Feature

Technology (live sonar and mobile lead) and skill as possible drivers of catch inequality in recreational spearfishing tournaments

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A spearfisher beside the inflatable boat, about to dive with a removable weight belt of about 10 kg, made of several lead blocks. Photo credit: Marco Bardi, Technical Director of the FIPSAS men's spearfishing team.

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Abstract

Catch inequality is common in fisheries, indicated by a minority of fishers catching a disproportionate number of all fish. Skill, experience, and heterogenous investment of time and resources are typical factors proposed to underly catch inequality in recreational fisheries. Technological innovations that impact catch outcomes may either increase (if only adopted by a minority) or decrease catch inequality (if adopted by a majority and such adoption reduces skill differences among fishers). Understanding how fishers' skill and technologies, including the uptake of live sonar technology, drive inequality is important, as uneven catch distribution can undermine the effectiveness of management measures and influence recreational fisher satisfaction. We investigated the effects that technology adoption and average fishers' skill levels have on catch inequality in recreational spearfishing, relying on data from Italian spearfishing tournaments from 2004 to 2025. We also examined whether technological innovations influenced the composition of catches. Catch inequality was quantified using the Gini coefficient. We assessed the effect of technological innovations (specifically the use of live image sonar and use of mobile lead in the dive) and average fisher skill (represented by different categories of tournaments) on catch inequality. No evidence that new technologies affected catch inequality was found, although a weak increasing trend of inequality over time was detected in some tournament categories. Inequality was highest in pair and semifinal tournaments, which gather more heterogeneous competitors, and lowest in finals, restricted to the most skilled spearfishers. These findings suggest that under standardized tournament conditions, average fishers` skill present in a given tournament plays a stronger role in shaping catch inequality than the uptake of technological innovations. Thus, in spearfishing tournaments, regulating technology is unlikely to reduce inequality in catch outcomes.

Keywords: fisher skill, Gini coefficient, live image sonar, spearfishing tournaments

Introduction

Inequality of catches is a common feature of commercial (Fabinyi et al., 2015; Gutiérrez & Inguanzo, 2019) and recreational fisheries (Baccante, 1995; Dedual & Rohan, 2016; Seekell, 2011; Seekell et al., 2013; Thompson, 1976). It occurs when few fishers catch a disproportionate number of all fish, which can happen either due to a skill effect or when many fishers catch few or even nothing (Cook et al., 2001; Seekell et al., 2013). The factors that determine catch inequality are poorly explored. Seekell (2011) analyzed catch rate distributions collected from a freshwater trout recreational angling fishery, demonstrating that unequal catch distributions among anglers were predominantly caused by individual fisher effort; as the time spent fishing increased, the inequality among anglers decreased. The key relevance of individual fishing time for affecting catch outcomes is reflected in a popular jargon among some recreational fishers—time (effort) is fish (catch). In addition, fishing skill determines individual catch rates (Futamura et al., 2025; Monk & Arlinghaus, 2018). Therefore, fishing skill can contribute to catch inequality—an aspect that Seekell (2011) was unable to address because of the difficulty in gathering independent measures of skill in creel surveys or diaries. Observational data sets, however, have repeatedly shown that fisher characteristics potentially correlated with skill, such as angler experience, affect catch rates positively (Diogo et al., 2017; Heermann et al., 2013; Lincoln Smith et al., 1989; Zarauz et al., 2015). In addition, experimental evidence for a skill effect exist in recreational angling (Futamura et al., 2025; Monk & Arlinghaus, 2018).

Spearfishing tournaments may provide an opportunity to investigate the potential influence of fisher skill on catch inequality. The culture of fishing tournaments is inherently built around a skill effect as time fishing on a given event is controlled (Schakowski et al., 2026). If fishing skill would be irrelevant, the distribution of winners in tournaments would be random or simply proportional to participation frequency. In reality, specific individuals are often overrepresented among winners in fishing tournaments, suggesting a systematic advantage for more skilled participants. In spearfishing tournaments, differences in tournaments categories (e.g., semifinals and finals) may serve as a proxy for variation in average and heterogeneity of skill level, as progression to higher-level tournament categories requires prior competitive success. This framework offers observational settings in which average skill varies while other conditions, such as fishing time, fishing areas, and competition rules, remain relatively standardized. In contemporary recreational fishing, a skill effect may also encompass the proficient use of novel technologies (Cooke et al., 2021), which have reported to increase catch rates in some recreational fishing conditions (Henry et al., 2025; Runde et al., 2026; Smith et al., 2025), but not in others (Kerkhove et al., 2024; Neely et al., 2023a, 2023b; Wilkinson et al., 2026). For example, the experimental study by Wilkinson et al. (2026) revealed that live sonar could increase the size of the catch in a freshwater recreational angling fishery, while Runde et al. (2026) reported increases in catch rates when targeting pelagic marine predators in angling tournaments. Therefore, if live sonar and other novel technologies elevate catch success also in recreational spearfishing, its use could, in turn, contribute to catch inequality.

Recent technological innovation in recreational fishing has allowed fishers to adopt a plethora of sophisticated technologies that may facilitate fish location and capture (Cooke et al., 2021, 2025; Kerkhove et al., 2024). There are many examples of technological improvements in recreational fishing (Cooke et al., 2021), one of the most relevant being sonar technology (i.e., live sonar; live-imagining sonar, forward

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facing sonar; hereafter refers to as "live sonar"). Echosound technology is being used by recreational fishers to measure depth and locate fishes since at least 1970 (Neely et al., 2023a), but the technology has undergone many improvements over time (Cooke et al., 2021). Modern sonars technologies substantially improve fish detection and location, allowing fishers find fish in vast areas that were previously hard to find (Feiner et al., 2020; Kerkhove et al., 2024; Matthias et al., 2014; Neely et al., 2023a, 2023b; Runde et al., 2026; Smith et al., 2025). Importantly, all the available evidence derives from recreational angling (for positive findings Henry et al., 2025; Runde et al., 2026; Smith et al., 2025; for negative findings, Kerkhove et al., 2024; Neely et al., 2023a, 2023b; Wilkinson et al., 2026), whereas no study has yet evaluated the effects of live sonar in recreational spearfishing.

Spearfishing, unlike other types of recreational fishing, is an active underwater fishing activity in which the fisher can visually identify and select which individuals to catch (Sbragaglia et al., 2023). In addition to the adoption of sonar technology, the parallel implementation of a mobile lead technique has recently spread among spearfishers, influencing the way spearfishing is practiced. The mobile lead allows skilled spearfishers to dive in variable weight and reach greater depths with less effort and greater safety (see *Methods* from more details). As a result, skilled spearfishers can access deeper and less exploited fishing spots, potentially increasing catch rates and the ability to selectively target trophy-sized specimens and other valuable species. Therefore, the use of new technologies, by disproportionately improving catch efficiency and access to fishing opportunities for a specialized group of fishers, may increase catch inequality.

The objective of this study was to understand how catch inequality in recreational spearfishing tournaments is affected by the use of new technologies and by differences in spearfishers' average skill levels, assuming that average skill level co-varies with tournament categories. We take advantage of systematic catch records collected during Italian spearfishing tournaments (Terlizzi et al., 2022) to test two hypotheses. The first hypothesis (H1; Figure 1) assumed that the adoption of new technologies (live sonar and mobile lead) increases catch inequality among tournaments' participants. In spearfishing, the effective use of such tools requires not only access to, and experience with the novel technology, but also advanced physical capabilities and specific technical skills (e.g., deep freediving, equipment handling). Consequently, even within high-level tournaments, only a subset of competitors is expected to exploit these technologies, possibly amplifying performance differences and increasing inequality. The second hypothesis (H2; Figure 1) is that spearfishing tournaments of different rank categories (pairs, semifinals, finals) show different levels of catch inequalities. Specifically, we hypothesised that catch inequality in high-rank tournaments (e.g., finals of the individual category, which is the most prestigious annual appointment of the entire national spearfishing tournament season) is lower than in low-level tournaments (e.g., semifinals). This hypothesis was based on the assumption that the overall level of spearfishing skills is more similar among participants in high-rank tournaments, and, consequently, catch inequality is expected to be lower, than in low-rank ones where catch inequality is expected to be higher. To confirm our assumptions of different tournament categories attracting different average skill levels, we evaluated the repeatability of participants' performance across tournaments. In addition to testing H1 and H2, we explored whether the adoption of new technologies is associated with changes in the composition of species caught. Shifts in target species may provide insights into additional mechanisms through which technology influences fishing outcomes.

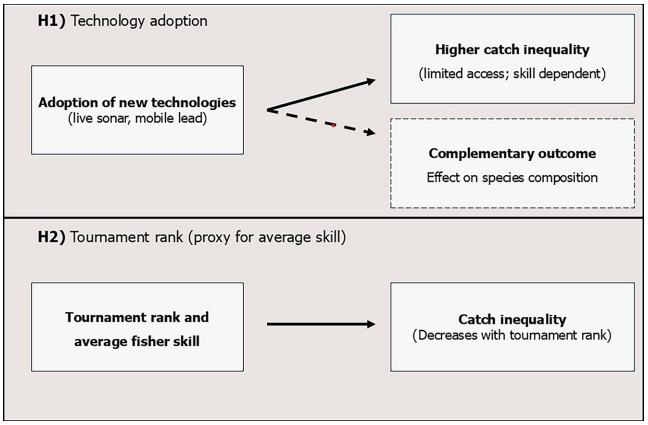


Figure 1 Conceptual framework and hypotheses. (H1) Adoption of new technologies increases catch inequality among participants. A complementary analysis evaluated the effect of new technologies on species composition. (H2) High-rank categories, with more homogeneous skill levels, were expected to show lower catch inequality with respect to low-rank categories.

Methods

Data source

We used data collected during the monitoring program of Italian spearfishing tournaments held by the Italian Federation of Sport Fishing and Underwater Activities (FIPSAS) since 2009 (Terlizzi et al., 2022). The Italian marine spearfishing tournament system is composed of three categories. The first and most prestigious section is the individual league, which takes place every year. The individual league comprises the Italian championship (national finals), the qualifying championship (national semifinals), and qualifying rounds (regional tournaments, which we did not use for the analysis). The access to the national final (a tournament of 2 d once per year) is granted to the top 15 participants of the previous year's national final and the top 20 participants of the previous year's semifinal (a tournament of 2 d once per year; semifinals from 2007 to 2012 were divided into two geographical sections for northern and southern Italy). Access to the semifinals is granted to athletes ranked as high as 16th in the previous year's national finals, the top 30 participants from regional tournaments, the winning couple from previous year's Italian pairs championship (see below), and members of the winning team from the previous year's Italian team championship (see below). The second category is the pairs league, which takes place every year. The access to this tournament is open to

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everybody and despite participants competing in pairs, they cannot fish simultaneously. The third category is the team league, which takes place every year. The access to this tournament is open to one or two teams of three participants representing their respective spearfishing club or association. Despite the teams being composed of three participants, only two of them can fish simultaneously. The skill of spearfishers is expected to change systematically across competition categories; national finals should have the highest average level of skill and the lowest heterogeneity among participants, followed by semifinals, team tournaments, and finally pair tournaments, where participation is generally more inclusive and therefore likely to involve a broader range of skill levels. The participants deliver their catches at the end of the tournament under the supervision of the judge who, together with the technical committee, classifies the species and the weight of each individual fish. The analyses presented in this study were conducted exclusively on male competitions, as the tournament score database used to complement the FIPSAS monitoring programme only included men's competitions. Women's competitions are organized separately by FIPSAS and, during the study period, involved only a limited number of participants and events due to low participation. The FIPSAS monitoring program consist of systematically recording the catches of the participants while maintaining the anonymity of the fishers. Furthermore, the FIPSAS monitoring data set is fully anonymized and, therefore, does not include individual demographic information such as age. We supplemented this data set with further information: (1) the duration of each tournament day and (2) the number of participants. To extend the time span of the analyses, we used participants' score data for all tournaments (finals, semifinals, pairs and team championships) from 2004 to 2025. We chose 2004 as the baseline date of the interval considered, because before this date, the most prestigious tournaments (i.e., the finals and individual semifinals) were held on a single tournament day. The scores of individual tournaments were provided by a website maintained by an enthusiast who has systematically recorded the results of national and international spearfishing tournaments over the years (http://www.garesub.com/). The final data set comprised 82 different tournaments held between 2004 and 2025 (Supplementary Table 1). Overall, the data set comprised 2,874 tournament participations (664 finals, 1,085 semifinals, 595 pairs tournaments, and 525 team tournaments; Supplementary Table 1). These values represent overall individual participations considering that fishers could take part in multiple tournaments across years and categories.

Regulation of spearfishing tournaments

A set of rules, updated and amended over the years, clarifies all aspects of tournaments. A minimum weight is set depending on the species and the prestige of the tournament. Specimens below this weight do not count for the calculation of participants' final score but are recorded anyway. Furthermore, a daily bag limit is in place dependent on the species. It is not permitted for participants to deliver a greater number of specimens than the bag limit or to catch fishes below the minimum weight limit, in both cases a penalty to the score is applied. The score of each spearfisher, pair, or team is determined by the total weight of valid catches, calculated in grams (one gram correspond to one point). To the score calculated from the weight of the prey three bonus coefficients are added, equal to the minimum weight set for the category. In the event that the participant catches the bag limit of individuals for one or more species or catches a species considered rare, two more bonuses are added. In the case of tournaments that span multiple days, the score for each day is calculated as a percentage, multiplying the participant's score by 100 and dividing the result by the score of the first classified. The tournament rules have undergone a number of changes over time. We reviewed changes in tournament regulations over the years, including modifications in the allowed displacement methods for participants. During the finals and semifinals in 2004 and 2005, participants could only move around the tournament area by swimming. Subsequently, from 2006 to 2008, only a boat displacement was allowed halfway during the tournament day. From 2009 to 2012, participants were allowed to make two boat trips, one at the start of the tournament and the other in the middle of the day. Finally, from 2012 to the present, participants could move freely by boat around the tournament area.

Table 1 Results of the beta regression model testing the effect of technology diffusion and year on the Gini coefficient for (A) finals and (B) semifinals. The reference category for *Diffusion.Tech* is "Very few"; coefficients indicate differences relative to this baseline. Estimates are on the logit scale; *p*-values are from two-sided Wald *z*-tests. Significance codes: * $p < 0.05$.

Predictor	Estimated (β)	SE	*z*-value	*p*-value
(A) Finals				
Intercept very few	−0.625	0.271	−2.305	0.021*
Few	0.135	0.296	0.454	0.650
Several	0.183	0.439	0.416	0.677
Many	0.498	0.596	0.836	0.403
Year (centred)	−0.007	0.037	−0.197	0.844
(B) Semifinals				
Intercept very few	0.017	0.1700	0.101	0.919
Few	−0.174	0.2420	−0.718	0.473
Several	−0.466	0.4100	−1.135	0.256
Many	−0.560	0.4281	−1.165	0.244
Year (centred)	0.058	0.0290	1.972	0.049*

Estimating inequality of catches

We used the Gini coefficient (Gini 1912; for an application to fishing, see Baccante, 1995) as a quantitative metric to assess inequality of catches, which ranges between 0 and 1 (Figure 2). A Gini coefficient of 0 indicates absolute equality, whereas a Gini coefficient of 1 indicates complete inequality. To calculate the Gini coefficient, we used the REAT package function from R (Wieland, 2019). We calculated the Gini coefficient,

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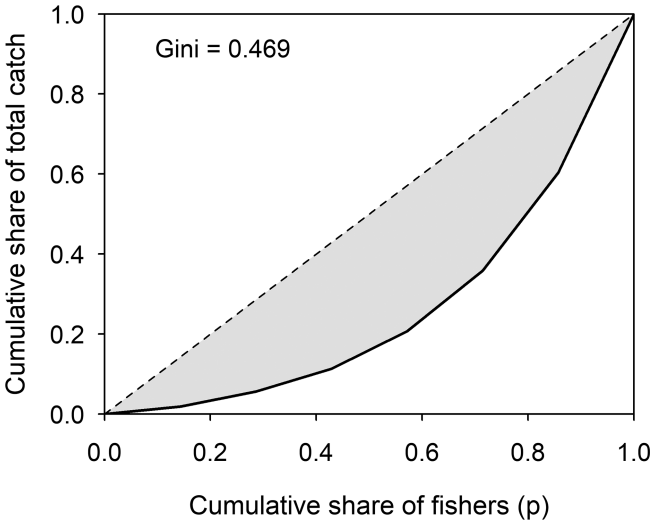


Figure 2 Lorenz curve of catch distribution. The 45° dashed line denotes perfect equality; the solid line is the empirical Lorenz curve. The shaded area between the two is proportional to inequality (Gini = 2×shaded area). In this example, Gini = 0.469.

for all tournaments available in the data set, using (1) the biomass harvested by each participant, (2) the number of specimens by each participant, and (3) the score each participant achieved on each day of each tournament. Subsequently, we calculated the correlation between the average Gini coefficient calculated for the three aforementioned variables: (1) the biomass taken by each participant (2), the number of catches of each participant, (3) the participants' score for each day of tournament using the Spearman's correlation coefficient (Supplementary Figure 1). Before checking for the correlation, we excluded the average Gini coefficient calculated for the pair tournament held in 2010. This tournament was the only one in the data set involving fewer then 13 participants ($n = 7$), whereas all remaining tournaments included between 13 and 61 participants (mean = 35; SD = ± 10.86). Because estimates of the Gini coefficient obtained from very small samples are known to be affected by finite-sample bias (typically between 2 and 10 observations; Deltas, 2003), we considered the 2010 pair tournament, with $n = 7$, not directly comparable with the remaining tournaments and, therefore, we excluded it from the correlation analyses. The Gini coefficient on the percentage score was significantly ($p < 0.001$) and positively (Spearman's $\rho = 0.774$; $\rho = 0.816$) correlated with the Gini coefficient calculated on the number of catches and biomass respectively (Supplementary Figure 1). Considering that the Gini coefficient calculated on the percentage score covers a longer period (2004–2025), we performed the subsequent analysis using the Gini coefficient calculated on the percentage score and, for 2-day tournaments, on the average of the 2-day percentage score.

Technological development and data collection

The use of live image sonar constitutes probably the most disruptive technology in recreational fishing in recent years. In the case of spearfishing tournaments, the use of live image sonar may provide advantages in general scouting the fishing area for potential good spots days before the tournament (something that was done by freediving before). The live image sonar allows users to identify deep isolated and small rocky structures and individual fishes shown live on the screen. Therefore, it allows spearfishers to have a more complete view of the fishing area and more efficiently prepare the tournament strategy and, consequently, may increase chances to win the tournament. The second technology considered was the use of mobile lead as a weight during the dive. Those spearfishers who employ the mobile lead may plan their spearfishing tournament strategy on deep and isolated areas (i.e., maybe those found by mastering the live image sonar) where fish might be more abundant or less disturbed and, consequently, increases chances to win the tournament. The use of the mobile lead has its basis in the discipline of free diving with variable weight. The spearfisher, utilizing a weight secured to a rope, descends to a considerable depth (sometimes up to more than 50 m). Upon reaching such depth, the spearfisher release the weight, which can be retrieved from the boat and, after completing the fishing action, returns to the surface by finning. By employing a weight secured to the boat, the spearfisher can perform a dive with less physical effort and, subsequently, ascend to the surface with reduced weight in his belt (nevertheless increasing the risk of diving sickness and, therefore, forcing spearfishers to reduce the number of dives).

We collected information on the frequency of use and the perceived influence on outcomes of mobile lead and live image sonar during individual finals and semifinals using a seven-item multiple-choice questionnaire (four items for mobile lead, three for sonar; Supplementary Materials). The questionnaire was administered to the technical director of the Italian men's national spearfishing team, who has been closely involved in competitions for decades (former multitime national champion and later national team coach). For each tournament category, the two ordinal dimensions (frequency of use among participants and perceived influence on tournament outcomes) were combined using an a priori, monotonic decision matrix (Supplementary Tables 2A–2B); any increase in either dimension never decreased the assigned level. The approach yielded a four-level ordered intensity index (Q1 = very few; Q2 = few; Q3 = several; Q4 = many) for each technology. Where the sonar's influence was not assessed, a prespecified fallback mapping based on frequency alone was applied (Table S2C). To obtain a single technology-use indicator per tournament category, we collapsed across technologies by taking the maximum of the two intensity levels (Q1 < Q2 < Q3 < Q4), reflecting the notion that the most intensively used technology was the most likely to affect outcomes.

Finals and semifinals were analyzed separately. This procedure reduced complexity while remaining transparent and reproducible through the full mapping provided in the Supplementary Materials. Although based on expert judgement, the index was prespecified and applied consistently via a monotonic decision matrix, yielding a transparent, reproducible summary of technology diffusion over time and improving comparability across tournaments.

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Data and statistical analyses

To test the first hypothesis (H1), that the adoption of sonar and mobile lead influenced catch inequality, we compiled a data set including the Gini coefficient and the four-level ordinal variable describing the intensity of technology use for each final and semifinal tournament. The ordinal variable was defined based on expert judgement and reflect the progressive adoption of these technologies over time. Beta regression models were fitted with the Gini coefficient as the response variable and technology intensity as the main predictor, while controlling for year and locality. Finals and semifinals were modeled separately due to differences in participant composition and structural changes in semifinals prior to 2012. For finals, we fitted a mixed effects beta regression model, including year as a fixed effect and location as a random effect. For semifinals, due to limited repeated tournaments per location, we fitted a simple beta regression with year (centered) and technology intensity as a fixed effect. All models assumed a beta distribution for the Gini coefficient bounded between 0 and 1. Model assumptions were assessed by examining residual patterns, dispersion, and influential observations. Models were fitted using the betareg package (Cribari-Neto & Zeileis, 2010) for fixed effects models and glmmTMB (Brooks et al., 2017) for mixed-effects models.

The second data set included Gini coefficient values for a broader set of competitions and was used to test the second hypothesis (H2), which posits that the average skills of participants affect catch inequality. This data set included information on tournament type, location, year. We fitted generalized linear mixed models with a beta distribution and logit link, using the Gini coefficient calculated for each tournament as the response variable. Tournament type (with four levels: finals, semifinals, pairs, and teams) was included as a categorical predictor. To account for nonindependence of observations collected within the same competition event defined by location and date, we included a random intercept at the tournament event level. Model diagnostics were conducted using randomized residuals, testing for uniformity (Kolmogorov–Smirnov), dispersion, and outliers, and inspecting residuals vs. fitted values and predictors. We expected higher Gini values in lower-category tournaments, where participants are expected to exhibit a broader range of competitive skill levels, and lower Gini values in higher-category tournaments, where qualification mechanisms progressively select competitions with higher and more homogeneous skill levels. A significant effect in this direction would support the hypothesis, whereas a lack of association, or an opposite trend would refute it.

Repeatability analysis of individual performance

To assess whether individual differences in performance were consistent across tournaments, we estimated repeatability as the intraclass correlation coefficient (ICC) from a linear mixed-effect model fitted to tournament scores—a method common in animal personality research (Nakagawa & Schielzeth, 2010). The repeatability measures the consistency by which individuals score in different tournaments. The response was the tournament score, and the model included random intercepts for participant identity, year (temporal variation), and macro area (geographic differences). Parameters were estimated by restricted maximum likelihood with lme4 (Bates et al., 2014) implemented in R (R Core Team, 2024). We quantified repeatability primarily as the participant-level ICC, i.e., the proportion of variance attributable to between-participant differences relative to total variance. Uncertainty around repeatability estimates was quantified using parametric bootstrapping (1,000 iterations), from which 95% confidence intervals were derived. Support for participant-level repeatability was further assessed by likelihood ratio tests comparing models with and without the participant random effect. For completeness, we also report the overall ICC (proportion of variance explained collectively by the random-effects structure: participant, year, macro area). Model assumptions were evaluated by inspecting residual quantile-quantile plots and residuals vs. fitted values, and with auxiliary checks from the performance package (normality, heteroscedasticity, and outliers); we also verified the absence of singular fits (variance components ≈ 0). These diagnostics supported the adequacy of the model for inference on participant-level repeatability.

Exploratory analyses of species composition in relation to fishing technology

To explore whether the use of new fishing technology was associated with shifts in the species composition, we analyzed final and semifinal tournaments separately. Because species-level data were available only for a subset of the study period through the FIPSAS monitoring records, finals (which included a larger number of tournaments) were pooled into three technology phases—low (2009–2014), intermediate (2016–2019), and high (2021–2025)—to reflect technological progression while accommodating temporal coverage. These broader temporal groupings were created exclusively for the exploratory analysis of species composition and should not be interpreted as a redefinition of the technological phases used in the main analyses. Because harvesting groupers became permitted from 2020 onward following a regulatory change, we additionally repeated the final tournament analysis after excluding groupers as a complementary sensitivity analysis to assess whether temporal patterns in species composition were robust to this regulatory effect. For each tournament, we built species-by-event-matrices, converted counts to relative composition and square-root transformed them. We then computed Bray–Curtis dissimilarities. Subsequently, we used nonmetric multidimensional scaling (NMDS) to assess the association with temporal distance. To identify taxa characterizing each phase, we performed indicator species analysis with permutation-based *p*-values and Benjamini–Hochberg false discovery rate correction. The semifinals data set included fewer tournaments; therefore, years were grouped into three broader phases of technology adoption—early adoption (2009–2014), growing diffusion (2015–2017), and widespread adoption (2018–2024)—derived from the original four-level technology intensity classification and restricted to years with species data. As for finals, Bray–Curtis dissimilarities were computed from square-root-transformed relative composition, NMDS ordinations were obtained, and temporal structure was assessed by fitting year as a vector onto the ordination (envfit,

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9,999 permutations). Given the limited sample size and lack of clear patterns, indicator species analysis was not applied to semifinals. For all NMDS ordinations, we evaluated goodness of fit via stress and Shepard plots and retained stable solutions across ≥100 random starts (accepting stress < 0.2 as adequate). Before interpreting phase-related differences, we tested homogeneity of multivariate dispersions among technology phases using betadisper with 9,999 permutations to ensure that any group separation was not driven by unequal dispersion. Associations with time were assessed using Mantel tests (Spearman 9,999 permutations) and by fitting year as a vector onto the ordination with envfit (9,999 permutations). For finals, indicator species analysis (IndVal) used permutation-based *p*-values with Benjamini–Hochberg false discovery rate correction; due to limited sample size and lack of clear structure, IndVal was not applied to semifinals.

Results

Over the period 2004–2025, we analyzed 81 national spearfishing tournaments, 21 finals, 25 semifinals, 16 pairs, and 19 team competitions. The tournaments-level Gini coefficient ranged from 0.22 to 0.70 (mean ± SD = 0.45 ± 0.11; $n = 81$). Individual performance showed significant repeatability across tournaments, participant-level ICC ranged from 0.128 (95% CI: 0.079–0.193) in semifinals to 0.309 (95% CI: 0.213–0.396) in finals (mean ≈ 0.22). Catch composition was heterogeneous across tournaments (Bray–Curtis: finals mean = 0.31; 0.18–0.56; semifinals mean 0.31, 0.16–0.50), with a temporal shift only in finals (Mantel $r = 0.31$, $p = 0.019$).

H1. The effect of technology

We first evaluated whether the level of technology diffusion influenced catch inequality measured as the Gini coefficient in finals. When accounting for potential temporal trends through a beta regression model with logit link, we neither found a significant effect of technology diffusion on the Gini coefficient nor any temporal trend (Table 1). Estimated marginal means back-transformed to the original scale (0–1) supported the following findings: Predicted Gini values ranged from 0.35 (Very few, Q1, lowest technology intensity level) to 0.47 (Many, Q4, highest technology intensity level), with overlapping 95% confidence intervals across tournament categories (Very few: 0.239–0.477; Few: 0.320–0.443; Several: 0.294–0.498; Many: 0.308–0.635; Figure 3). We also evaluated whether the level of technology diffusion influenced catch inequality, measured as the Gini coefficient, in the semifinals. A Kruskal–Wallis test showed a nonsignificant trend among the four levels of technology diffusion ($H = 7.13$, $df = 3$, $p = 0.068$). Results from the beta regression model, however, indicated that technology diffusion did not significantly affect catch inequality, whereas a trend close to be significant was observed, with Gini slightly increasing over the years (estimate = 0.0615, $z = 2.034$, $p = 0.042$; Table 1). Estimated marginal means back-transformed to the original scale (0–1) supported these findings: predicted Gini

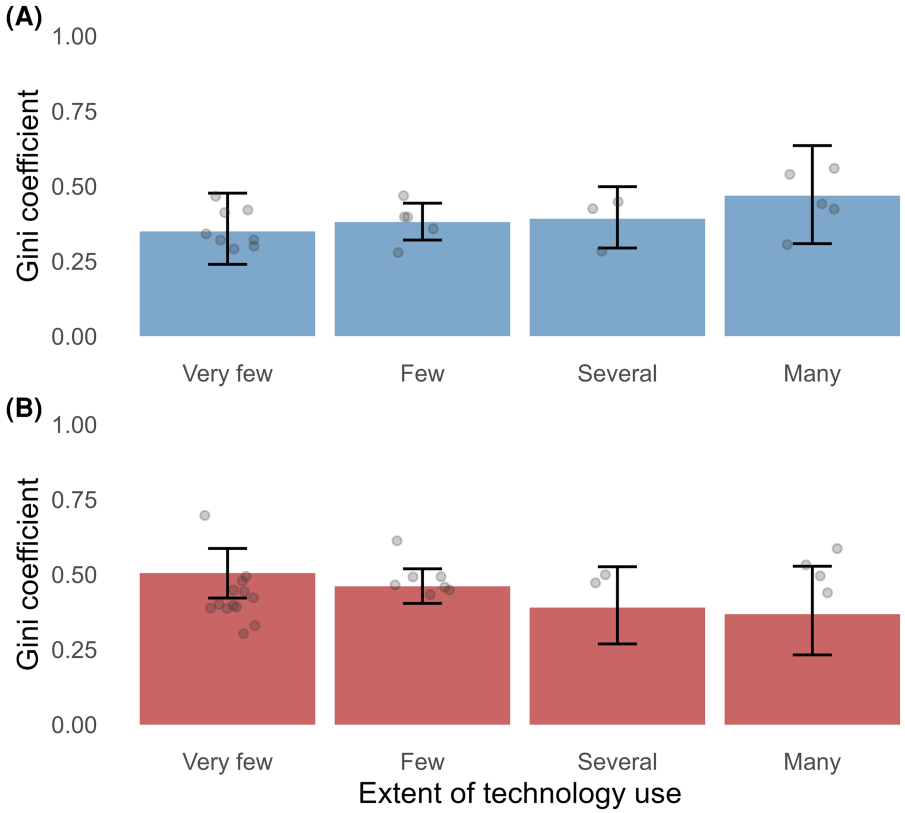


Figure 3 Estimated marginal means of the Gini coefficient for finals (back-transformed to the 0–1 scale) by level of technology diffusion, with 95% confidence intervals. Bars represent model-based estimates and error bars indicate 95% confidence intervals; points represent observed tournament-level Gini values. (A) Finals, (B) Semifinals.

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Table 2 Summary of temporal analyses of species composition in finals and semifinals. Mantel tests were computed on Bray–Curtis dissimilarities of square-root-transformed relative abundance (Spearman correlation, 9,999 permutations). Nonmetric multidimensional scaling year associations were assessed with envfit. Indicator species were identified with IndVal.g and Benjamini–Hochberg-adjusted *p*-values (BH-*p*). Significance levels: $p < 0.05$ *, $p < 0.01$ **, $p < 0.001$ ***; marginal trend indicated by ".". Only species showing significant or marginal associations after Benjamini–Hochberg correction are reported; all other tested species did not show significant indicator values for any technology phase.

Analysis	Finals	Finals—excluding *epinephelus* spp.	Semifinals
Mantel test (Bray–Curtis; Spearman)	*r = 0.309, p = 0.0188**	*r = 0.023, p = 0.435*	$r = -0.052$ $p = 0.560$
NMDS—Year vector (envfit)	$R^2 = 0.647$, $p = 0.0108$	*$R^2 = 0.606$, p = 0.025*	$R^2 = 0.148$, $p = 0.614$
Indicator species (IndVal.g; BH-adjusted)	*Epinephelus aeneus* and *E. costae*, (BH-$p = 0.022$); *Seriola dumerili* (BH-$p = 0.082$)	*S. dumerili* (BH-$p = 0.0236$)	Not performed

values ranged from 0.46 (Very few) to 0.49 (Many), with overlapping 95% confidence intervals across tournament categories (Very few: 0.392–0.590; Few: 0.387–0.528; Several: 0.392–0.623; Many: 0.387–0.638; Figure 3). As a robustness check, we conducted a complementary time series-based analysis assessing temporal trends in catch inequality using segmented regression model (see Supplementary Materials). This analysis did not detect significant temporal changes in catch inequality in finals. In semifinals, a weak but statistically detectable temporal trend was observed; however, no significant change in slope was supported by Davies' tests, and overall model fit was modest (Supplementary Table 3; Supplementary Figure 2).

Changes in species composition over time

In finals, the Mantel test detected a significant positive association ($R = 0.309$, $p = 0.0188$; Table 2), indicating a progressive temporal shift in catch composition. This shift was primarily associated with the occurrence of White Grouper *Epinephelus aeneus* and Goldblotch Grouper *E. costae* in more recent years, which were identified as indicator species of the high-technology phase by the indicator-species analysis. The NMDS ordination was consistent with this pattern: The fitted year vector was significant ($R^2 = 0.647$, $p = 0.0108$; Table 2), providing statistical evidence for a structured temporal gradient in species composition (Figure 4). Indicator-species analysis (IndVal.g. 9,999 permutations; Benjamini–Hochberg adjusted *p* [BH-*p*]) identified White Grouper and Goldblotch Grouper as significant indicators of the high-technology period (BH-$p = 0.022$ for both). Greater Amberjack *Seriola dumerili* showed a marginal association with the low technology phase (BH-$p = 0.082$). When groupers were excluded, the Mantel test no longer detected a significant association between community dissimilarity and temporal distance ($r = 0.023$, $p = 0.435$), whereas the year vector remained significant in the NMDS ($R^2 = 0.606$, $p = 0.025$). Indicator species analysis identified Greater Amberjack as a significant indicator of the low-technology phase (BH-$p = 0.024$). In semifinals, no clear temporal pattern in catch composition was detected. The Mantel test did not indicate a relationship between temporal distance and community dissimilarity ($r = -0.052$, $p = 0.560$; Table 2, and the year vector in the NMDS was nonsignificant ($R^2 = 0.148$, $p = 0.614$; Table 2). Given the absence of trends, indicator species analysis was not performed.

Performance repeatability

To evaluate the consistency of individual performance of tournament participants over time, we fitted linear mixed-effects models with random intercepts for participant identity, year, and geographic macro area, and derived overall intraclass correlation coefficients (ICC_{total}) separately for finals and semifinals. In finals, ICC_{total} was 0.449; the participant-level ICC was 0.309, with additional contributions from year (0.115) and macro area (0.026). Bootstrap confidence intervals excluded zero (95% CI: 0.213–0.396), indicating a moderate and supported degree of individual repeatability scores, meaning that performance in the tournaments was not random and instead systematically different among individual tournament participants. In semifinals, ICC_{total} was 0.637, while the participant-level ICC was lower (0.128; 95% CI: 0.079–0.193), with most variance attributable to year (0.479) and macro area (0.030). This indicated a weaker but nonnegligible degree of individual repeatability in semifinals, consistent with greater temporal variability and heterogeneity in participant performance.

H2. Impact of average skill levels on inequality

Model estimates indicated differences in catch inequality among competition types (Table 3; Figure 5). Pairwise Tukey-adjusted comparisons showed that tournaments conducted in pairs competitions (two spearfishers competing jointly) had significantly higher Gini values than all other competition types with finals as the reference category ($\beta = 0.879$, $SE = 0.114$, $z = 7.70$, $p < 0.001$); semifinals exceeded finals in terms of inequality ($\beta = 0.311$, $SE = 0.096$, $z = 3.25$, $p = 0.001$); and teams competitions (multimember teams competing collectively) showed only a marginal increase compared with finals ($\beta = 0.204$, $SE = 0.108$, $z = 1.89$, $p = 0.059$). The model's random intercept ($SD = 0.280$) accounted for between-tournament variability, improving model fit.

Discussion

We found no support for H1, and statistical support for H2. Regarding H1, we did not detect a significant effect of

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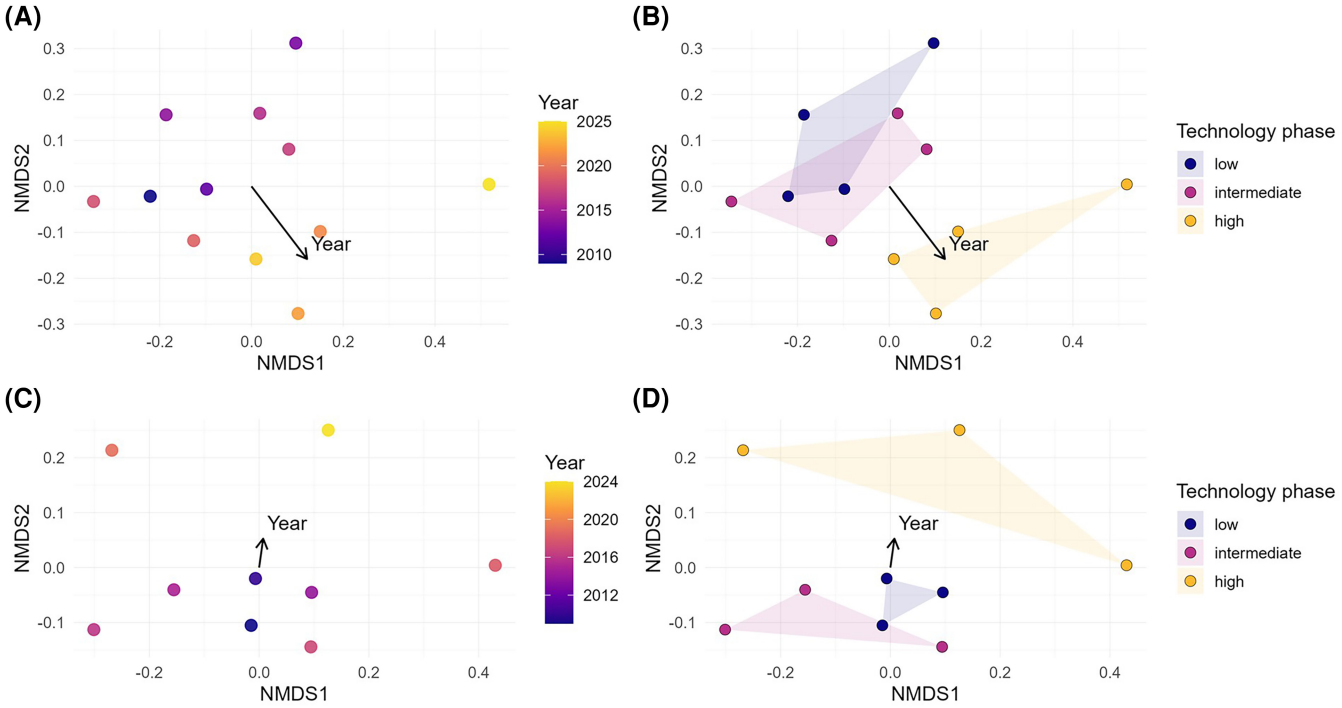


Figure 4 Nonmetric multidimensional scaling (NMDS) ordinations of finals based on Bray–Curtis dissimilarities of square-root-transformed relative species composition. Panels (A–B) show finals and panels (C–D) show semifinals. In panels (A) and (C) points represent tournaments colored by year. In panels (B) and (D) the same ordination are shown with tournaments grouped by technology phase (low, intermediate, high). The fitted year vector (envfit, 9,999 permutations) indicates a significant temporal gradient in community composition in finals ($R^2 = 0.647$, $p = 0.0108$; stress = 0.121) but not in semifinals ($R^2 = 0.148$, $p = 0.614$).

Table 3 Beta regression model (logit link) of per-day Gini with competition type as a fixed effect and tournament as a random intercept. Estimates (β), standard errors (SE), *z*-values, and *p*-values are reported. The random effect (σ^2) accounts for variability between tournaments. Significance levels: $p < 0.01$ **, $p < 0.001$ ***.

Predictor (ref = finals)	Estimate (logit)	SE	*z*-value	*p*-value
Semifinals	0.311	0.096	3.245	0.0018**
Pairs	0.879	0.114	7.698	<0.0010***
Teams	0.210	0.108	1.886	0.0593
Random effect (σ^2)	0.280			

technology use on catch inequality in either finals or semifinals in spearfishing tournaments. Because the classification of technology uptake and use in each tournament was informed by the judgement of the technical director of the Italian men's national spearfishing team (see *Methods*), we conducted an independent temporal analysis as a robustness check. This complementary time series analysis did not reveal temporal changes in catch inequality. In finals, inequality remained stable over time, whereas in semifinals, a weak positive temporal trend was detected with modest explanatory power and no significant change in slope. Importantly, this limited temporal effect suggests that the patterns identified by the expert-informed classification of technology diffusion are unlikely to reflect simple time-driven trend. Overall, the complementary analysis did not contradict the main results and supported the robustness of our inference. Further, temporal changes in catch composition were observed in finals but not in semifinals. As regards H2 related to catch inequality across tournament categories, we confirmed that individual performance was consistent across years, ensuring that tournaments ranking represented reliable skill-based patterns rather than random variation. Results further revealed significant differences among tournament categories, supporting the second hypothesis that competition categories, and, thus, average skill level of participating fishers, shapes catch inequality, in the direction that catch inequality is lowest in tournaments with the highest average skill levels, i.e., finals. In the following sections, we discuss each key result in detail.

We found no evidence that the diffusion of new technologies, specifically live sonar and use of mobile lead, significantly increased catch inequality in either finals or semifinals in spearfishing tournaments. This result contrasts with our initial expectation that uneven adoption of differential exploitation of new technologies by a subset of highly skilled spearfishers would amplify performance disparities. However, we lack direct information on individual-level adoption and intensity of use of these technologies across participants. Several non-mutually exclusive mechanisms may explain the observed stability of Gini coefficients across levels of technology diffusion. First, widespread adoption among competitors could have reduced potential asymmetries, whereas limited or regulated use under tournament condition may have constrained the performance advantage conferred by technology. In addition, learning effects and rapid diffusion of know-how

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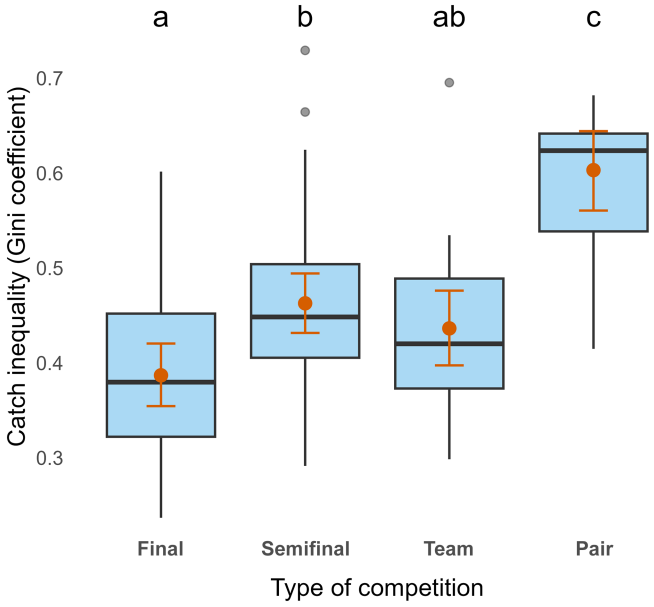


Figure 5 Distribution of observed Gini coefficients by type of competitions, overlaid with model-based predicted values (orange point) and their associated 95% confidence intervals (vertical bars). Boxplot shows the interquartile range (25–75th percentiles), with the horizontal line indicating the median. Predicted values are marginal means adjusted for between tournament variability. Different letter above the boxed indicate statistically significant differences between types (Tukey-adjusted, $p < 0.05$).

could have further homogenized outcomes. One mechanism that may facilitate this process is the social structure of spearfishing tournaments themselves. Participants are affiliated with local spearfishing clubs (which, in turn, are under the umbrella of the national federation that is responsible to organize and regulate the tournaments), where information, fishing strategies, and practical knowledge are likely to be exchanged among members (both in person or using other forms of communications, such as social media; e.g., (Sbragaglia et al., 2020). Such information exchange may accelerate the diffusion of new technologies and contribute to homogenizing tournament performance. Investigating the role of club affiliation and information exchange, therefore, represents an interesting avenue for future research. Second, research conducted in offshore marine recreational fisheries has shown that the adoption of omnidirectional sonar can substantially increase catch rates when targeting highly mobile pelagic species, including three istiophorid billfishes, Dolphinfish *Coryphaena hippurus*, Wahoo *Acanthocybium solandri*, and Yellowfin Tuna *Thunnus albacares* (Runde et al., 2026) while experiments in a boat-based fishery targeting structure-associated Smallmouth Bass *Micropterus dolomieu* failed to find a catch rate increasing effect of live sonar use (Wilkinson et al., 2026). In this context, a possible explanation is that the effectiveness of live sonar depends on the ecological context in which it is applied (Gary et al., 2026). Although empirical evidence remains limited, the contrasting findings currently available suggest that the benefits of sonar may vary according to both the ecology of the target species and the way fishers search for them, moderated by the depth and habitat structure of the ecosystem (Gary et al., 2026). Unlike offshore recreational fisheries, where sonar is primarily used to locate highly mobile pelagic fish moving through the water column (Runde et al., 2026), competitive Mediterranean spearfishing is largely based on identifying productive bottom features, such as isolated rocky structures or reefs, where relatively resident target species are expected to occur. Under these conditions, live sonar may primarily facilitate the identification of productive bottom habitats and associated fish, rather than the direct tracking of highly mobile individuals in the water column, potentially reducing the extent to which technological improvements translate into increased catch performance. More broadly, these contrasting findings suggest that the effects of fish-finding technologies may depend on the interaction between fishing technique, environmental context, and target species, although evidence across fisheries and fishing modalities remains limited. Overall, the fact that Gini coefficients remain relatively stable regardless of the level of technological diffusion suggests that, in the context of spearfishing competitions in Italy, technological innovation has not led to an increase in inequality in catch yields. As detailed in the supplementary temporal analysis (see Supplementary Materials), segmented regression identified potential breakpoints around 2011 in semifinals and 2022 in finals. However, these changes were not statistically significant (Supplementary Table 3), indicating that no abrupt shifts occurred and that overall trends remained weak and gradual (Supplementary Figure 2). Interestingly, these years roughly corresponded to the transition from occasional to frequent technology use reported in the questionnaire data, suggesting that the model captured the timing of early adoption phases moving into a majority adoption. However, because slope changes were not statistically significant, these results should be interpreted with caution.

Several explanations may explain our findings that technology update did not alter catch inequality. First, individual skills may be the dominant factor shaping fishing performance when fishers fish on similar spots with identical fishing efforts, consistent with longstanding evidence in fisheries science more generally that skill exerts a stronger influence than gear alone (Futamura et al., 2025; Heermann et al., 2013; Hilborn, 1985; Monk & Arlinghaus, 2018). As our analysis was based on spearfishing tournaments, the average skill level of the participants may have already been very advanced, reducing skill variance and, thus, the ability to detect significant effects. Second, environmental and situational factors can strongly mediate catch rates in recreational fishing (Lennox et al., 2017; Stoner, 2004), which can outweigh technological advantages or fisher characteristics in affecting catch outcomes (Heermann et al., 2013). Third, while advanced sonar technologies clearly increase chances of fish detection and the capacity to identify structures and refuges (Feiner et al., 2020; Neely et al., 2023a, 2023b), their benefits are highly context- and user-dependent, constrained by operator expertise, species-specific behavior, and local conditions (Cooke et al., 2021; Henry et al., 2025; Gary et al., 2026; Kerkhove et al., 2024; Runde et al., 2026; Smith et al., 2025; Wilkinson et al., 2026). Our findings do not fully align

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with theoretical expectations from models of technology adoption, which predict that early adoption temporarily widens inequalities before gaps narrow as access becomes widespread (Cooke et al., 2021; Giné & Klonner, 2006). However, the temporal windows covered by our data set may not capture the critical transition phase between an initially elite, skill-concentrated adoption stage and a later phase of more homogeneous diffusion. As such, the observed pattern may reflect a partial segment of a broader dynamic process. In our data, catch inequality did not decrease with increasing technology diffusion and even showed a weak positive temporal trend in semifinals. An additional, non-mutually exclusive explanation is that increasing accessibility of these technologies may have lowered the skill threshold required for effective use, potentially reducing relative performance differences among competitors and offsetting inequality-enhancing effects. Experimental and tournament-based studies have shown that technological innovations can increase mean catch rates (e.g., Detmer et al., 2020; Gary et al., 2026; Runde et al., 2026), yet such collective efficiency gains may leave relative differences among individuals unchanged. In other words, although technology may increase overall fishing efficiency, it does not necessarily change the relative differences in performance that generate catch inequality especially among already skilled fishers. Moreover, any efficiency gains associated with technological innovation may not be uniform across fishers, as their magnitude could depend on individual characteristics such as skill, experience, motivation, fishing avidity, and access to or familiarity with the technology. These factors were not directly measured in the present study and should, therefore, be considered as possible mechanisms rather than explanations demonstrated by our data. This suggests that assessments of technological effects may benefit from considering the interaction between the technology and the characteristics of the fisher using it, rather than treating technological adoption as an independent source of efficiency. Another possible explanation is that species-specific bag limits imposed during competitions may partially constrain the measurable benefits of improved fishing efficiency. To examine whether species-specific bag limits could have limited the effects of the technologies investigated, we quantified how frequently tournament's participants approached or reached the maximum number of individuals allowed for each regulated species (Supplementary Table 4). Competitors generally remained well below these limits, and reaching one or more bag limits during a competition day was uncommon. Therefore, species-specific bag limits are unlikely to explain why no detectable effect of technological innovations on tournament performance was observed.

The slight increase in inequality observed in semifinals suggests that technological change may have interacted with pre-existing differences in skill and knowledge, rather than uniformly homogenizing performance. This interpretation is consistent with experimental evidence emphasizing the primacy of catching ability (Futamura et al., 2025; Monk & Arlinghaus, 2018), while indicating that the effects of technology on inequality are context-dependent and not solely driven by efficiency gains associated with technology adoption. Collectively, our finding highlights that the relationship between technology and catch inequality may be context and fishery dependent, shaped by competition design and basal fisher heterogeneity. The convergence between the expert-based classification and the independent temporal analysis of catch inequality reinforces the robustness of our conclusions: Technological diffusion may influence spearfishing tournament outcomes under specific circumstances, but it did not emerge as a consistent or dominant driver of catch inequality.

To further interpret our results, it is useful to consider the structure of the tournaments and the characteristics of their participants. In the context of our study, finals consist predominantly of the top-ranked competitors who could had likely already adopted and mastered advanced technologies throughout the 2004–2025 period. Consequently, any additional effect of technology on catch inequality was expected to be minimal in these tournaments. The tournament context may also influence how technological effects are expressed, because competitors share the common objective of maximizing competitive performance rather than necessarily targeting a single species or resource. This may differ from nontournament contexts in which fishers can vary more widely in their target species, fishing strategies, and motivations. By contrast, a marginally nonsignificant trend was detected in semifinals, where beta regression models indicated a slight increase in inequality before 2022. In addition, segmented regression identified a potential breakpoint around 2011, although Davies' test did not confirm a significant change in slope. This apparent inflection may reflect the early diffusion of new technologies among participants, preceding their broader adoption later in the decade, but should be interpreted with caution given the lack of statistical support. Consistent with the segmented regression results, which did not detect any significant breakpoints, overall changes in inequality over time appeared to have been gradual and limited. This pattern may reflect transitional dynamics, whereby uneven adoption of technology temporarily influenced outcomes in competitions characterized by greater participant heterogeneity, i.e., semifinals. Similar transitional phases have been reported in other recreational fisheries, where the adoption of electronic devices, such as sonar and imaging tools, can initially alter catch outcomes in context- and user-dependent ways (Feiner et al., 2020; Henry et al., 2025; Kerkhove et al., 2024; Neely et al., 2023a, 2023b; Runde et al., 2026; Smith et al., 2025; Wilkinson et al., 2026). In our data, the trend leveled off after 2022, suggesting that any such effect was short-lived or compensated for by other factors. Taken together, our findings reinforce the idea that technology can influence tournament outcomes under specific circumstances, but it was neither a consistent nor dominant driver of catch inequality among tournament participants.

The exploratory analysis found little evidence that technological innovations influenced catch composition. Although a temporal shift was detected in finals, this pattern was primarily associated with the occurrence of *E. aeneus* and *E. costae* in the catches of the most recent tournaments. This interpretation was further supported by the sensitivity analysis excluding *Epinephelus* spp., which indicated that the temporal

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pattern was largely driven by the occurrence of these taxa. However, this pattern should not be interpreted as evidence that technology altered catch composition. Instead, it is likely explained by the regulatory changes introduced in 2020, when the capture of *E. aeneus* and *E. costae* became permitted exclusively in finals. Indeed, no temporal variation was detected in semifinals, where the set of protected species remained unchanged throughout the study period. This stability suggest that species catch composition was largely unaffected by the spread of new technologies. Previous studies have shown that sonar can increase the ability of fishers to accurately target specific species or size-classes (Cooke et al., 2021, 2025; Feiner et al., 2020; Gary et al., 2026; Henry et al., 2025; Smith et al., 2025; Wilkinson et al., 2026), with sonar providing information not only on fish presence but also on their behavior (Neely et al., 2023a). However, all the studies conducted so far have focused on recreational angling, and it is, therefore, reasonable to expect that the impact of technology may vary according to the type of fishing technique. For instance, several recent studies have reported that sonar use can increase angling efficiency or facilitate the capture of larger individuals in some fishing techniques and target species, while showing limited or no detectable effects in others (Feiner et al., 2020; Gary et al., 2026; Henry et al., 2025; Smith et al., 2025; Wilkinson et al., 2026). Consistent with this context-dependent effect, Neely et al. (2023a) found no differences between live sonar users and nonusers in the size of Black Crappie *Pomoxis nigromaculatus* and White Crappie *P. annularis* caught, while Wilkinson et al. (2026) reported increases in the mean length of Smallmouth Bass. Taken together, these finding highlight that the influence of new technologies on catch composition and size of captured fish is highly context dependent and not necessarily consistent across fisheries or fishing techniques. Live sonar seems to exert its greatest influence in the search for pelagic predators (Runde et al., 2026) and in less structured, deeper lakes (Gary et al., 2026). The absence of a clear effect of technology on species composition may reflect the characteristics of the tournament considered, which involved highly skilled spearfishers targeting reef associated fish for whom new technologies likely exerted only a limited influence on fishing strategies or species selection (see also Gary et al., 2026; Neely et al., 2023a). A broader temporal perspective might reveal stronger effects, as documented in other fisheries where technological innovations have progressively increased fishing efficiency in tournaments (Detmer et al., 2020; Runde et al., 2026) and other contexts (Henry et al., 2025; Smith et al., 2025).

A precondition to use tournament categories as representing different average skill levels is that there is consistent variation in performance among individual tournament participants. To that end, we examined the temporal consistency of individual performance. The corresponding repeatability analysis revealed contrasting patterns in repeatability of individual performance between finals and semifinals. In finals, a substantial proportion of the variance in tournament performance was attributable to participant identity, indicating moderate individual consistency in fishing performance across years. In semifinals, however, most of the variance was explained by year effects, suggesting that performance was less repeatable at the individual level and more influenced by temporal or contextual factors. This contrast likely stems from the competitive structure of tournaments: finalists from a relatively homogeneous group of highly skilled fishers, whereas semifinals include a broader mix of abilities, including both advancing regional competitors and a few relegated finalists, resulting in greater annual variability in performance. This analysis underscored the methodological decision to treat individual tournament categories as represented different average skill levels and their impact on catch inequality.

Consistent with H2, our results revealed a consistent effect of competition type on catch inequality. Pair tournaments and semifinals exhibiting significantly greater Gini coefficients than finals, while team competitions showed an intermediate pattern. This indicates that the average skill composition of participants, shaped by qualification rules and entry criteria, strongly influences the distribution of catches among participants. Finals, restricted to athletes who successfully pass the semifinals, showed the most homogeneous catch outcomes. Semifinals, which combine relegated finalists with qualifiers from local tournaments, produced a more heterogeneous mix of skills and higher inequality. Pair tournaments, open to all club members regardless of competitive experience, further amplified disparities, whereas team competitions showed intermediate inequality due to internal preselection imposed by the one team per club rule. Our interpretation aligns with evidence from recreational fisheries, where experience and skill has repeatedly been shown to be key determinants of catch outcomes (Futamura et al., 2025; Heermann et al., 2013; Monk & Arlinghaus, 2018; Schakowski et al., 2026; Ward et al., 2013). Similar patterns have been reported in spearfishing, where experience, physical capacity, and ecological knowledge strongly shape success (Sbragaglia et al., 2023). Taken together, these findings indicate that in high-level spearfishing tournaments, the mechanisms of access and selection embedded in competition design result in average skill levels outweighs the role of technology in shaping catch inequality. Minor and context-dependent technological effects remain possible, particularly in more heterogeneous fisheries, highlighting the value of comparative studies across different cultural and ecological settings.

Our study has limitations, which must be acknowledged. First, our findings are restricted to competitive men's spearfishing tournaments, which impose specific rules and objectives that differ from those of nontournament recreational fisheries and which could have reduced the impact of technology on catch outcomes by reducing variance. Furthermore, because women's competitions were not included in the present study, the findings should not be generalized across genders. Second, we focused on a limited set of technologies, and it remains unclear how other tools might affect inequality, particularly in more heterogeneous fisher populations. Third, while our data spanned multiple years and locations, it was confined to a single national context, and generalization to other areas and fisheries should be made with caution. Finally, our study is observational in

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nature, lacks an independent measure of individual skill, and assessment of technology update was indirect via a survey answered by one main informant that has deep knowledge on the history of tournaments. Thus, we lack individual-level data on technology use, resulting in our results being correlative and not causative in nature. Despite these limitations, our findings indicate that fisher ability shapes catch success and, in turn, catch inequality, whereas the technologies examined did not generate systematic disparities among highly skilled fishers in spearfishing tournaments. Under standardized tournament conditions, performance may remain primarily structured by individual skill and competition design, rather than by the adoption of new technologies. To conclude, our work suggests that restricting technology in competitive spearfishing is unlikely to reduce catch inequality. Previous studies have shown that technological disparities can affect perceived equity and satisfaction among recreational fishers, potentially leading to social tensions between users and nonusers (Hummel & Foster, 1986; Kerkhove et al., 2024; Smith et al., 2025). Recognizing these issues is important because satisfaction and perceptions of fairness among recreational fishers can influence preferences towards management measures, compliance with regulations, and acceptance of fisheries management, with implications for effective and sustainable fisheries governance (Birdsong et al., 2021).

Tournament's organizers and managers may benefit from explicitly considering the role of fishers' ability and of competition structure when designing rules designed to promote equity and fairness, while placing less emphasis on technology, as long as the use of technology is perceived to be fair to all participants. More broadly, management responses to technological innovations should be based on evidence of its effects on both fishing efficiency and the distribution of catches, rather than assuming that technological adoption necessarily increases inequality. In addition, management assessments may need to consider potential behavioral responses to new fish-finding technologies, including changes in fishers' expectations, target species, or fishing strategies. Such responses were not assessed in the present study but could become relevant where technological innovations alter not only how efficiently fish are located and caught, but also how fishers choose where and what to fish. Future research should extend beyond elite tournaments to include more diverse fisher populations and cultural contexts, to evaluate whether the patterns observed in our study hold more generally. Particular attention should be given to the joint influence of skill, fishers' avidity, and technology, as improved fish-finding ability may amplify inequalities in recreational fisheries where participant heterogeneity is greater than in our work. Before such research becomes available, our insights highlight that equity in spearfishing tournament outcomes depends less on the diffusion and uptake of technology and more on the interaction between fisher ability and competition design.

Supplementary material

Supplementary material is available at *Fisheries* online.

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Data availability

The raw data supporting this article will be made available upon reasonable request.

Ethics statement

Ethical review and approval were not required for the animal study because Data were provided by the FIPSAS during national tournaments.

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Conflicts of interest

None declared.

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