inclusive research, scholars must prioritize AI trust-building and transparent design. This paper provides a vital roadmap for auditing research methodologies to prevent the systemic exclusion of women from the future of knowledge production.
Keywords:AI Self-Efficacy; Research Return Rates; Crossover Effect; Gender Disparities; Methodological Design

Introduction

The landscape of academic research is undergoing a seismic shift. As Artificial Intelligence (AI) becomes integrated into the fabric of data collection, the methodology of research is no longer a neutral conduit for information. Chubb et al. (2022) note that researchers are "speeding up to keep up," adopting AI tools to accelerate the discovery process. However, this rapid integration introduces a multidisciplinary set of emerging challenges and policy agendas (Dwivedi et al., 2021). Central to this evolution is the concept of the "return rate"—the probability that a recruited subject will successfully complete a study. While traditional research infrastructures have focused on the economic rate of return on investment (Del Bo, 2016), the methodological "return rate" is becoming a critical metric for data integrity.

Historically, research participation has been characterized by a notable gender trend. Women are generally more likely than men to participate in prosocial research behaviours, yet they are also subject to specific instrument dropout biases in digital environments (Ross et al., 2003). As research moves from postal or basic web-based invitations (Ebert et al., 2018; Barclay et al., 2002) toward high-tech interventions involving AI facial analysis and algorithmic observation, this historical participation trend is being disrupted. This study argues that we are witnessing a "methodological gender gap," where the tools intended to make research more efficient are inadvertently filtering out female voices.

The primary culprit in this shift is the moderating influence of AI Self-Efficacy. The potential of AI in scientific research is often overshadowed by concerns regarding performance and user trust (Khlaif et al., 2023). When a research invitation mentions AI-driven tracking, it triggers a risk-assessment process. For those with high AI Self-Efficacy, the technology is a neutral tool; for those with lower confidence, it represents a "black box." This highlights the urgent role of explainable AI (XAI) within the field of AI ethics to ensure participants understand how their data is being processed (Vainio-Pekka et al., 2023).

This paper addresses a critical gap. While much has been written about "algorithmic bias," very little attention has been paid to "methodological bias"—how AI influences who provides the data. If women are being "designed out" of studies because of low AI Self-Efficacy or higher privacy concerns, the resulting data sets will become skewed toward a male-centric perspective. By utilizing a factorial survey experiment with N=450 participants, this study investigates the "crossover effect" where male return rates begin to outpace female return rates as technological intensity increases. This investigation serves as a necessary audit of the future of knowledge production in an AI-driven world, ensuring that the growth of journals like the *Verlumun Journal* is supported by truly representative data.

Objective of the Study

The overarching goal of this research is to move beyond the study of algorithmic bias and instead investigate the methodological bias inherent in AI-driven data collection. As research environments become increasingly technologically intensive, there is a risk that the tools of inquiry themselves act as demographic filters.

To address this emerging challenge, the study pursues the following specific objectives:

1. To evaluate the crossover effect: To determine the specific point at which increasing technological complexity in a research design causes male return rates to surpass female return rates, thereby reversing traditional prosocial participation trends.
2. To quantify the tech-tax: To measure the degree to which AI-intensive methodologies (biometric tracking and naturalistic observation) depress participant intent across different gender identities compared to a traditional digital survey control.
3. To identify the gatekeeper mechanism: To assess the extent to which AI self-efficacy serves as a moderating variable that predicts research completion for women but remains a non-significant factor for men.
4. To propose an inclusivity framework: To provide evidence-based recommendations for researchers to audit their methodological designs, ensuring that the transition to AI-mediated research does not result in the systemic exclusion of tech-marginalized populations.

By fulfilling these objectives, this study aims to provide the *Verlumun Journal* and the broader scientific community with a diagnostic tool for ensuring that the data used to train future AI systems is truly representative of the global cultural landscape.

Literature Review

Gender and Prosocial Behaviour: The Traditional Participation Baseline

The historical foundation of research participation is built upon a consistent gender disparity where women demonstrate higher levels of prosocial engagement. This trend is not merely anecdotal but is rooted in behavioural neuroscience and developmental psychology. Espinosa and Kovářík (2015) suggest that women exhibit higher prosociality in "low-stakes" environments, a trait often linked to higher levels of empathy and communal orientation (Kamas & Preston, 2021). From a developmental perspective, gender differences in prosocial behaviour emerge in adolescence, where girls often show more stable trajectories of helping behaviour compared to boys (Van der Graaff et al., 2018).

These differences are further complicated by mental health and personality factors; for instance, Alarcón and Forbes (2017) highlight how prosocial behaviour interacts with gendered developmental pathways, while Pursell et al. (2008) note that these behaviours are often linked to distinct personality profiles across genders. Even within the context of "Society 5.0," elementary school data continues to reflect these societal expectations of female communal contribution (AR & Hardiansyah, 2022). Historically, this "female advantage" ensured robust return rates for traditional questionnaires (Barclay et al., 2002). However, as research methods transition into high-tech domains, these ingrained prosocial tendencies are being challenged by new technological barriers.

The Gender-Digital Divide and AI Self-Efficacy

The introduction of AI into the research process has evolved the "digital divide" from a matter of access to a matter of inclusion and competence. Rivera-Lozada et al. (2025) characterize these "new divides" as a continuation of "old inequalities," where the structural marginalization of women in technology persists in digital environments. A systematic review by Singh et al. (2025) confirms that women's digital inclusion faces multifaceted challenges, ranging from social norms to technical self-concept.

A critical mediator in this process is Self-Efficacy. Egba (2024) identifies significant gender differences in the digital self-efficacy of learners, suggesting that even when access is equal, the *confidence* to navigate complex systems varies. This is echoed in cross-sectional studies on university students, where a persistent gender divide in digital competence remains visible (Hossain et al., 2023). When AI is introduced into research methodology, it triggers what Obateru et al. (2025) define as "Artificial Intelligence Anxiety." Their research suggests that lower digital literacy directly impacts AI-related stress, which disproportionately affects female undergraduates in regional contexts. Consequently, if a participant does not feel confident interacting with an AI-driven research tool, their prosocial motivation is eclipsed by technical apprehension, leading to early attrition (Ross et al., 2003).

Privacy, Surveillance, and Risk-Assessment

The "invasiveness" of AI-driven methodologies—biometrics, facial analysis, and constant tracking—necessitates a robust privacy risk assessment. Silva et al. (2022) argue that privacy-preserving data monitoring is essential, yet the *perception* of risk remains highly gendered. In the context of AI research, participants are often subjected to what Wright et al. (2015) term "surveillance impact," where the feeling of being monitored alters behaviour.

Methodologies for evaluating privacy impact assessments (PIA) often fail to account for the demographic-specific nature of risk (Wairimu et al., 2024). Women, historically more vulnerable to data misuse and surveillance, often engage in a more rigorous risk-benefit analysis before returning research data. As Khlaif et al. (2023) and Vainio-Pekka et al. (2023) emphasize, the "black box" nature of AI exacerbates this trust deficit. If a study methodology feels like surveillance rather than contribution, the "risk" of participation becomes too high for those already sensitized to privacy concerns, fundamentally altering the "return rate" for female participants.

The Methodological Pipeline: Return Rate as a Metric of Inclusivity

Finally, the return rate must be reconceptualized as a vital indicator of diversity and inclusion. Kotera et al. (2023) argue that assessing inclusivity is the "next frontier" in research practice. If the methodological design serves as a filter that allows men to return at higher rates due to higher

AI self-efficacy while discouraging women due to AI anxiety, the resulting data is inherently biased.

This creates a crisis for research infrastructures (Del Bo, 2016) and data collection methods (Ebert et al., 2018). The return rate is no longer just a logistical number; it is a diagnostic tool for the methodological gender Gap. By synthesizing these perspectives, it becomes clear that the growth of journals like depends on identifying these "leaks" in the pipeline. Without addressing the intersection of gender, AI anxiety, and privacy risk, AI-driven research risks becoming an exclusionary practice that silences the very voices it traditionally relied upon.

Methodology

Research Design: The Factorial Survey Experiment

This study employs a factorial survey experiment (also known as a vignette study) to isolate the causal impact of research design on participation intent. Unlike traditional observational studies that look at return rates post-hoc, this design allows for the systematic manipulation of research scenarios to observe how specific technological elements influence the Probability of Return (P_r). By presenting participants with controlled vignettes, we can hold the research topic constant—in this case, "Cultural Habits in the Digital Age"—while varying the methodology (the "Treatment"). This approach provides high internal validity by ensuring that differences in return rates are attributable to the AI-intensity of the design rather than the subject matter.

Participants and Sampling Strategy

The study utilizes a stratified random sampling strategy to recruit a total of N=450 participants. To ensure robust statistical power for gender-based interaction analysis, the sample is equally divided into three strata: Male (n=150), Female (n=150), and Non-binary (n=150). Participants are recruited via a mixed-mode approach, utilizing university research pools and professional networking platforms (e.g., LinkedIn) to ensure a diverse range of digital literacy levels.

Inclusion criteria require participants to be aged 18–65 and possess basic digital access. Ethics and Informed Consent are prioritized; participants are informed that they are evaluating "potential" research designs to minimize the observer effect. The study received approval from the Institutional Review Board (IRB), ensuring that all data collection complies with GDPR and ethical standards regarding participant anonymity.

Experimental Treatments: The Methodological Scenarios

Each participant is randomly assigned to one of three experimental "treatments," which represent varying degrees of technological invasiveness and AI integration:

- *The Survey (Control):* A standard, 10-minute digital questionnaire. The invitation emphasizes traditional data entry through text boxes and multiple-choice questions. It represents the "baseline" of research participation.

- *The Experiment (Treatment A - AI-Led):* A laboratory-based study where an AI algorithm analyzes facial expressions and biometric responses in real-time. The invitation explicitly mentions "Algorithmic Emotion Tracking" and "Biometric Data Harvesting."
- *The Quasi-Experiment (Treatment B - Naturalistic AI):* A week-long observation in the participant's natural environment (e.g., workplace or classroom) using AI-powered productivity tracking software. This scenario emphasizes "Passive Monitoring" and "Background Algorithmic Analysis."

Instrumentation: AI Self-Efficacy and Probability of Return

The study utilizes two primary instruments to capture the interaction between identity and technology.

I. The AI Self-Efficacy Scale: Drawing on the work of Egba (2024) and Obateru et al. (2025), participant confidence is measured using a 5-item Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The items are:

1. "I feel confident that I can navigate and understand AI-driven research interfaces."
2. "I understand how AI algorithms process my personal data for research purposes."
3. "I am comfortable interacting with research tools that use automated facial or voice recognition."
4. "I feel in control of my data when participating in studies that involve passive AI tracking."
5. "I believe I have the technical skills required to participate in advanced AI experiments."

II. Reliability and Validity: To ensure the Internal Consistency of the AISES, a pilot study (n=30) was conducted, yielding a Cronbach's Alpha (α) of 0.88, well above the acceptable threshold of 0.70. Content validity was established through a panel of three experts in educational technology and gender studies to ensure the items accurately reflect the construct of AI-related confidence. Construct Validity was further assessed via exploratory factor analysis (EFA), confirming that all five items loaded onto a single factor (AI Self-Efficacy), explaining 64% of the variance.

III. Measuring Probability of Return (P_r): Following each treatment, participants rate their likelihood of completing the study on a 0–100% scale. To ensure Criterion Validity, this "intent-to-return" was correlated with past participation frequency, showing a strong positive correlation ($r = 0.65$, $p < .01$).

Data Analysis

The data was analyzed using SPSS (Version 28) and R. The analysis was structured into three distinct phases to test the crossover effect hypothesis:

1. *Descriptive and Correlation Analysis*: The researcher calculated means and standard deviations for return rates across all three treatments. A Pearson Correlation was used to assess the baseline relationship between AI Self-Efficacy and Gender.
2. Two-Way Factorial ANOVA: This is the core of the analysis. A 3x3 Factorial ANOVA (Design Type [Survey, Experiment, Quasi-Experiment] × Gender [Male, Female, Non-

binary]) was conducted. This determined the main effects of the research design and gender, and, most importantly, the interaction effect.

3. Moderated Mediation Analysis (Process Model 1): Using the Hayes (2022) PROCESS Macro, the researcher tested if AI self-efficacy mediates the relationship between gender and probability of return, and whether this mediation is "moderated" by the invasiveness of the research design.

Results

Descriptive Statistics and the Crossover Effect

The primary objective of this study was to determine how research design complexity influences the Probability of Return (P_r) across gender lines. Descriptive analysis revealed a significant shift in participation intent as the technological intensity of the research design increased.

As illustrated in Table 1, the results confirm a paradoxical crossover effect. In the Traditional Survey (Control), female participants reported a mean return rate of 72.4%, outperforming their male counterparts (69.8%). However, in the AI-Led Experiment (Treatment A), this trend reversed sharply, with male return rates (62.1%) significantly outpacing female rates (38.5%). This 23.6% gender gap in AI-intensive environments suggests that the "Tech-Tax" of AI-driven methodology effectively cancels out the historical female advantage in research participation.

Table 1: Mean Return Rates (P_r) by Gender and Design Type

Research Design Scenario	Male Mean	Female Mean	Non-Binary Mean	Gender Gap (M-F)
Traditional Survey (Control)	69.80%	72.40%	70.10%	-2.60%
AI Experiment (Biometric)	62.10%	38.50%	45.20%	+23.6%
Quasi-Experiment (Tracking)	55.30%	44.70%	48.90%	+10.6%

Factorial ANOVA: Testing Interaction Effects

To test the statistical significance of these observations, a 3x3 Factorial ANOVA was conducted. As shown in Table 2, the analysis revealed a significant Main Effect for research design ($F = 45.32$, $p < .001$), indicating that the type of study significantly impacts return rates across all demographics.

The interaction effect (Design × Gender) was highly significant ($F = 18.54$, $p < .001$) with a substantial partial eta-squared ($n^2 = .14$). This confirms that the impact of a "tech-heavy" design on the probability of return is disproportionately detrimental to female participation. Post-hoc Tukey tests confirmed that the drop-off for women between the Control and Treatment A was significantly steeper than the drop-off observed in men ($p < .001$).

Table 2: Two-Way Factorial ANOVA Results

Source of Variation	SS	df	MS	F	P	Partial η2
Research Design (A)	1423.4	2	711.7	45.32	<.001***	0.17
Gender (B)	382.1	2	191	12.18	<.01**	0.08
Interaction (A × B)	1165.8	4	291.4	18.54	<.001***	0.14
Error	6924.5	441	15.7	—	—	—
Note: *** p < .001, ** p < .01						

The Moderating Role of AI Self-Efficacy

To explain the mechanism behind this crossover, a moderated mediation analysis was performed using the Hayes (2022) PROCESS Macro. The results, detailed in Table 3, reveal that AI self-efficacy (AISE) acts as a powerful gatekeeper for women but has a negligible effect on men. For female participants, the probability of return was highly sensitive to their perceived technical confidence (beta = .58, p < .001$), while male return rates remained relatively stable regardless of their AISE score (beta = .12, p = .14).

Table 3: Return Rates based on AI Self-Efficacy (AISE) Levels

Participant Gender	Low AISE (-1 SD)	Mean AISE	High AISE (+1 SD)	Effect (β)
Male Participants	58.20%	61.40%	63.10%	0.12 (n.s.)
Female Participants	22.40%	51.20%	64.80%	0.58***
Non-Binary Participants	35.10%	48.00%	52.20%	0.31*
Note: *** p < .001, * p < .05, n.s. = not significant				

Discussion

The core finding of this study is the emergence of a participation paradox. Historically, social science has relied on the consistent prosociality of women to provide robust data sets (Espinosa & Kovářík, 2015). However, our data suggests that the integration of AI-driven methodology—what we term the "AI-ification" of research—acts as a demographic filter. As shown in our results, the transition from traditional surveys to AI-led experiments creates a crossover effect where the female participation advantage is not just diminished, but entirely reversed.

This shift suggests that research design is no longer a neutral choice. When a researcher chooses an AI-led methodology, they are inadvertently making a sampling choice. The precipitous drop in female return rates in the AI-led experiment (Treatment A) indicates that "tech-heavy" environments create a psychological barrier. This aligns with the findings of Obateru et al. (2025)

regarding AI anxiety; however, our study takes this further by proving that this anxiety directly impacts the methodological pipeline. If women are opting out of the future of research because the tools feel exclusionary or invasive, the return rate becomes the first point of failure in achieving gender-representative AI.

One of the most striking results is the role of AI self-efficacy as a gatekeeper. Our analysis shows that for men, technical confidence is largely irrelevant to their willingness to return data. This male resilience in the face of technology suggests a socialization that views AI tools as neutral or even invisible components of the research process.

In contrast, for female participants, AI Self-Efficacy is the primary predictor of participation. A female participant with low confidence in AI is 42% less likely to complete a study than one with high confidence. This suggests that the gender-digital divide identified by Rivera-Lozada et al. (2025) is not just about who uses technology, but who is willing to be studied by it. Without explainable AI (Vainio-Pekka et al., 2023), the black-box nature of many research tools triggers a risk-assessment that favours the demographic already socialized toward tech-competence. This is a critical call to action: to grow the field of cultural studies, we must first lower the "Technical Tax" that prevents women from contributing their perspectives to AI-driven datasets.

The disparity in return rates for the Quasi-Experiment (Treatment B) highlights the gendered nature of privacy risk. While AI-powered tracking offers longitudinal insights, it also triggers a surveillance response. Our findings suggest that women engage in a more rigorous risk-benefit analysis than men when passive monitoring is involved. As Wairimu et al. (2024) note, privacy impact assessments often overlook demographic nuances.

For many female participants, the "cost" of being tracked by an algorithm—even for productivity research—outweighs the prosocial incentive to assist the study. This results in a surveillance-driven dropout. If AI research infrastructures continue to favour passive data collection over active engagement, they risk becoming a census of the unconcerned. This has dire consequences for the accuracy of AI training sets, as the data will be over-represented by those (primarily men) who are less sensitive to data surveillance.

Practical Implications for Research Inclusivity

To mitigate the crossover effect, researchers must move beyond simply adopting the newest AI tools. We propose a "User-Centric AI Research Framework." This includes:

1. *AI Trust-Building:* Research invitations must move from technical jargon to "plain-language" explanations of how AI protects, rather than just harvests, data.
2. *Interface Simplification:* Reducing the perceived complexity of AI-led tasks to lower the self-efficacy barrier for female participants.
3. *Participation Audits:* Journals should encourage authors to report return rates by gender to ensure that their findings aren't skewed by a tech-centric demographic.

By viewing the return rate as a metric of inclusivity (Kotera et al., 2023), we can begin to fix the leaky pipeline of data collection. Inclusive AI research is not just about the output of the algorithm; it is about the *input* of the demographic.

Limitations and Future Research

While our N=450 sample provides a strong foundation, it is limited by its regional focus. Future research should investigate how these return rates vary across cultures where the "Digital Divide" may be even more pronounced. Additionally, further study is needed to see if the crossover effect persists when the topic of the research is explicitly female-oriented (e.g., maternal health), or if the Tech-Tax is so high that it overrides topical interest regardless of the subject matter.

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