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Framing effects and social context as determinants of dishonest behavior

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Abstract
This study investigates how framing (gain vs. loss), social context (online vs. in-person) and gender influence dishonest behavior (DB). Based on Prospect Theory and Social Distance Theory, we hypothesized that loss framing and online settings would increase DB. A total of 238 participants completed the Difference Spotting Task, under both framing conditions in either an online or in-person setting. Contrary to the hypothesis, framing had no significant effect on DB, suggesting that loss aversion does not universally drive cheating, potentially due to context-dependent factors like task design or low stakes. In contrast, DB was significantly higher in online settings, supporting the role of anonymity and social distance in reducing norm adherence. While women cheated more frequently, no significant gender differences were found in the extent of DB or its interaction with other factors. Social context appears more influential than framing in shaping DB.

Keywords Dishonesty, Cheating, Loss aversion, Framing, Online and In-Person, Gender

1 Introduction

Imagine a context in which you achieve a significant and highly regarded title, such as in the realm of sports, or accomplish a momentous achievement in your profession. As the subsequent season or period approaches, however, the threat of losing that achievement becomes increasingly prominent. This threat may arise from a decline in one's own performance or from competitors' improvements. Now, compare the joy experienced upon winning the title with the fear of losing it. What actions might one take to avoid such a loss? How far would one go to preserve a victory or reclaim the euphoria of success?

Lance Armstrong, a multiple Tour de France winner, addressed a similar dilemma in an interview. It is mentioned that he "… was simply determined to do whatever it took to win. He believed it was impossible to win the Tour de France without doping, so he doped, which meant he had to lie about doping to keep on winning" [1]. In this case, the joy of winning this prestigious event through honest means was overshadowed by the fear of losing the title, ultimately leading to deviant behavior such as doping and physical or mental intimidations against opponents [1]. This process, however, is not limited to significant milestones but also extends to smaller, everyday situations. For example, consider the emotional response to purchasing a common product on sale, thereby "gaining" the price difference, compared to buying the same item at a suddenly increased price, resulting in an additional "loss". Which scenario is more aversive? While this example highlights an emotional contrast between the joy of gain and the fear of loss, its' purpose is to illustrate the broader principle of Prospect Theory's concept of loss aversion. Importantly, although loss aversion is often accompanied by emotional reactions, the current study does not seek to measure or manipulate affect directly. Instead, it aims to address the research question of how psychological framing (specifically gains and losses) affects dishonest behavior (DB) across different social environments.

2 Theoretical framework – prospect theory and dishonesty

The Prospect Theory, introduced by Kahneman and Tversky (1979), provides a theoretical framework for understanding such discrepancies in emotional weight. It highlights the psychological impact of losses compared to gains, emphasizing that losses loom larger and are experienced more intensely than equivalent gains [2]. This principle, known as loss aversion, influences decision-making by driving individuals to prioritize avoiding losses over acquiring gains [3, 4]. Central to Prospect Theory is the idea that individuals evaluate outcomes relative to a reference point, typically their status quo or expected outcome [2]. Gains and losses are thus interpreted as deviations from this baseline.

Loss aversion has been shown to drive behavior across various contexts, from ethical dilemmas to affective forecasting, where individuals often overestimate the emotional impact of anticipated losses [5, 6]. Additionally, framing decisions in terms of potential losses rather than gains can significantly alter choices, amplifying the motivation to avoid losses [3, 7]. Applied to ethical decision-making, this suggests that individuals might be more willing to engage in DB when attempting to avoid a loss than when pursuing an equivalent gain. Prospect Theory has been applied to ethical decision-making by suggesting that individuals may justify DB to avoid perceived losses [8, 9]. However, most of these studies have used between-subjects designs [6, 8–11], which can be susceptible to interindividual variability. Recent critiques of loss aversion distinguish between a "strong" form, where losses consistently outweigh gains, and a "weak" form, which acknowledges context-dependent effects [12]. It has also been argued that the magnitude of stakes influences loss aversion effects. For small monetary outcomes, gains may sometimes loom larger than losses [13], complicating straightforward predictions.

The present study addresses these concerns by applying a within-subject design, allowing for more precise measurement of framing effects on DB at the individual level. Additionally, we test whether such framing effects generalize to low-stakes and non-consequential tasks, by using modest financial incentives. This offers a valuable test case for the applicability of Prospect Theory's loss aversion to DB in low-stakes environments, helping clarify the boundary conditions of loss aversion's predictive power.

The following sections integrate insights from social psychology and economics to establish a theoretical foundation for understanding why individuals engage in DB, along with a brief description of experimental methods commonly used to assess it. This is followed by a review of empirical findings on the effect of loss aversion on DB, along with studies examining how social context and gender shape DB and moderate the effect of loss aversion.

2.1 Why do individuals engage in DB?

Economic and social psychology perspectives offer complementary insights into DB. The economic view, based on the concept of *homo economicus*, posits that individuals rationally compare the benefits of cheating against its costs, such as the fear of detection or punishment [14, 15]. It suggests that DB occurs only when material incentives outweigh these costs. However, a meta-analysis revealed that people often refrain from cheating maximally, even when the potential benefits are significantly increased [16]. This challenges a purely economic explanation. In contrast, the social psychology perspective, with *homo sociologicus*, highlights the role of internal norms and intrinsic costs of DB, proposing that individuals are motivated by how their behavior aligns with moral values and ethical standards [17–19]. Self-licensing theory adds to this perspective by categorizing individuals as ethical (avoiding DB entirely), economic (experiencing no intrinsic costs), or mixed types (balancing finite intrinsic costs) [20], with the extent of DB remaining relatively consistent across tasks at an intrapersonal level [21]. Together, these frameworks suggest that DB is influenced by both material incentives and self-perception, shaped by ethical principles and situational norms [22]. It is important to emphasize that *homo oeconomicus* and *homo sociologicus* are theoretical ideal types that simplify reality to highlight specific behavioral tendencies. Real human behavior, however, is far more complex and cannot be fully captured by models based solely on economic rationality or social role conformity [23, 24].

2.2 Experimental tasks to measure DB

Measuring DB is challenging due to its reliance on violating norms and participants' reluctance to admit or display it openly. Aggregate-level methods, such as coin-flip [25] or die-roll tasks [26], measure DB by comparing reported outcomes to expected statistical distributions, ensuring anonymity but preventing links to individual traits [18]. However, there are also adaptations of these tasks that allow DB to be measured at the individual level. For instance, the die-roll task can be conducted using a Bluetooth-enabled die, which transmits the actual outcome to a device [27], or with the use of a hidden camera [28]. Classic Individual-level measures include, but are not limited to, deception games [29], ability tests like the matrix task [15] and unsolvable paradigms [9]. Deception games, such as sender-receiver games, assess DB by analyzing how participants choose between truthfully or deceptively communicating information to influence the receiver's decision [30]. The matrix task compares self-reported mathematical performance with actual results but is prone to honest mistakes due to miscalculations [31]. Unsolvable paradigms reduce such errors by using tasks designed to have no solution, offering more reliable insights into individual level DB [32].

2.3 Literature Review – DB and loss aversion

The empirical evidence regarding the effect of loss aversion on DB is inconsistent. Several studies report that loss-framing leads to heightened DB [10, 11, 33, 34]. For example, Cameron and Miller (2009) found that in an unsolvable anagram task participants were more likely to cheat under a loss frame compared to a gain frame [9]. Similarly, Schindler and Pfattheicher (2017), using an aggregate-level measure to asses DB, reported that participants in a loss-framed die-roll task showed significantly higher DB compared to a gain-framed scenario [8]. Steinel et al. (2022) proposed a more detailed result by using a modified version of the die-roll task [35]. They found that participants in the loss frame used major lies, while in the gain condition more modest lies were present. These results align with the broader theory-driven findings that losses loom larger than gains [36]. Gender and individual differences further moderate these effects. Men appear to respond more strongly to loss frames than women [10], and power dynamics amplify cheating under loss frames [37]. Contrasting findings, however, complicate this narrative [6, 38, 39]. For example, Charness et al. (2019) and Ezquerra et al. (2018) used a die-roll task to assess DB but found no evidence of loss aversion for males or females [40, 41]. Few studies even suggest that gain framing can elicit greater DB under specific conditions. Harinck et al. (2007) argued that for small monetary amounts, gains often loom larger than losses, prompting individuals to cheat to secure even modest rewards [13]. Recent research by Wyszynski and Bauer (2023) extends framing effects to rule-regulated social dilemmas, showing that framing a situation as "take-some" (gain) leads to more rule-breaking compared to a "give-some" (loss) scenario [42]. These findings challenge the universality of loss aversion effects on DB.

In sum, while loss framing often increases DB, the empirical results are nuanced, context-dependent and conflicting. Factors such as task type, reward magnitude, individual characteristics, and framing implementation can influence outcomes, warranting further investigation to reconcile these mixed findings. Nonetheless, based on Prospect Theory's loss aversion, which suggests that losses have a greater psychological impact than gains, we hypothesize that DB will be higher in a loss frame than in a gain frame, as individuals seek to minimize emotional distress.

2.4 Literature Review – DB and social setting and gender

While Prospect Theory's loss aversion provides the foundation for the study's main hypothesis regarding framing effects, DB is also shaped by social and contextual factors. The transition from laboratory to online settings significantly alters behavior by influencing the norms individuals follow [43]. Social distance theory explains these differences by the perceived remoteness (both locational and emotional) between individuals [44]. In face-to-face environments, reduced anonymity and the presence of authority figures, peers, and social cues lead to closer social distance, reinforcing norm compliance and accountability [45]. This aligns with the concept of social presence, defined as the sense of being with another individual [46], which leads subjects to adjust their behavior in socially desirable ways [47]. Conversely, the anonymity of online settings increases social distance by eliminating social presence and therefore reducing the perceived risk of being caught or judged while encouraging self-interest-driven behavior, which may weaken self-control against DB [48].

Empirical findings on the influence of social distance in online versus in-person settings remain mixed. Cohn et al. (2022) tested the same participant pool in a coin-flip task and found that a shift in environments does not affect the prevalence of DB [49]. In contrast, Kroher and Wolbring (2015) found greater cheating in an online die-roll task than in-person [50]. However, Waeber (2021) provided a more nuanced perspective, reporting no systematic differences in DB across social settings using a decision-making task via a stock market scenario [51]. Notably, men were more dishonest online, while no differences were observed for women. These findings align with theories of social distance, social presence and norm enforcement, which propose that monitoring or the sense of being monitored [52], as well as the perceived degree of anonymity and proximity of others can influence DB. Following these insights, it is hypothesized that DB is higher in online contexts, where external social constraints are attenuated and internal cost-benefit calculations may dominate.

From the perspective of Prospect Theory, social setting may further moderate the perceived salience of gains and losses. In anonymous, online environments, individuals may feel freer to act in self-interest and might be more motivated to avoid losses when the risk of reputational damage is low. In contrast, in socially monitored environments, such as in-person settings, the social cost of DB may counteract the psychological pull of loss aversion. To the best of our knowledge, no prior research has investigated whether social context moderates the effect of loss aversion on DB. Therefore, the current study additionally examines this potential interaction on an exploratory basis.

In addition to social context, individual characteristics, particularly gender may shape how people respond to gain and loss frames. Prior research on the main effect of gender on DB has produced mixed results. While many studies suggest men are more likely to engage in DB than women [14, 53, 54], others report no gender differences [41, 55] or even higher levels of dishonesty among women in specific scenarios [56, 57]. Gender differences in DB may be attributed to general differences between men and women, like socialization patterns and prosocial orientations [53, 58], moral licensing and trustworthiness [59], or competitiveness [60].

Prospect Theory's loss aversion offers a potential lens to interpret these discrepancies. For instance, men may be more responsive to loss-framing in competitive or instrumental contexts, while women may weigh social and moral costs more heavily. By additionally exploring gender differences across framing, the present study seeks to better understand how these variables interact in shaping DB. Notably, most research on loss aversion and DB have not systematically examined gender as a moderating factor [8, 9, 11, 33, 39, 40]. One of the few studies that addressed this question is Ezquerra et al. [41], who employed the die-roll task and found that although both men and women engage in DB under gain and loss frames, there are no significant gender differences within each framing condition.

The current study addresses this gap by exploratorily testing whether gender interacts with framing, therefore offering additional insights into how individual traits influence loss aversion and DB. Due to the limited research on this influence, a non-directional hypothesis is proposed. It is assumed that based on Prospect Theory's concept of loss aversion, the effect of gain and loss framing on DB differs between men and women.

This highlights the role of anonymity, social context, and gender in shaping ethical behavior across different environments. While these variables have been studied in isolation, little is known about how they may interact with framing. We explore these interactions not to test a fully specified model, but to examine whether effects observed in prior studies generalize across contexts and subgroups. By doing so, we address calls for more nuanced, ecologically valid assessments of DB.

3 Materials and methods

3.1 Sample

Based on the findings of Schindler and Pfattheicher [8], who reported a medium effect of the two framings (Gain vs. Loss) on DB in alignment with the main hypothesis of

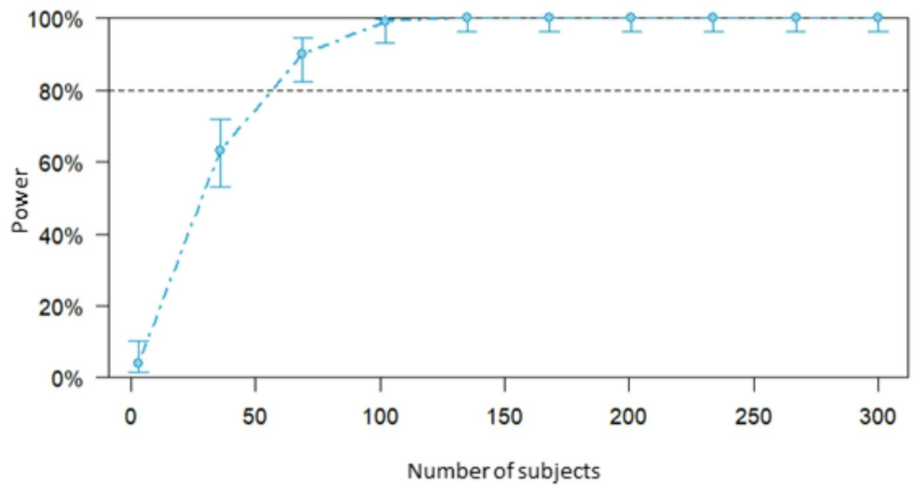

Fig. 1 Simulation based sample size estimation for the within-subject main effect

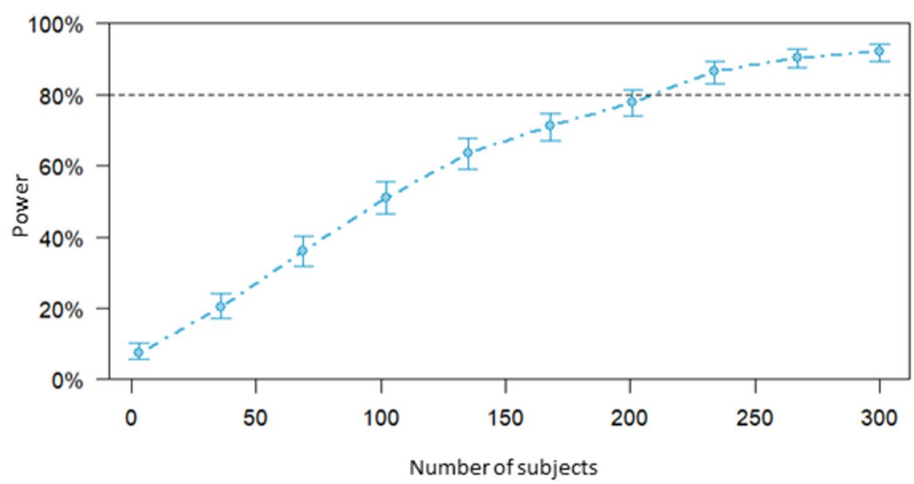

Fig. 2 Simulation based sample size estimation for the two within and between interactions

this paper, we considered a sample size estimation to detect a medium effect (d_z = 0.5). We conducted a simulation-based power analysis for a linear mixed-effects model using the simr package in R [61]. The simulated model included a random intercept for participant ID, one within-subject factor (two levels), and two between-subject factors (two levels each), reflecting the planned experimental design. For the primary hypothesis concerning the effect of framing, we assumed a fixed effect size of $\beta_{Std.} = 0.4$. Residual variance and random effect structure were derived from simulated datasets, based on the experimental design. Power was estimated across sample sizes ranging from 0 to 300, in increments of 40, using 500 simulations per sample size. The estimated power to detect the within-subject effect of framing reached 80% at approximately $n = 60$ (see Fig. 1). A similar approach was used to estimate the required sample size for the two exploratorily hypothesized two-way interactions of framing and gender, as well as framing and social setting. Assuming the same effect size ($\beta = 0.4$) and using 500 simulations per sample size, the estimated power to detect these interaction effects reached 80% at around $n = 200$ (see Fig. 2).

A total of 238 participants were tested in either an online ($n = 125$) or an in-person ($n = 113$) environment. In the online condition, 36 participants were male (29%) aged 19 to 75 years ($M = 27$, $SD = 13.72$) and 89 were female (71%) between 19 and 75 years of age ($M = 30.2$, $SD = 12.78$). The gender distribution for the in-person condition was nearly balanced with 56 male participants (50%) aged 19 to 37 years ($M = 24.71$, $SD = 3.13$) and 57 female participants (50%) between the ages of 19 and 27 ($M = 23.05$, $SD = 2.14$). All participants had normal or corrected-to-normal vision and five reported colorblindness (online: $n = 2$, in-person: $n = 3$)[1]. Participants for the in-person condition were recruited at the Institute of Sport and Sports Science at Heidelberg University, where they were informed about the study's duration, monetary compensation, and required tasks. As a result, the sample primarily consisted of sport and some psychology students. Recruitment for the online condition was conducted in two waves. In the first wave, 69 participants (55%) were selected through word-of-mouth recommendation in sport clubs and friendship groups and received an email with study information and a participation link. In the second wave, 56 participants (45%) were recruited via self-selection from the participant pool of the Institute of Sport Science at Saarland University, which mainly consists of sports and a few psychology students. No stratified quotas by gender or age were imposed ex ante to preserve feasibility across recruitment channels and achieve adequate power for the pre-registered within-subject framing test. We therefore address demographic imbalances in the study groups in the limitations section and in the supplementary material.

Prior to data collection, potential participants received an email with the study description and a participation link. No specific inclusion or exclusion criteria were defined. Informed consent was obtained from all participants before testing, and participants were assured that their data would be anonymized and treated confidentially in subsequent analyses. The main hypothesis concerning the framing effect (gain – loss) on DB, and the exploratory interaction with gender, as well as the experimental design, and the planned statistical analyses were preregistered prior to data collection (https://aspredicted.org/rkd6-34j7.pdf). The data and the analyses scripts that support the findings of this study are openly available in OSF at: https://osf.io/hmqgd/?view_only=5a6b631a719849f9bdae8c38eb7e5372.

3.2 Procedure – Data collection

A plausible distraction task was included to divert attention from the actual aim of the study. Participants were informed that the primary goal of the study was to investigate cognitive learning, with the initial task serving as a training phase for the following performance test on visual search ability. To reinforce this belief, a computerized Visual Search ability task was introduced, in which participants were presented with 10 image pairs. Each trial lasted 30 s, and each image pair contained exactly 10 differences. Participants were instructed to accurately mark as many differences as they could identify within the allotted time. They were also informed that their performance in this task would serve as the actual measure of interest. To further motivate engagement in this distraction task on visual search ability, participants received a reward of 2 cents per

[1] The Difference Spotting Task stimuli were taken from Liu et al. [32] and rely on structural rather than color-based differences. Therefore, color vision deficiencies were not expected to affect task performance.

correctly marked difference[2], creating the impression that the experiment aimed to assess their visual search performance rather than their decision-making behavior in the DST (see supplement for further details).

Test sessions for both conditions were similar and designed to last approximately one hour. The in-person data collection took place in a laboratory at Heidelberg University and was performed in groups of five or six participants. Each workstation was separated by partition walls to prevent visual contact between participants. The researcher was positioned with their back to the participants to minimize any feeling of being observed. The timeframe and location for data collection in the online condition was flexible and determined individually by each participant. The study's main task was administered using SoSci Survey [62] and JavaScript. To ensure comparability with the in-person condition, the questionnaire for the online setting was not accessible via mobile phones or tablets, but only through computers. The study was approved by the ethics committees of Heidelberg University and Saarland University.

Participants in both settings began by answering computer-based questionnaires on personal information, such as gender and age, followed by assessments of psychometric data, including values, achievement motivation, and personality traits (see supplement for psychometric scales). Afterwards, the main task to measure DB was completed. In the online environment, a feedback loop was included, allowing participants to reread the instructions and complete a practice trial. They were only able to continue once they confirmed that they had understood the task.

3.3 Instruments

3.3.1 Difference spotting task – dishonest behavior

With the Difference Spotting Task, Liu et al. [32] introduced a cognitive assessment tool to measure DB at both the item and individual level. This non-verbal task is suitable for widespread use across culturally and educationally diverse populations [32]. The computerized DST presents participants with sequential comparisons of image pairs. It consists of 80 pairs in total, including 40 solvable trials with 10 differences each (see Fig. 3A) and, unbeknownst to the participants, 40 unsolvable trials (see Fig. 3B), where the pairs

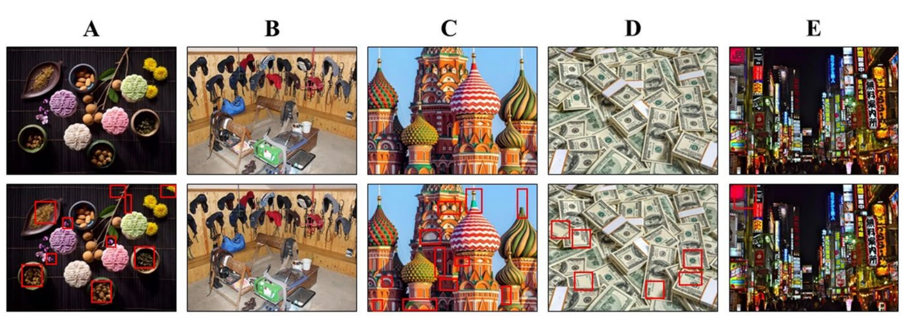

Fig. 3 Examples of the visual stimuli used in this study (Adapted from Liu et al. [32]). **A** Example of an original stimulus pair in solvable items. **B** Example of an original stimulus pair in "unsolvable items," containing no differences. Participants were instructed that there would be two additional difficulty levels besides (**C**) "easy" (10 differences), namely (**D**) "medium" with six differences, and (**E**) "hard" with one difference. Note, however, that the instructions differed from the actual stimulus pairs. Differences between the target stimuli are highlighted by red boxes for illustration purposes.

[2] Please note that this payment scheme applied only to the distraction task described here and therefore differed from the procedure used in the subsequent task.

are identical. To reinforce participants' belief that the study focused on cognitive learning, they were instructed that all items are solvable and that difficulty levels would range from easy (10 differences, Fig. 3C) to intermediate (6 differences, Fig. 3D) and hard (containing only one difference, Fig. 3E), while in reality all solvable 40 items have exactly 10 differences.

During each trial, participants are asked to indicate whether they had spotted at least one difference by selecting either "✓ Yes" or "✗ No", without further specifying the number or exact location of differences. While participants may have identified more than one difference, they were only required to find a single one to legitimately respond "Yes". They were instructed to double-check their responses and only confirm that they had found at least one difference if they were absolutely certain. If they were uncertain, they were advised to respond "No" and proceed to the next trial. Participants were also instructed that changing their response after the initial selection was not possible. The number of "✓ Yes" responses in the unsolvable trials, where participants claim to have spotted a difference, is considered an indication of dishonesty and is used as a measure of DB. The maximum extent of DB for the DST is therefore 40. The sequences of picture pairs, and therefore the order of solvable and unsolvable trials, are randomized to eliminate potential order effects. To reduce the likelihood of honest errors and enhance the reliability of the task, participants are given a 60-second break after 40 trials.

To analyze the hypothesized differences in DB between gain- and loss-framing, the DST was adapted to a within-subject design for both environments. To control for sequence effects, participants in both the online and in-person conditions were randomly assigned to one of two protocols: Gain-Loss or Loss-Gain. In the Gain-Loss order, participants initially completed the first 40 image pairs under gain-framing, where they earned 3 cents for finding at least one difference ("Yes" response). A "No" response resulted in no earnings (+ 0 Cents). These results were presented following every trial (Fig. 4A). The amount of 3 cents per trial was chosen to align with the original implementation of the DST [32], ensuring comparability with prior studies using this paradigm. Following this gain-framing block (40 trials), a break was introduced, during which the loss-framing was instructed. The break length was set to a minimum of 90 s, but could be extended by each participant individually. Importantly, participants were told that their earnings from the first block were retained, ensuring that the reference point at the start of the loss-framing condition was identical for all participants and thus independent of their actual prior performance. Participants were credited with an initial balance of 120 cents, equivalent to the maximum possible earnings in the gain-framing. Under loss-framing, participants lost 3 cents from their balance for each trial in which

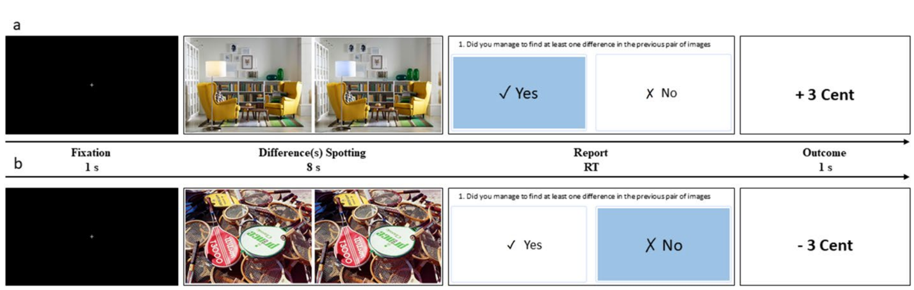

Fig. 4 Sequence of a single trial in the DST with example rewards for gain (**a**) and loss (**b**) framing (Adapted from Liu et al. [32]). In the gain frame (a), any "Yes" response always results in a reward of "+3 Cent". In the loss frame (b), any "No" response results in a deduction of "-3 Cent". All other responses lead to no change, displaying "+0 Cent"

they reported finding no difference ("No" response). The corresponding feedback was displayed after each trial, indicating either a 3 Cent deduction ("No" response) or no change in balance ("Yes" response) (Fig. 4B). At the end of the DST, participants were shown their final results, including their total earnings. Similarly, participants in the Loss-Gain sequence completed the task in reverse order, starting with loss-framing and an initial balance of 120 cents before switching to gain-framing after 40 trials. Due to the split of the DST, the maximum extent of DB for both the gain and loss frames is 20 each. The money earned by participants in the first loss-framing block was retained, and everyone started the gain-framing block with no initial balance. Again, break length was set to a minimum of 90 s, but could be extended by each participant individually. Critically, this design ensured that participants in both sequences began each framing condition with the same monetary reference point, thereby controlling for prior earnings and maintaining experimental equivalence. Each framing condition was introduced independently and participants did not risk losing previously accumulated personal earnings.

3.4 Statistics

The statistical analyses were conducted using R Statistical Software (version 4.4.0) for Windows [63]. We used a log-linear Poisson regression model to analyze the frequency counts of honest and dishonest participants, incorporating the effects of gender, setting, and frame. The model included interaction terms to account for potential dependencies between these factors. This model allowed us to test for group-level differences in the likelihood of engaging in any DB, complementing the mixed-effects analyses that focus on the extent of dishonesty. Full model results are provided in the Supplementary Material. To test if DB was present for each gender, setting and framing, one-sample Wilcoxon tests were used to compare the empirical values against zero. The main hypothesis was analyzed for pooled conditions (online, in-person) using a linear mixed-effects model with participant as a random factor to examine the influence of the within-subjects factor framing (2: gain, loss), on the mean extent of DB. The additional and exploratory hypothesis, analyzing the influence of framing (2: gain, loss), condition (2: online, in-person) and gender (2: male, female) on the mean extent of DB, was tested using a linear mixed-effects model with participant as a random effect. To address concerns regarding the interpretability of main effects when interaction terms are included, we additionally computed a separate linear mixed-effects model that included only the main effects of framing, condition, and gender, based on the suggestions by a Reviewer. As the results did not differ qualitatively from those of the full model, we present the detailed output of this analysis in the supplementary material (see Supplement).

The mixed-effects models were conducted with the nlme R package [64]. Descriptive statistics were calculated via the psych R package [65]. Effect sizes were computed by using the rcompanion R package [66]. No participants were excluded from the analyses and all measures and transformations are reported. For all analyses the alpha level was set to 0.05.

4 Results

4.1 General results: is DB present?

To assess whether the likelihood of engaging in any dishonest behavior varied by gender, setting, or framing, we first ran a log-linear Poisson regression on the frequency counts of dishonest vs. honest participants (see Supplementary Material for full results). Overall, 58% ($n = 53$) of male participants engaged in DB, reporting at least one unsolvable pair as solved in the DST, while 72% ($n = 105$) of female participants were dishonest. This difference was statistically significant (β = 0.75, 95% confidence interval (CI) [0.01, 1.51], $p = .049$). In the online setting, 67% of men ($n = 24$) and 71% of women ($n = 63$) engaged in DB, showing no significant difference (β = -0.61, $p = .265$). Regarding framing effects, DB frequencies decreased slightly in the gain frame, but the differences were not statistically significant: 53% of men ($n = 19$) and 56% of women ($n = 50$) reported DB. In the loss frame, 53% of men ($n = 19$) and 64% of women ($n = 57$) were dishonest (β = 0.18, $p = .819$). In contrast, within the in-person condition, 52% of men ($n = 29$) and 74% of women ($n = 42$) engaged in DB at least once, but this interaction was not statistically significant (β = -0.61, $p = .265$). Similarly, no significant gender differences were observed in the gain frame, where 43% of men ($n = 24$) and 61% of women ($n = 35$) engaged in DB. In the loss frame, 38% of men ($n = 21$) and 60% of women ($n = 34$) reported at least one instance of DB (β = 0.18, $p = .819$).

One-sample Wilcoxon tests revealed significant differences from zero for both men and women in the online and in-person conditions, with large effect sizes, across both the gain and loss frames (see Table 1).

4.2 Differences in DB for gain and loss frames

We used a linear mixed-effects model (estimated using maximum likelihood) to predict the extent of DB with the within-subjects factor framing (2: gain, loss) and the random effect participant. The total explanatory power is large (condition R^2 = 0.80) while the part related to the fixed effects is very small (marginal R^2 < 0.01) and the models intercept is at 2.86 (*SE* =, 95% CI [2.20, 3.52], $t_{(237)} = 8.53$, $p < .001$). The model includes a random intercept for participant ID, with a standard deviation of 4.62 (variance = 21.36). The residual standard deviation was 2.31 (variance = 5.32), indicating substantial individual-level variability in DB across framing conditions. Within this model the effect of framing is statistically non-significant (β = 0.40, 95% CI [-0.01, 0.82], $t_{(237)} = 1.90$, $p = .058$). This result leads to the rejection of the main hypothesis, suggesting that gain and loss framing within the DST did not trigger DB differently (see Fig. 5). A Bayesian paired-samples t-test further supported the absence of a framing effect (BF_{10} = 0.43), providing moderate evidence for the null hypothesis. These findings reinforce the interpretation that framing did not meaningfully influence DB in this study.

Table 1 Dishonest behavior is present in gain and loss frames for both conditions and genders

			Test Statistics				
			M	***SD***	***z***	***p***	***r***
Online	Men	Gain	4.50	7.17	-3.98	**< 0.001**	0.88
		Loss	4.86	7.20	-3.98	**< 0.001**	0.88
	Women	Gain	3.08	5.30	-6.31	**< 0.001**	0.88
		Loss	3.56	5.33	-6.70	**< 0.001**	0.87
In Person	Men	Gain	2.00	4.20	-4.46	**< 0.001**	0.88
		Loss	2.09	4.05	-4.17	**< 0.001**	0.88
	Women	Gain	2.33	3.84	-5.31	**< 0.001**	0.88
		Loss	2.95	4.39	-5.22	**< 0.001**	0.88

Extent of cheating (mean, standard deviation), results of one-sample Wilcoxon test (*z*-value, *p*-value), and the effect size (*r*) are presented

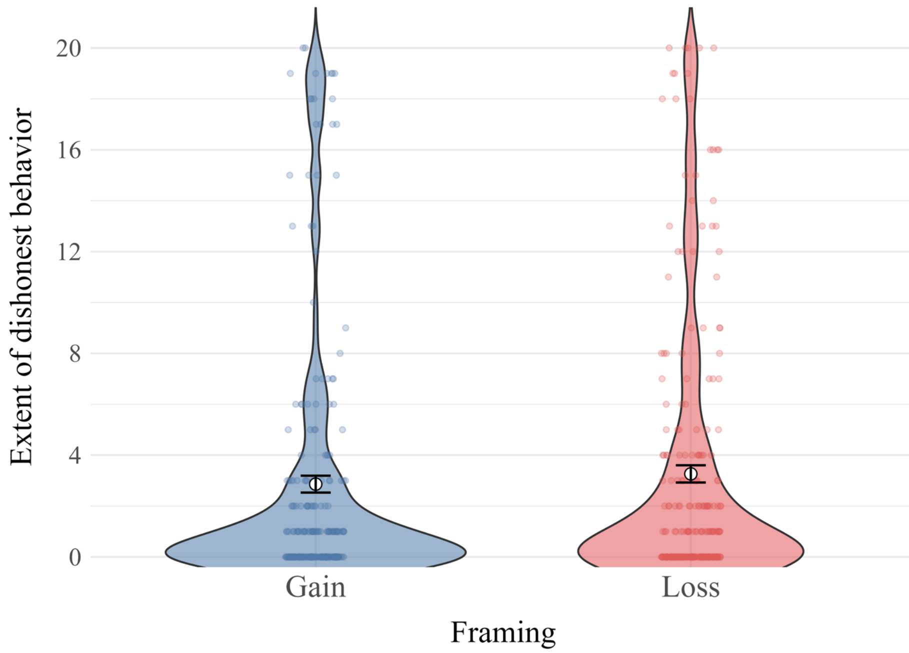

Fig. 5 Loss framing does not trigger higher DB than gain framing. Violin plots showing the distribution of DB under Gain and Loss framing conditions. Individual data points are displayed as semi-transparent dots. Black circles represent the mean, and vertical bars indicate ± 1 standard error of the mean (SEM)

The additional analysis also used a linear mixed-effects model (estimated using maximum likelihood) to predict the extent of DB with the within-subjects factor framing (2: gain, loss) and the between-subjects factors condition (2: online, in-person) and gender (2: male, female). The model's explanatory power is large (conditional $R^2 = 0.80$) and the part related to the fixed effects alone is small (marginal $R^2 = 0.03$). The model includes a random intercept for participant ID, with a standard deviation of 4.55 (variance = 20.70). The residual standard deviation was 2.30 (variance = 5.31), indicating individual-level variability in dishonest behavior across framing, condition, and gender. These values support the robustness of the model and confirm that individual differences were appropriately accounted for. Within this model, only the effect of condition is statistically significant and positive (β = 2.50, 95% CI [0.36, 4.64], $t_{(234)} = 2.28$, $p = .024$), indicating that DB is higher online than in-person, thus confirming the second hypothesis (see Fig. 6). All other main and interaction effects did not reach significance, leading to the rejection of the exploratory hypotheses on the influence of framing, setting and gender on DB (see Table 2). The additional analysis focusing solely on main effects revealed no qualitative differences in the estimation of main effects or in overall model fit when compared to the full model including interaction terms (see Supplement).

5 Discussion

The goal of this study was to examine whether gain and loss framings differentially influence DB, alongside the role of social setting and gender. Grounded in Prospect Theory, we hypothesized that DB would be higher in a loss frame than in a gain frame, as participants strive to minimize emotional distress. Additionally, we expected that the anonymity of online settings would increase DB due to greater social distance and reduced accountability.

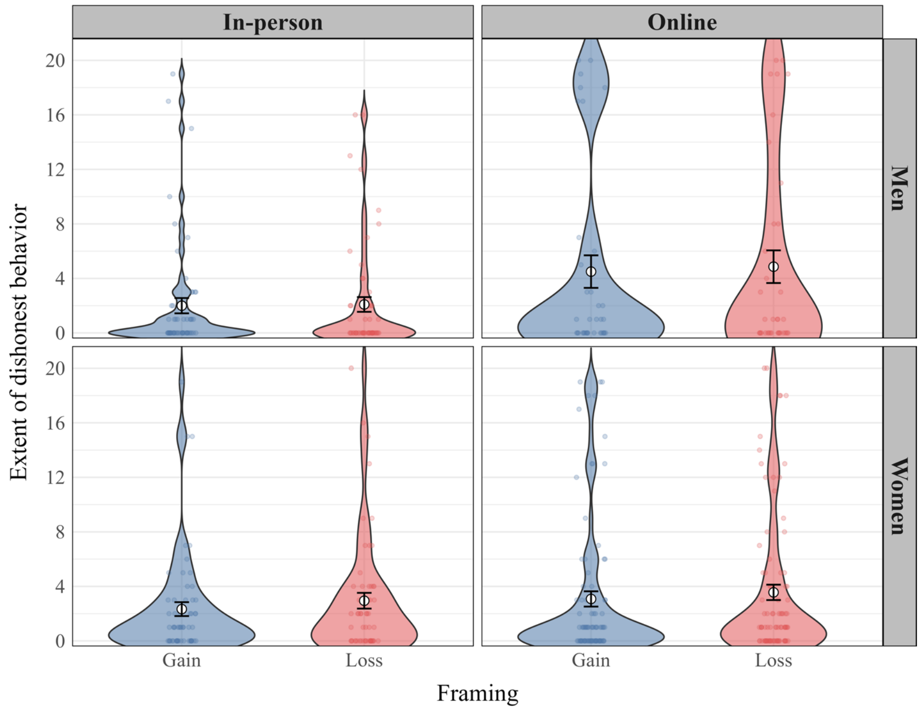

Fig. 6 DB is not influenced by framing, but is higher online compared to in-person. Violin plots showing the distribution of DB under Gain and Loss framing conditions. Individual data points are displayed as semi-transparent dots. Black circles represent the mean, and vertical bars indicate ± 1 standard error of the mean (SEM)

Table 2 Results of the linear mixed-effects model

	Test Statistics					
	Estimate	***SE***	**95% CI**		***t***	***p***
			LL	**UL**		
Intercept	2.00	0.69	0.66	3.34	2.91	**0.004**
Framing	0.09	0.44	-0.77	0.95	0.20	0.839
Condition	2.50	1.1	0.36	4.64	2.28	**0.024**
Gender	0.33	0.97	-1.56	2.22	0.34	0.731
Framing*Condition	0.27	0.7	-1.1	1.64	0.39	0.699
Framing*Gender	0.52	0.62	-0.68	1.73	0.85	0.397
Condition*Gender	-1.75	1.4	-4.49	0.98	-1.25	0.212
Framing*Condition*Gender	-0.40	0.90	-2.15	1.35	-0.45	0.654

5.1 Loss aversion and DB

Our analyses did not reveal a significant effect of loss aversion on DB. Thus, the main hypothesis, that loss framing would trigger higher DB then a gain frame, must be rejected. These findings contradict the theoretical predictions of Prospect Theory's loss aversion [2], which formed the basis of our hypothesis. However, they align with prior empirical studies that also found no evidence of loss aversion influencing DB or rule-breaking behavior [6, 40–42]. Nevertheless, this study contributes meaningfully to the existing literature. While most previous research employed a between-subjects design to compare gain and loss framing effects, a within-subjects design, as used here, is essential for minimizing measurement issues [67]. Individual differences, as suggested by the concept of *homo sociologicus* and self-licensing theory, may influence one's propensity to engage in DB, highlighting the importance of controlling for interindividual variation.

However, while controlling for individual differences, the within-subject design may have reduced framing effects due to increased transparency and consistency pressures [68]. This is supported by meta-analytic evidence of McDonald et al. (2021), who found that valence framing effects on moral judgments are robust overall but small when accounting for publication bias and highly variable across designs, with within-subject studies often yielding weaker effects [69].

Another key distinction from prior studies is the choice of experimental tasks. Many studies rely on self-reported, one-shot tasks involving random events (e.g., die rolls or coin tosses) to measure DB at the aggregate level. Despite the methodological advancements of measuring DB at the individual level, our results align with previous studies that found no significant effect of loss aversion on DB [39, 40]. This suggests that the absence of a loss framing effect is not merely an artifact of experimental design but may reflect a more generalizable pattern. This further underscores the complexity of the relationship between loss aversion and DB, suggesting that additional factors (individual differences, task characteristics, or context-specific norms) could play a crucial role.

The reason for these discrepancies may lie in a more nuanced understanding of loss aversion. Gal and Rucker [12] argue for the existence of both a strong and a weak version of loss aversion. Our findings align more closely with the weak version, as the absence of a significant framing effect on DB suggests that participants did not universally perceive losses as more impactful than gains.

This perspective is further refined by considering the role of an individual's reference point. If the reference point is the status quo, then any negative outcome is perceived as a loss and any positive outcome as a gain. However, when the reference point is set above the status quo, individuals can experience a positive outcome even when moving below it [70]. In our study, it remains unclear whether participants adopted the initial endowment as their new reference point or whether they continued to use their baseline financial status. If the latter was the case, the loss manipulation may not have been perceived as a true loss, which could explain the absence of a significant framing effect on DB.

Another perspective to consider is the hedonic principle, which suggests that individuals aim to maximize pleasure and minimize pain when making decisions [13]. This principle challenges the idea that losses always loom larger than gains by emphasizing that the impact of gains and losses depends on their magnitude. Research has shown that for small amounts of money, gains may actually loom larger than losses, as people have more experience coping with minor losses and do not perceive them as particularly consequential [12]. This could explain why loss aversion effects are not always observed in studies involving low stakes. If participants viewed small losses as relatively inconsequential, they may not have been as motivated to engage in DB to avoid them. Instead, minor gains might have been perceived as more rewarding, potentially negating the expected loss aversion effect. Therefore, the relatively low monetary stakes in our study may have attenuated the framing effects. While the incentive was sufficient to induce DB, it may not have been large enough to trigger strong motivational or emotional responses associated with loss aversion.

5.2 Social setting and DB

Our extended model revealed a significant main effect of condition, confirming the second hypothesis that DB is higher in online settings compared to in-person settings.

However, neither gender nor framing had a significant effect on the extent of DB, once again contradicting the predicted loss aversion of Prospect Theory. The confirmation of hypothesis two aligns with the theories of social distance, social presence and anonymity while further supporting previous research [50, 51, 71]. Participants in the in-person condition were not fully anonymous due to the presence of other individuals and the experimenter, leading to a lower perceived social distance. In contrast, the online setting allowed participants to complete the experiment alone, increasing both perceived social distance and anonymity by eliminating social presence, which likely contributed to higher levels of DB.

Additionally, the laboratory setting may have induced a context-dependent shift in norms, as individuals are often more inclined to conform to ethical expectations in structured environments [43, 72, 73]. In contrast, participants online at home may have adhered more strongly to their personal moral standards, which can vary widely and may allow for greater justifications of DB. This finding suggests that individuals in online settings may be more susceptible to DB, possibly due to the reduced external social pressures and norms that typically regulate it.

Lastly, the observed gender differences in DB, independent of social condition, should be discussed. While overall, women engaged in DB more frequently than men, this pattern did not hold consistently within specific conditions or framings. Additionally, when examining the extent of DB, a non-significant trend emerged, suggesting that although men engaged in DB less frequently than women, they tended to do so to a greater extent when they did. This pattern suggests that gender differences in DB may manifest more in the decision to cheat at all rather than in the extent of DB once that threshold is crossed. Similar patterns have been observed in prior research, where women exhibit higher participation in minor norm violations, while men tend to engage in fewer but more severe violations when they occur [29, 54]. Women might engage in low-level dishonesty to secure modest gains without disrupting social harmony, whereas men, when deciding to cheat, may do so more extensively to maximize payoffs. This is consistent with findings on gender differences in competitiveness and risk preferences [53, 60, 74]. Another factor to consider is moral self-concept maintenance [15]. Women may experience stronger internalized norms against large-scale DB, leading to a "many small lies" pattern rather than "few big lies". Conversely, men may tolerate greater deviations from their moral self-concept when situational justifications are available, resulting in higher variance in DB extent. These findings highlight the complexity of gender differences in DB, suggesting they are context-dependent and influenced by additional factors such as framing and social interactions [54, 74].

5.3 Limitations

Despite the contributions of this study, several limitations must be considered. First, the laboratory setting, while controlled, may not fully capture the complexities of real-world contexts. The presence of other participants in the in-person condition could have influenced behavior, and the online setting, although increasing social distance and anonymity, might not reflect the full range of social pressures individuals experience outside the lab. Considering the sample composition, the limitation that the online sample included proportionally more women than the in-person sample has to be noted. An uneven gender distribution can reduce the precision of exploratory subgroup comparisons.

Therefore, future studies should aim for more balanced recruitment to enhance comparability across conditions.

Additionally, while the (DST) is a useful measure of DB, its ecological validity may be limited, as it focuses on relatively simple cognitive tasks rather than more complex real-life ethical decision-making scenarios. Another potential limitation concerns the relatively low monetary incentive (3 cents per trial), which may have limited the motivational impact of the gain and loss frames. However, this amount was intentionally chosen to remain consistent with the original DST design [32], ensuring methodological comparability. Future research should examine whether increasing the magnitude of incentives amplifies framing effects on DB in the DST.

Moreover, the repeated-measures design involving 40 trials per frame allowed small effects to accumulate across decisions, which may partially mitigate the impact of low individual stakes. Although modest in absolute terms, this reward was sufficient to incentivize DB in both framings. Another limitation concerns the smaller effect sizes often observed in within-subject designs, likely due to increased transparency and participants' motivation for internal consistency [68, 69]. To mitigate these influences, researchers have proposed strategies such as masking trials (filler items unrelated to the main manipulation) or inserting time delays between frames. However, empirical evidence suggests these measures provide only limited benefit [68]. An alternative approach involves psychophysical methods, such as adaptive staircase or titration procedures, which gradually adjust payoffs or probabilities across trials to reduce the salience of frame changes. Future research could combine these techniques to clarify whether the absence of a framing effect reflects a true boundary condition or a methodological artifact. Adding additional control groups which do not change the framing at all (gain-gain, loss-loss) in future research may further elucidate potential framing effects.

Furthermore, while gender was accounted for, no significant interaction effects were found in this study. However, this result should be interpreted with caution, as the sample was not perfectly balanced, and further research with more gender-diverse samples is needed.

Lastly, the weak effect of loss framing may be attributed to the nature of the reference point, as participants may not have perceived the losses as substantial enough to activate loss aversion. By using windfall gains at the start of the loss-frame condition, participants may not have felt that they had truly "earned" the initial balance. As a result, they may not have fully internalized the money as part of their entitlement, preventing an adequate shift in their reference point.

6 Conclusion

Returning to the example introduced at the beginning, our findings suggest that while fear of loss may strongly influence decision-making in real-world contexts (e.g., sports or financial decisions), its' effect on DB in controlled experimental settings remains inconclusive. This discrepancy highlights the role of situational and psychological factors, such as the weak version of loss aversion, the hedonic principle, or varying reference points, that may moderate the framing effect on ethical decision-making.

In contrast, the social setting had a clear impact on DB, with significantly higher rates observed in the online condition. These results have important implications for both research and educational practices. If tasks are conducted online, whether in experimental studies or academic settings, they may be more susceptible to DB, potentially leading to biased or unreliable outcomes.

Overall, these findings challenge the assumption that loss aversion universally drives dishonesty. Instead, they emphasize the importance of contextual and methodological factors, such as reference points and monetary stakes, in shaping DB. Additionally, the results reinforce the role of social context, suggesting that reducing anonymity and increasing accountability could be effective strategies for mitigating DB in real-world settings. Future research should further investigate the boundary conditions of loss aversion in ethical decision-making and explore how different social and environmental factors interact to influence DB.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s44202-025-00494-6.

Supplementary Material 1.

Preregistration

The main hypothesis concerning the framing effect (gain – loss) on DB, and the exploratory interaction with gender, as well as the experimental design, and the planned statistical analyses were preregistered prior to data collection (https://aspredicted.org/rkd6-34j7.pdf).

Author contributions

K.L. Conceptualization; Methodology; Formal Analysis; Data Curation; Writing - Original Draft; Writing - Review and Editing.L.W. Investigation; Data Curation; Writing - Review and Editing.W.P. Methodology; Formal Analysis; Writing - Review and Editing.S.S. Conceptualization; Methodology; Writing - Review and Editing; Supervision.

Funding

Open Access funding enabled and organized by Projekt DEAL. The authors disclosed receipt of the following financial support for the research and publication of this article: This work was funded by Saarland University (salary).

Data availability

The data, codebook and the analyses scripts that support the findings of this study are openly available in OSF at https://osf.io/hmqgd/?view_only=5a6b631a719849f9bdae8c38eb7e5372.

Declarations

Ethics approval and consent to participate

The study was approved by the ethics committees of Heidelberg University and Saarland University.

Informed consent

Informed consent was obtained from all individual participants included in the study.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 27 June 2025 / Accepted: 16 October 2025

Published online: 05 December 2025

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