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Tracing the lines of deceit. Male cheating behavior increases in online versus face-to-face environments over time

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ABSTRACT

This study investigates the development of cheating behavior over time in online versus in-person environments among university students, with a particular focus on potential gender differences. Previous research suggests that online anonymity increases cheating (Charness et al., 2007), and cheating increases over time (Garrett et al., 2016). In the current study, 137 participants (online: $n = 75$, in-person: $n = 62$) with a balanced gender distribution completed a fine-motor tracing task in four sessions. Individuals made a performance prediction before each trial prior to competing against each other for the highest scores. During the task, participants rated their own errors, so self-reported performance could be compared to expert-coded outcomes. Cheating was defined as the discrepancy between self-reported and actual errors. We distinguish between all instances of cheating (inconsequential for the score), and "meaningful cheating", which refers to cases where cheating improved the score. Findings suggest greater cheating for men as compared to women in the online condition when cheating led to an increase in performance scores, but not when all cheating is considered. In addition, "meaningful cheating" increased over time in the online condition, especially in men. This indicates that online situations could introduce cheating-opportunities in interpersonal situations, which may be used strategically by some individuals to gain advantages.

1. Introduction

In an increasingly digital world, understanding the factors that drive and change human behavior in in-person versus online settings is crucial. With the rise of online interactions, the traditional dynamics of honesty and accountability are shifting, and the absence of immediate social feedback in these settings can alter individuals' behavior. Online platforms offer a unique context where traditional social cues and accountability mechanisms may be diminished, potentially fostering dishonesty (Cartwright & Xue, 2020). Understanding these dynamics is critical as society becomes more reliant on digital communication. Additionally, this necessitates a close examination of how the perceived social distance and reduced social control influence cheating. This paper therefore focuses on cheating behavior among university students completing a fine motor learning task as part of a seminar course. The task simulates a learning context in which performance is evaluated, feedback is provided after each trial, and outcomes can be strategically influenced by participants. We investigate whether online as compared to in-person environments lead to increased cheating in a behavioural tracing task where self-reported outcomes are compared to the actual performance. Cheating is defined as the discrepancy between each individual's initially reported errors and a re-evaluation by two independent raters conducted after data collection. In line with research on self-serving justifications and bounded ethicality (Mazar et al., 2008; Shalvi et al., 2015), it can be argued that certain forms of cheating, particularly those that result in a clear benefit to the individual, reflect more deliberate and consequential forms of cheating. To capture this distinction, we propose differentiating between all instances of cheating and what we term "meaningful cheating". The latter refers specifically to cases where cheating directly enhances a participant's outcome by bypassing a baseline penalty or scoring rule. This distinction is important because it identifies situations in which participants gain more substantial benefits from cheating, compared to other forms that result in less significant personal gain. Additionally, the paper examines how cheating changes over time, considering that social interactions are often not a one-time occurrence, but are repeated. By integrating a brief discussion of terminology, and by incorporating perspectives from social psychology and economics, the aim is to provide a comprehensive understanding of

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cheating in digital contexts.

1.1. Theoretical background

The concept of dishonesty encompasses a broad spectrum of behaviors that in general violate social or institutional norms for personal benefit. In the empirical literature, related terms such as unethical behavior (Wang & Chen, 2021), deviance (Pascaru-Goncear, 2023), lying (Childs, 2012), deception (Burgoon et al., 2003), and cheating (Ezquerra et al., 2018) are frequently used interchangeably to describe these actions. Although these behaviors share a common foundation of intentional norm violation (Kennette & Jelenic, 2023), the terminology often lacks conceptual precision (Grolleau et al., 2016). In this study, we adopt dishonest behavior and cheating as umbrella terms to capture acts intended to mislead others or gain unfair advantage, regardless of whether formal rules are explicitly broken. Specifically, we define cheating as a subtype of dishonest behavior, referring to the deliberate misrepresentation of one's performance to obtain a benefit that would otherwise not be earned.

The economic and social psychology perspectives try to explain why people cheat. With the concept of ***homo economicus*** the economic view suggests that humans are rational and selfish, while weighing the expected benefits of cheating (wealth maximizing) against its costs (probability of being caught; potential punishment; self-perception) (Gerlach et al., 2019; Henrich et al., 2001; Mazar et al., 2008; Rosenbaum et al., 2014). The self-licensing theory complements this by considering internal norms and intrinsic costs of cheating, thus viewing the idea of ***homo sociologicus*** as a more accurate description of human behavior (Kroher & Wolbring, 2015; Rosenbaum et al., 2014). It includes people's intrapersonal stability of deviant behavior, categorizing them as either ethical (never dishonest), mixed (finite intrinsic cost of DB) or economic types (zero cost of DB) (Kajackaite & Gneezy, 2017; Leisge et al., 2024). Integrating these perspectives reveals that individuals consider both material gain and the impact of their behavior on self-perception and social image (Bursztyn & Jensen, 2016; Waeber, 2021). This raises the question of whether the reduced social control and isolation of participants in their own homes during an online setting might reduce concerns about self-perception and social image, thereby increasing the likelihood and extent of cheating (Cohn et al., 2022).

The move from laboratory to online settings changes behavior and the norms individuals follow (Davis et al., 2002; Lieberman & Schroeder, 2020). Different contexts evoke different norms, where group dynamics and authority figures influence behavior (Bandura, 2002). Norms are less influential in anonymous interactions, while face-to-face settings make communication skills and sanctions relevant (Bohnet & Frey, 1999). The theory of social distance suggests that perceived remoteness between individuals influences conformity to social norms. In online environments, an increased social distance creates a context that reduces adherence to norms, the concern of being caught, the perceived punishment and the impact on self-perception when lying (Hoffmann et al., 1996; Waeber, 2021). In these settings, enhanced anonymity leads to reduced social control and accountability, shifting the focus towards self-interest without concern for others (Gerlach et al., 2019; Hoffmann et al., 1996; Varvarigos & Xin, 2020). This isolation, coupled with emotional and physical distance, supports the prediction of social distance theory of altered behavior in remote settings (Charness et al., 2007; Charness & Gneezy, 2008). In a laboratory group setting, the physical presence of experimenters and participants, along with identification and monitoring of performance, can encourage normative behavior and therefore reduce cheating (Bohnet & Frey, 1999; Cohn et al., 2022; Dickinson & McEvoy, 2021; Sudo, 2017).

1.2. Literature review

Research on cheating in online versus in-person settings shows mixed findings. When the same subject pool is tested using the "*coin flip*" task (Cohn et al., 2022) in both in-person and online environments, it does not lead to more dishonesty for monetary gain. However, fully anonymous online participants are more likely to engage in cheating (Dickinson & McEvoy, 2021). Kroher and Wolbring (2015) used a "*die-roll*" task (Fischbacher & Föllmi-Heusi, 2013) and reported that online settings lead to more cheating. In a between-subjects design, Waeber (2021) used an individual decision-making situation (i.e., random number or financial market) and found no systematic differences in cheating between online and in-person settings. Instead, gender differences based on the environment were observed, with males being more dishonest online compared to the laboratory. However, it should be noted that previous studies have not reached a consensus on the influence of gender on cheating. While most studies report that males tend to show higher levels of dishonest behavior compared to females (Gerlach et al., 2019; Grosch & Rau, 2017; Kennedy & Kray, 2022; Lohse & Qari, 2021), some studies have found no gender differences (Aoki et al., 2010; Ezquerra et al., 2018; Leisge et al., 2024; Lohse & Qari, 2014), and others have reported higher levels of dishonesty (Clot et al., 2014; Ruffle & Tobol, 2014) and deception (Tyler & Feldman, 2004) in women compared to men.

Focusing on these prior studies, the effect of social distance may not be uniform across genders. Research suggests that men and women differ in their sensitivity to social cues and external monitoring, and that individuals with prosocial orientations, among whom women are more commonly represented, tend to exhibit higher levels of honesty (Eagly & Wood, 2012; Grosch & Rau, 2017; Kennedy & Kray, 2022). Men have been found to be more competitive than women (Pierce & Thompson, 2018), and may therefore be more inclined to exploit the anonymity and reduced social control of online environments to gain advantages over competitors. In contrast, women generally display higher trustworthiness and tend to meet others' positive expectations (Levine et al., 2018), while also experiencing greater emotional distress when acting against their moral standards (Cohen et al., 2011). This may lead to stronger resistance to dishonest behavior, even in the absence of immediate social feedback or control. Therefore, increased anonymity in online settings may disproportionately free men from normative constraints, leading to higher levels of strategic dishonesty (Waeber, 2021).

Based on these theoretical perspectives and prior results, it is hypothesized that participants in the online environment will engage in more cheating than those in the in-person setting, due to increased social distance and reduced social control. Additionally, we expect gender to moderate this effect, such that males will show higher levels of cheating, particularly in the online setting.

Studies on the temporal development of cheating indicate its potential to escalate with repetition. It is theorized that the affective signal accompanying self-serving dishonesty diminishes over time, leading to increased cheating behavior (Garrett et al., 2016). Social learning theories further support this notion (Burgess & Akers, 1966). The absence of negative reinforcements, such as being caught and punished for cheating, may encourage cheating over time (Burgess & Akers, 1966). When individuals observe that neither they nor others are punished for dishonesty, they find no reason to change their behavior. Using brain imaging and behavioural two party sender-and-receiver tasks, Garrett et al. (2016) observed that self-serving dishonesty and the magnitude of cheating increases over repeated opportunities. This adaptation suggests that the brain may reduce signals that typically curb dishonesty, leading to more frequent dishonest acts (Garrett et al., 2016). Similarly, Welsh et al. (2015) argue that small ethical transgressions can evolve into larger unethical acts. Their problem-solving "*matrix*" task demonstrated that cheating increases over time (Welsh et al., 2015). We hypothesize that repeated exposure to similar opportunities for dishonesty lead to increased cheating over time. While previous studies have not directly examined whether this development differs by social setting or gender, we tentatively expect the increase in cheating to be more pronounced in online environments due to reduced social control and heightened anonymity. Furthermore, based on prior findings suggesting that males are more likely to engage in dishonest behavior, we expect men to exhibit a steeper increase in cheating over time compared to women.

The current study measures cheating in a behavioural task repeatedly at an individual level in two conditions (online vs. in-person). Most previous studies focused on aggregate-level dishonesty metrics (see Gerlach et al., 2019 for an overview).

2. Method

2.1. Participants

A total of 137 (online: $n = 75$, in-person: $n = 62$) students were tested. In terms of gender, the sample is fairly balanced. The online condition includes 44 (59 %) men aged 19 to 33 years ($M = 22$, $SD = 2$) and 31 (41 %) women aged 18 to 38 ($M = 23$, $SD = 4$), while the in-person condition includes 31 (50 %) men with an age range from 20 to 29 ($M = 22$, $SD = 2$) and 31 (50 %) women aged 20 to 28 years ($M = 21$, $SD = 2$).

Due to the novelty of this study, the lack of effect sizes in the literature and due to the absence of reliable estimates for the standard deviation of the outcome measures in comparable designs, a power analysis for sample size estimation was not deemed appropriate. Measuring behavior and cheating repeatedly over the course of 20 trials increases the reliability of the data. We therefore assume that our study is sufficiently powered to detect the effects of interest. To support this assumption, a post hoc power analysis based on the observed effect size is reported at the end of the Results section.

Participants in both the online and in-person conditions were recruited through seminar courses at the university and participated as part of regular course activities. In both settings, participation was voluntary, and students received course credit for taking part. The testing sessions were part of different university courses at the Sport Science Institute at Saarland University. Therefore, participants were mainly sport and few psychology students, constituting convenience samples. Except normal or corrected-to-normal vision, no specific inclusion or exclusion criteria were defined prior to the study. Participants signed informed consent forms and were assured that their data would be anonymized and treated confidentially. The study was approved by the ethics committee of Saarland University.

2.2. Experimental task – tracing

The tracing task involves line tracing, thus requiring skill and accuracy. We used 20 different tracks (see Fig. 1) and the subjects' task was to trace the interior of the 2 mm wide corridor as far and accurately as possible for 30 s per trial. Scoring was based on the distance covered (one point for every five mm; maximum possible 125 points) and inaccuracies (touching the boundaries led to the subtraction of three points). Before each trial, individuals predicted the points they believed they could achieve for the upcoming tracing track. These predictions were recorded on the test sheets and were shared with the other participants in the group. If, after counting the errors and adjusting the points themselves, the actual performance met or exceeded the prediction, participants were credited with the predicted points. If the predicted performance was not achieved, this trial was scored as zero points. This procedure is based on the Selections Margins paradigm and proposes that there is an optimal level of task-difficulty for each individual that they can work on successfully (Schaefer et al., 2021, 2023). For example, if a participant predicted that he would achieve a score of 80 points but actually traced a distance of 90 with two errors, his final performance would be 84 (i.e., $90_{[\text{distance}]} - (2_{[\text{errors}]}*3_{[\text{deduction per error}]})$). This would meet the predicted score of 80 points and therefore grant 80 points. However, if five errors had been made instead of three, the total performance would be 75 (i.e., $90_{[\text{distance}]} - (5_{[\text{errors}]} * 3_{[\text{deduction per error}]})$), leading to a score below the prediction and thus resulting in a "Zero-Point-Trial". The self-rated points for each trial were publicly announced to the group.

Given that the sample primarily consisted of sport science students, the selection of a fine motor tracing task was deemed appropriate. These students are generally familiar with tasks involving physical performance and coordination, making such a task engaging and ecologically valid. However, to ensure that prior experience would not influence performance, we deliberately selected a novel task unfamiliar to all participants, allowing us to observe learning processes over time. While the participants' background may contribute to slightly higher baseline motor skills, the focus of the study was not on absolute performance, but rather on the accuracy of self-assessment. This makes the tracing task suitable for isolating dishonest reporting behavior independent from motor competence.

2.3. Procedure – data collection

In both the online and in-person conditions, data collection was part of regular university seminar sessions. In the online setting, participants completed the tracing task at home during the 2021 Corona pandemic using MS Teams. The experimenter was visible throughout the session via webcam, and all participants were at home alone in front of their laptop with their camera directed towards their face. Unlike the in-person setting, where group presence and physical oversight were inherent, the level of supervision in the online setting was considerably lower. The actual task execution (i.e. tracing and error-marking) was not visible to anyone other than the individual participant, which eliminated opportunities for external monitoring, increased anonymity and heightened social distance. As data collection took place during a live seminar session, distractions from others in the home environment were likely minimal. For the in-person setting assessed in 2023, participants performed in groups of 19 to 22 persons in a seminar room at the university. In this setting, the degree of supervision was high, as participants were seated close to each other in one room, and both peers and the experimenter were present and able to observe the task performance.

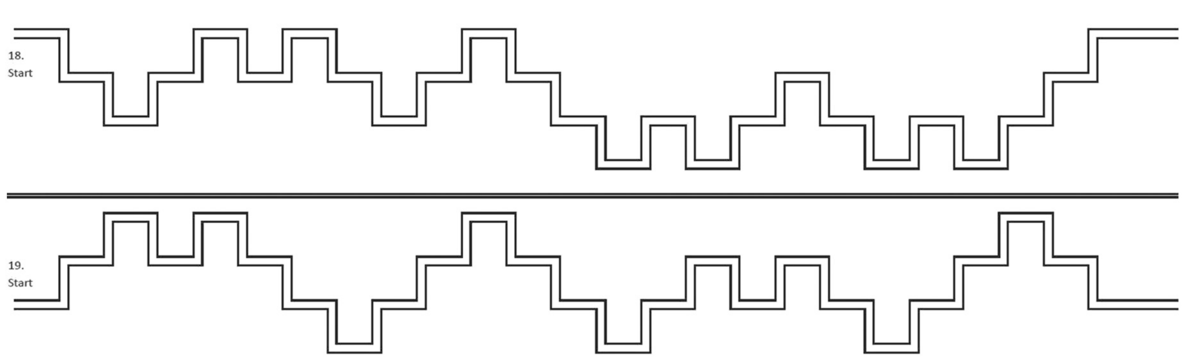

Fig. 1. Example of two tracing tracks.

This reduced anonymity and social distance.

For both conditions, participants completed 20 trials of the tracing task over four sessions, each spaced one week apart, with 5 trials per session. Test sessions of the tracing task lasted approximately 15 min each. Before commencing the actual test sessions, five shorter practice trials of 15 s each were conducted in the initial session. This allowed the test administrators, who were faculty members familiar to the participants, to ensure that instructions and tasks were comprehended. Participants demonstrated a clear understanding of the scoring procedure, as evidenced by their accurate communication of predicted scores and self-rated errors, which was further confirmed through checks of their test sheets after the initial sessions. At the end of the last testing session, the three most successful participants of each group (who had collected most points over the course of the four sessions) were publicly announced and honoured in an "*award ceremony*". Participants were not informed that after the test sessions, the tracing sheets were re-evaluated by two external and previously trained raters. As such, their self-assessments were made under the assumption that their own ratings were final and not subject to external verification. If the ratings of the two experts were different from each other by more than one error, a third rater was consulted, and the expert error score for this specific trial was decided upon in a group discussion.

The difference in errors between the self-assessments and the expert ratings was used as a measure of cheating for each individual trial. For example, a participant may have rated three errors for himself in a specific trial, but experts rated seven errors. This results in a cheating score of four. We will report this as the ***all*** cheating score, as cheating is recorded regardless of its consequences.

Since errors can result in the predicted performance not being achieved, we could identify cases of ***meaningful*** cheating where cheating meant avoiding a "Zero-Point-Trial". ***Meaningful*** cheating occurs when participants achieve the predicted score based on their own error assessment, although expert ratings resulted in a "Zero-Point-Trial". For example, a participant predicted 80 points for the upcoming trial and traces a distance of 90 with five errors but reports only three errors. Based on his own rating, the final performance would be adjusted to 81, thus awarding the predicted 80 points. However, expert ratings reduce the performance score to 75, which is lower than the predicted 80, thereby categorizing it as a "Zero-Point Trial" with a ***meaningful*** cheating extent of two.

2.4. Statistics

The statistical analysis was conducted using R Statistical Software (version 4.4.0) for Windows (R Core Team, 2022). The presence of ***meaningful*** and ***all*** cheating for each condition was tested using one-sample Wilcoxon tests by comparing the empirical values against zero. Two linear mixed-effects models with participant as a random factor were used to predict the influence of gender (with levels male and female) and condition (with levels online and in-person) on the mean extent of ***all*** and ***meaningful*** cheating for each trial. Trial was a repeated measures variable in these models. Follow-up analyses were done using similar models with the respective subsample and adapted predictors. Another mixed-effects model was conducted to analyse the connection between ***all*** and ***meaningful*** cheating in general. The primary outcome variable was the mean extent of cheating for the two types, and the model included fixed effects for gender, condition, and cheating type (with levels ***all*** and ***meaningful***), as well as their interactions. Additionally, a random intercept for participant was included. Post-hoc analyses using Wilcoxon tests were conducted to specifically examine differences across gender and condition, with the aim of clarifying the sources of the observed overall effects. The mixed-effects models were conducted with the nlme R package (Pinheiro et al., 2022). Descriptive statistics and *Cronbach's α* were calculated via the psych R package (Revelle, 2022). Effect sizes were computed by using the rcompanion R package (Mangiafico, 2023). No participants were excluded from the analyses. For all analyses the alpha level was set to 0.05.

3. Results

For the current study, participants were engaged in a game based on performance-predictions, traced distances, self-reported errors, and resulting points over the course of 20 trials. We present the data on these measures in Supplement 1.

Supplement 2 addresses the question whether participants may have had problems in recognizing errors in general, also when they rate somebody else's tracing performances. This was not the case. Our supplementary data show that participants were generally capable of accurately identifying errors in others' tracing paths. In fact, they even tended to be stricter than expert raters, and their accuracy and strictness improved over time.

3.1. General results: is cheating present?

On average, a difference between the participants' self-rated errors and those of the experts, indicating cheating, was detected in 58 % of all trials in the online condition, and in 66 % of all trials in the in-person condition. When focusing only on ***meaningful*** cheating, where differences between self-ratings and expert-ratings resulted in a "*Zero-Point-Trial*", cheating was observed in 27 % of all trials in the online condition, and in 22 % in the in-person condition. With a high effect size, one-sample Wilcoxon tests revealed that the empirical values for both ***all*** and ***meaningful*** cheating are significantly higher than zero for both men and women in the online and in-person conditions (see Table 1). Reliability analyses for ***all*** cheating showed excellent internal consistency for the online (α = 0.96) and the in-person condition (α = 0.92). For ***meaningful*** cheating, excellent internal consistency could be achieved for the online (α = 0.93) and acceptable internal consistency for the in-person condition (α = 0.79).

3.2. Does cheating increase differently over time for the two conditions?

Two linear mixed-effects models (estimated using maximum likelihood) were fitted to predict ***all*** and ***meaningful*** cheating over time, with fixed effects for gender, condition, and their interaction. The models included the participant identification variable as a random effect.

For ***all*** cheating, the total explanatory power is moderate (conditional R^2 = 0.48), with a small portion explained by the fixed effects alone (R^2 = 0.05). In this model, the interaction of time*condition is statistically significant and positive (β = 0.13, 95 % confidence interval (CI) [0.02, 0.23], $t_{(2371)} = 2.34$, $p = .019$). Follow up analyses reveal a significant increase in cheating over time in the online (β = 0.17, 95 % CI [0.10, 0.25], $t_{(1339)} = 4.57$, $p < .001$) but not the in-person condition (β = 0.05, 95 % CI [−0.02, 0.12], $t_{(1033)} = 1.28$, $p = .119$). Moreover, the triple interaction of time*condition*gender is significant and negative (β = −0.07, 95 % CI [−0.14, −0.01], $t_{(2371)} = -2.07$, $p = .038$). Follow-up analyses for the online environment indicate a significant increase over time for men (β = 0.10, 95 % CI [0.06, 0.14], $t_{(756)} = 4.96$, $p < .001$) and women (β = 0.03, 95 % CI [0.01, 0.05], $t_{(583)} = 2.31$, $p = .021$) with higher effects for men, while cheating behavior of men (β = 0.04, 95 % CI [0.01, 0.08], $t_{(498)} = 2.34$, $p = .020$) and women (β = 0.04, 95 % CI [0.02, 0.07], $t_{(535)} = 3.48$, $p < .001$) increases similarly in the in-person setting. The fixed effects of time, condition, gender, as well as the interaction of time*gender and condition*gender did not reach significance (see Table 2, Fig. 2a).

For the model predicting ***meaningful*** cheating over time, the total explanatory power is moderate (conditional R^2 = 0.43) with a small effect size for the fixed effects alone (R^2 = 0.07). Within this model the interaction of time*condition is statistically significant and positive (β = 0.11, 95 % CI [0.07, 0.16], $t_{(2371)} = 5.52$, $p < .001$) with a significant increase of cheating in the online (β = 0.11, 95 % CI [0.08, 0.15], $t_{(1339)} = 6.59$, $p < .001$) but not in the in-person condition (β < 0.01, 95 % CI

Table 1
Cheating is present in every condition for men and women.

			Test Statistics				
			M	SD	z	p	r
Online	All	Men	2.93	3.26	−5.56	**<0.001*****	0.87
		Women	1.40	1.79	−4.67	**<0.001*****	0.87
	Meaningful	Men	2.08	2.84	−5.49	**<0.001*****	0.87
		Women	0.84	1.39	−4.16	**<0.001*****	0.88
In-person	All	Men	2.98	1.82	−4.90	**<0.001*****	0.87
		Women	1.57	1.60	−4.99	**<0.001*****	0.87
	Meaningful	Men	0.33	0.33	−4.92	**<0.001*****	0.88
		Women	0.20	0.20	−4.51	**<0.001*****	0.88

Note. The Table presents the respective extent of cheating (mean, standard deviation), results of one-sample Wilcoxon test (z-value, *p*-value), and the effect size (r). Significant values are highlighted in bold for visual emphasis.
*** p < .001.

Table 2
Results of the linear mixed effects models for **all** DB and **meaningful** DB over time, and for the respective within-subject comparison.

	Test statistics					
	Estimate	SE	95 % CI		t	p
			LL	UL		
All cheating (Fig. 2a)						
Trial	0.05	0.04	−0.03	0.13	1.14	0.254
Gender	−1.16	0.62	−2.38	0.03	−1.86	0.064
Condition	−1.19	1.36	−3.85	1.47	−0.88	0.381
Trial*Gender	0	0.03	−0.05	0.05	−0.07	0.942
Trial*Condition	0.13	0.05	0.02	0.23	2.34	**0.019***
Gender*Condition	0.48	0.88	−1.24	2.20	0.55	0.583
Trial*Gender*Condition	−0.07	0.03	−0.14	−0.01	−2.07	**0.039***
Meaningful cheating (Fig. 2b)						
Trial	−0.01	0.02	−0.03	0.03	−0.08	0.941
Gender	0.08	0.49	−0.87	1.04	0.17	0.964
Condition	0.40	0.46	−0.49	1.29	0.88	0.380
Trial*Gender	0.01	0.02	−0.04	0.05	0.37	0.708
Trial*Condition	0.12	0.02	0.07	0.16	5.52	**0.001*****
Gender*Condition	−0.17	0.68	−1.51	1.17	−0.25	0.804
Trial*Gender*Condition	−0.10	0.03	−0.16	−0.05	−3.48	**0.001****
Model 3 (without Trial; Fig. 3)						
Type (within)	−2.66	0.23	−3.10	−2.22	−11.83	**<0.001*****
Gender	−1.22	0.51	−2.22	−0.22	−2.38	**0.019***
Condition	−0.15	0.48	−1.09	1.29	−0.32	0.752
Type*Gender	1.29	0.32	1.23	2.38	4.04	**<0.001*****
Type*Condition	1.81	0.29	−1.61	1.18	6.15	**<0.001*****
Gender*Condition	−0.22	0.72	−0.71	0.52	−0.30	0.766
Type*Gender*Condition	−0.99	0.43	−1.83	−0.15	−2.29	**0.024***

Note. Significant values are highlighted in bold for visual emphasis.
* p < .05.
** p < .01.
*** p < .001.

[−0.01, 0.01], $t_{(1033)} = -0.29$ $p = .770$). The triple interaction of time*condition*gender is significant and negative (β = −0.10, 95 % CI [−0.16, −0.05], $t_{(2371)} = -3.47$, $p < .001$). Follow up analyses for the online condition reveal a significant increase in cheating for men (β = 0.11, 95 % CI [0.07, 0.15], $t_{(756)} = 5.50$, $p < .001$) but not for women (β = 0.02, 95 % CI [−0.01, 0.04], $t_{(583)} = 1.37$, $p = .170$). Within the in-person setting, no significant difference in the increase of ***meaningful*** cheating over time was found for men and women. The fixed effects of time, condition, gender as well as the interaction of time*gender and condition*gender failed to reach significance (see Table 2, Fig. 2b).

A post hoc power analysis was conducted using G*Power 3 (Faul et al., 2007), employing a repeated-measures ANOVA (within-between interaction) as the base model. The analysis was based on a small observed effect size ($f = 0.075$), a total sample size of $n = 137$, four groups, and 20 repeated measurements. A conservative correlation among repeated measures was set at 0.8, and a nonsphericity correction of 0.5 was applied. The results indicated a high level of statistical power, with 1 − β = 0.97.

3.3. Differences between all cheating and meaningful cheating

We fitted a linear mixed-effects model (estimated using maximum likelihood) to predict the mean extent of cheating, incorporating the within-subject factor cheating type (with levels ***all*** and ***meaningful***, see Table 2). The model included participant as a random effect, and gender, condition, cheating type and their respective interactions as fixed effects. The total explanatory power of the model is high (conditional R^2 = 0.85), with a small portion explained by the fixed effects alone (R^2 = 0.18). In this model, the effect of gender is statistically significant and negative (β = −1.22, 95 % CI [−2.22, −0.22], $t_{(132)} = -2.38$, $p = .019$), indicating that cheating is lower for women compared to men. Additionally the effect of cheating type is significant and negative (β =

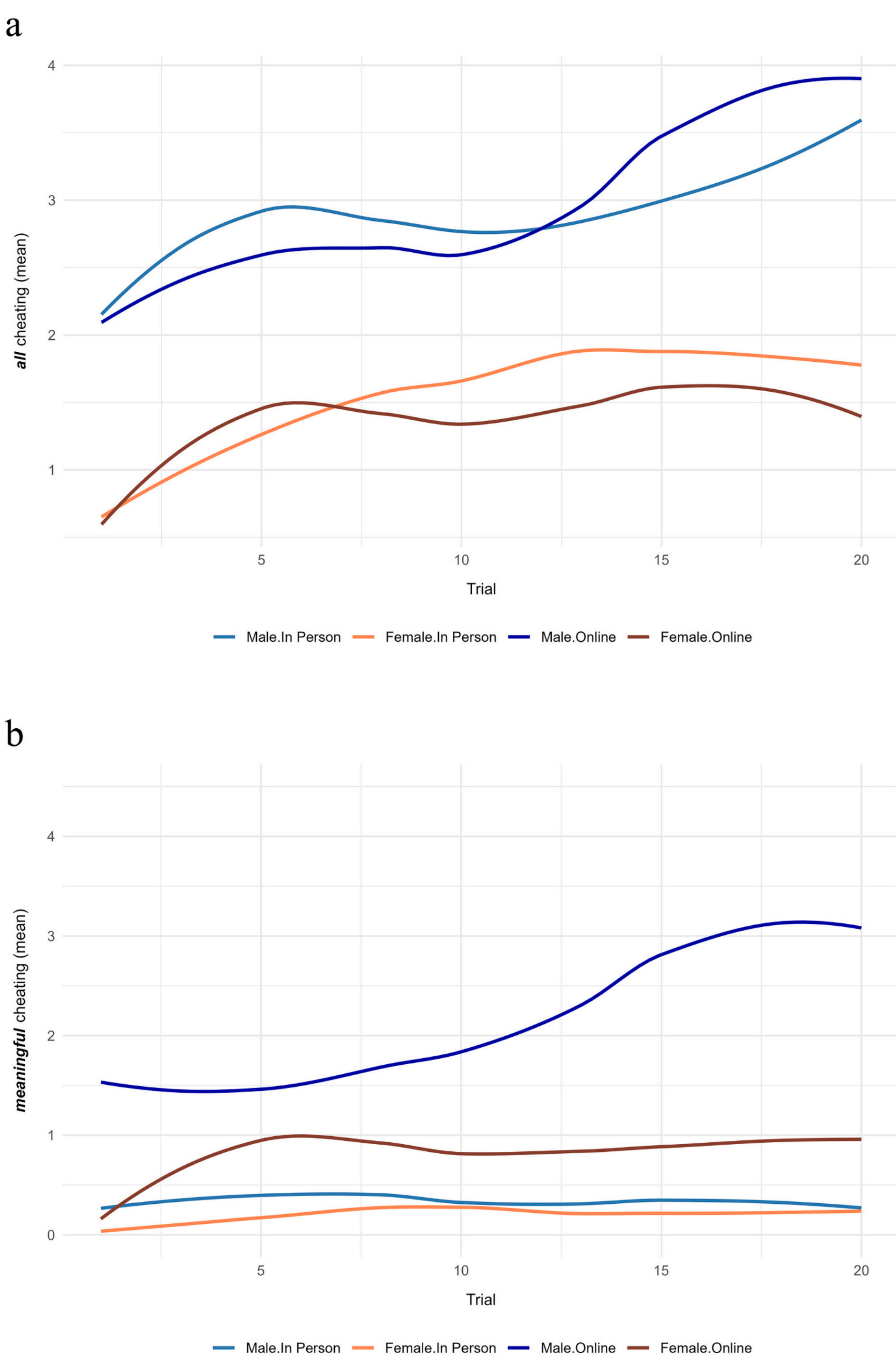

Fig. 2. Cheating increases over time, considering the factors of gender and condition, for (a) ***all*** and (b) ***meaningful*** cheating.
Note. A locally weighted scatterplot smoothing (LOESS) method was applied to the data to allow for clearer visualization of patterns while minimizing noise (see the supplement for unsmoothed plots).

-2.66, 95 % CI [-3.10, -2.22], $t_{(132)} = -11.82$, $p < .001$), with higher ***all*** compared to ***meaningful*** cheating. Moreover the interaction effects of gender*cheating type ($\beta = 1.29$, 95 % CI [0.67, 1.90], $t_{(132)} = 4.04$, $p < .001$), condition*cheating type ($\beta = 1.81$, 95 % CI [1.23, 2.38], $t_{(132)} = 6.15$, $p < .001$) and gender*condition*cheating type ($\beta = -0.99$, 95 % CI [-1.83, -0.15], $t_{(132)} = -2.29$, $p = .024$) are significant (for follow-up Wilcoxon tests see supplement 3). Regarding the primary hypothesis, the results indicate significantly more ***meaningful*** cheating among men in online compared to in-person settings ($z = -3.03$, $p = .002$, $r = 0.35$) (see Fig. 3). However, no significant difference was observed for women ($z = -0.48$, $p = .634$, $r = 0.06$). All cheating differed significantly between men and women while the condition did not reveal a significant influence (online: $z = -2.31$, $p = .021$, $r = 0.27$; in-person: $z = -3.13$, $p = .002$, $r = 0.40$).

4. Discussion

This experiment was designed to repeatedly measure **cheating** on the individual level in a fine motor task over multiple sessions. The goal was to investigate the extent of cheating across different contexts (online

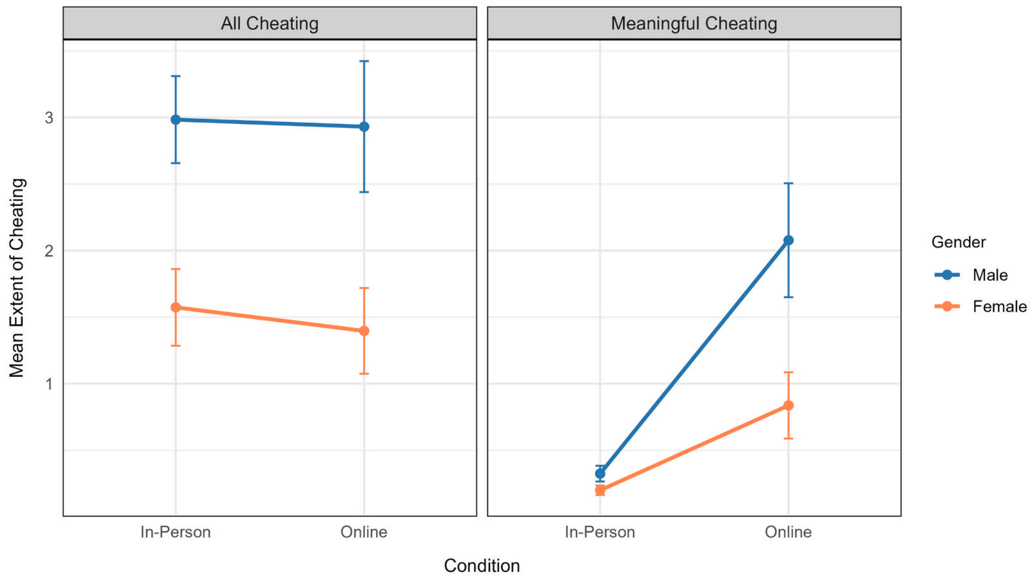

Fig. 3. Increase in the extent of meaningful cheating for men in the online compared to the in-person setting. Error bars represent the standard error of mean.

versus in-person) and to track potential changes over time. Unlike traditional cheating paradigms (e.g., coin flip or die roll), our design involves skill-based performance, public prediction, and self-assessment, all of which interact to shape behavior. This complexity can be seen as a strength of the study, as it mirrors real-world scenarios where dishonesty often arises in ambiguous, self-regulated contexts.

The initial repeated measures analysis of each individual trial for ***all*** cheating revealed no significant differences between the online and in-person conditions. Consequently, the hypothesis that ***all*** cheating would be higher in the socially distanced online condition was not supported.

However, when focusing on ***meaningful*** cheating, where the discrepancy between self-ratings and expert ratings resulted in a "Zero-Point-Trial", a different pattern emerged. Significant differences were observed for men between the online and in-person conditions, with more ***meaningful*** cheating in the online setting. This finding suggests that cheating is higher online for men when it leads to a personally meaningful outcome (achieving the prediction and thus scoring points and having the chance to be awarded in a public "award ceremony"). These results align with the theoretical framework of social distance. This study provides further confirmation of the results reported by Kroher and Wolbring (2015) and Waeber (2021). It appears that the perceived social distance is higher in the online condition, even though participants in the online MS teams meeting had turned on their cameras, recognized each other, and were addressed with their name during the session. However, being "caught" by another participant or by the experimenter while cheating was only possible in the in-person setting, where others may watch participants scoring their own errors. Higher ***meaningful*** cheating for men online suggests that the absence of direct social control leads to increased strategic dishonesty.

For the current study, our analysis revealed gender differences in the mean extent of cheating. Specifically, men showed a greater extent of ***all*** cheating in online as well as in-person settings compared to women. However, when focusing on ***meaningful*** cheating, the differences between men and women became more context-dependent. Although ***meaningful*** cheating is not significantly higher for men than for women in the in-person condition, it is higher in the online condition. Beyond this, there were also different increases of cheating over time (see below).

The observed gender differences in meaningful cheating, particularly in the online setting, may be driven by a combination of social and psychological mechanisms. As noted in the introduction, women are more likely to exhibit prosocial orientations and stronger adherence to social norms (Eagly & Wood, 2012; Grosch & Rau, 2017). These tendencies may translate into a greater internalization of moral standards, which continue to exert influence even in low-supervision, high-anonymity environments. Additionally, women have been found to show greater emotional distress when violating moral expectations (Cohen et al., 2011), which could increase the psychological cost of dishonest behavior. Risk aversion may also play a role: Previous studies suggest that women tend to be more risk-averse than men (Croson & Gneezy, 2009), and although the likelihood of being caught was low in the online setting, the perceived reputational or self-image risks associated with cheating may still have been a deterrent. Finally, intrinsic incentives - such as maintaining a sense of integrity or living up to internal standards - may be more salient for women, making them less likely to engage in strategic dishonesty even when the external pressures are minimal. This suggests that the absence of a significant increase in meaningful cheating among women in the online condition may not reflect a lack of opportunity, but rather a greater internal resistance to exploiting those opportunities. Unlike men, whose behavior appeared more sensitive to the reduction in external control, women's behavior remained comparatively stable, reinforcing the idea that their dishonesty is less contingent on context and more grounded in internalized values.

4.1. Trial

The influence of trial on dishonesty was also significant in this study. In the online condition, both ***all*** and ***meaningful*** cheating increased significantly over time, consistent with the findings of Garrett et al. (2016) and Welsh et al. (2015). This supports the hypothesis that the psychological barriers to dishonesty decrease with repeated exposure to the task in a socially distanced and less controlled setting.

Conversely, in the in-person condition, a significant increase over time could only be observed for ***all*** but not for ***meaningful*** cheating. This finding can be interpreted through the lens of social distance theory, which posits that the physical presence of experimenters and other participants may maintain a level of social control that deters the escalation of dishonest behavior. The possibility to visibly monitor others in the in-person setting likely sustained the participants' fear of being caught, thereby mitigating the increase in cheating over time.

Men exhibited a significant increase in ***meaningful*** cheating over time in the online condition, whereas women did not show such an increase. In contrast, in the in-person condition, neither men nor women demonstrated a significant increase in ***meaningful*** cheating over time. This pattern suggests that gender differences in cheating are influenced by both the context and the type of cheating. Since our supplementary analysis (see Supplement 2) demonstrates that participants were generally capable of accurately identifying errors in standardized tracing paths, we interpret ***meaningful*** cheating as a conservative and valid indicator of intentional dishonesty. This supports the notion that the observed increase in meaningful cheating over time, especially in the online condition, is not merely a result of perceptual error, but reflects a strategic and intentional form of dishonesty.

4.2. Limitations

While this study provides valuable insights into the dynamics of cheating in online and in-person settings, several limitations must be acknowledged.

Firstly, the study utilizes the theory of social distance to examine variations in cheating between online and in-person settings. However, this theory may not encompass all factors influencing dishonesty, such as the nuances of different online interactions or psychometric variables like achievement motivation or personality traits.

Secondly, the sample consisted primarily of sport and few psychology students, which may reduce the generalizability of the findings. On the one hand, sport students may exhibit heightened competitiveness and a strong motivation to succeed, potentially increasing their susceptibility to strategic dishonesty in a performance-based task. This competitive orientation might amplify tendencies to exploit the reduced social control in online contexts, thereby influencing the extent of cheating observed. On the other hand, sport education often emphasizes values such as fair play, integrity, and respect for rules, which could also lead to greater internalized moral standards in competitive situations. These contrasting forces may interact in complex ways, potentially moderating the likelihood of dishonest behavior in this population. Therefore, the specific characteristics of this sample limit the extent to which these results can be generalized to other populations. The participants' relatively homogeneous backgrounds in terms of age and education, coupled with the fact that many knew each other prior to the study, could have influenced the results. Knowing each other may have led to concerns about reputation, particularly in the in-person condition, where a cheater may be “caught” by other participants or the experimenter.

Additionally, the tracing task used to assess cheating might not capture the full complexity of dishonest behavior across different contexts, as it focuses on a specific type of skill-based dishonesty. Personal meaningfulness of the task may differ between subjects, and influence the willingness to increase one's score by cheating. It is also important to recognize that the tracing task differs from those traditionally employed in dishonesty research, such as the coin flip, die roll, or matrix problem tasks. These established paradigms typically involve random outcomes and assess cheating only at the aggregate level. In contrast, our tracing task engages participants' physical skills and allows for repeated, individual-level measurement of dishonest behavior, which is essential for examining temporal patterns. Furthermore, while our findings indicate that gender differences in cheating were context-dependent, it is possible that gender differences in fine motor accuracy or risk perception could influence strategic responses. Nevertheless, because cheating was operationalized as the discrepancy between self-reported and expert-coded errors, our measure minimizes the confounding influence of actual performance ability and provides a focused assessment of dishonest intent.

4.3. Conclusions and implications

The findings of the current study suggest greater cheating for men as compared to women in the online condition, when cheating led to an increase in performance scores. In addition, cheating increased over time in the online condition, especially in men. This indicates that online situations could introduce cheating-opportunities in interpersonal situations, which may be used strategically by some individuals. Situations in which participants perform a task online as compared to an in-person setting (e.g., in the context of an online experiment for scientific research, or when course content of a teaching module is assessed by an online exam) could therefore lead to biased results. To address this, it is recommended to reduce anonymity, for instance, by introducing visible identity cues or accountability reminders, which may help mitigate cheating, particularly among individuals who are more sensitive to social control. From a policy perspective, educational institutions and research ethics boards may need to establish guidelines or codes of conduct that address the heightened risk of dishonest behavior in unsupervised online environments. These measures could help protect data integrity in both scientific research and educational assessments.

CRediT authorship contribution statement

Kai Leisge: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Anna Heggenberger:** Writing – review & editing, Investigation. **Christian Kaczmarek:** Writing – review & editing, Investigation. **Werner Pitsch:** Writing – review & editing, Formal analysis. **Sabine Schaefer:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval and consent

This study was approved by the ethics committee of Saarland University. All participants provided written informed consent prior to their involvement in the research.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actpsy.2025.105373.

Data availability

The data, analyses script and the tracing sheets are openly available at: https://osf.io/67x3r/.

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