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Glimpsing the impossible: How artificially enhanced targets improve elite performance

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Abstract

In 2009, elite swimming introduced polyurethane "supersuits" which artificially enhanced performances and facilitated 43 world records at the World Championships, before being prohibited from 2010. This transient, artificial improvement-spike created a natural experiment to examine the effect of 'impossible' targets on subsequent performances. Analyses revealed that swimming speeds at global championships in the post-supersuit period (2011–2017) were substantially faster than predicted from the pre-supersuit period (2000–2007). These results suggest that the transient, artificially enhanced performances of the supersuit era recalibrated targets upwards—acting as goals—and improved subsequent performances beyond previous trajectories (d = 0.64; 0.70%). Contributing to psychological goal-setting theory, the positive relationship between the size of the transient, artificial improvement (i.e., goal difficulty) and subsequent performance was curvilinear, increasing at a decreasing rate before improvements plateaued. Overall, the research demonstrates the potential for elite athletes to exceed perceived human limits, after expectations have been recalibrated upwards.

Keywords: performance, elite performance, goal-setting, goal difficulty, expectations, sport psychology

Glimpsing the impossible: How artificially enhanced targets improve elite performance

Human progress throughout history, in life and sport, has often involved doing what was previously thought impossible, from space exploration to running a sub-4-minute mile. If we were able to see the world of tomorrow, now—to glimpse the impossible—would it alter our expectations and accelerate our own improvement? This research examines this question in the context of elite sport to illuminate ongoing debates in psychological goal-setting theory. To do so, it draws on a unique set of circumstances that unfolded recently in elite swimming, enabling these issues to be examined systematically at the scale of an entire sport.

Supersuits in elite swimming

In 2008 and 2009, the sport of elite swimming experienced an era of rapid and unparalleled improvement attributed to the introduction of new swimsuit technology (Foster et al., 2012). These polyurethane "supersuits" improved muscular power through compression and often covered the entire torso and limbs to enhance hydrodynamics and buoyancy (Cortesi et al., 2014). While the prototype supersuits were introduced before the 2008 Olympic Games, the refined versions appeared in 2009 when 43 world records were broken or re-broken across 32 of the 40 pool-based events at the World Championships (Omega, 2019). In response to this artificial performance inflation, swimming's international governing body, Fédération Internationale de Natation (FINA), prohibited these supersuits from 2010 onwards, stipulating that athletes must only wear swimsuits of standard materials with minimal torso coverage (FINA, 2010; Slater, 2009).

New technology has substantially improved sporting performances before, of course, such as the use of lighter carbon-fiber vaulting-poles in athletics (Caine et al., 2012). However, it is relatively rare for such technological changes to be revoked, and unprecedented for this to happen so extensively and suddenly across an entire elite sport. As such, swimming's supersuit era provides a unique opportunity to study the effect of seemingly impossible targets on future performances, and to do so systematically with the highly accurate and objective performance data that elite sport generates.

While swimming performances improved substantially in the supersuit era of 2008–2009 (Foster et al., 2012), the long-term effects of these improvements on future performances have not been examined. The longevity of the world records established in 2009 (FINA, 2019) implies an artificial spike in performance followed by a sustained relative dip, but this has not been verified empirically so this paper does that first. Having established that, this effectively creates a unique, natural experiment where athletes have glimpsed superior performances, enabling the effect this has on their subsequent performances to be examined over time. The research is underpinned by goal-setting theory, which is now reviewed.

Goal-setting theory

Goal-setting theory arose from the work of Locke and colleagues in the 1960s, consolidating and extending earlier research on motivation and performance. Their experiments found performance on cognitive and psychomotor tasks was highest in response to higher intentions (Locke, 1966) and to specific and difficult goals rather than "do[ing] your best" (Locke & Bryan, 1966). Emergent theorizing focused on the importance of harder, specific goals for high performance (Locke, 1968), leading to further experiments which culminated in the first full goal-setting model by Locke et al. (1981). Locke et al.'s model specified the mediators through which goal-setting improved performance (i.e., focusing attention and effort, enhancing persistence, and developing strategies), and the moderating conditions under which it is most effective (i.e., challenging and specific goals which are accepted, and provision of feedback, rewards, and support). Later research extended this model, notably including goal commitment, self-efficacy (Locke & Latham, 2002), and ability as further moderators (Locke & Latham, 2019).

Most earlier goal-setting research focused on work tasks, but inspired related research in sport psychology (Locke & Latham, 1985). Initial research found no difference in exercise performance between short-term, long-term, and "do your best" goals (Weinberg et al., 1985), and while specific, difficult goals improved muscular endurance, there was no difference between feedback during or after the task (Hall et al., 1987). Further research found no difference between muscular endurance performance improvement in response to goals of different difficulty, including those considered highly improbable (Weinberg et al., 1987). Responding to a methodological critique of goal-setting research in sport (Locke, 1994), Weinberg and Weigand (1996) acknowledged that future research should identify optimal goal difficulty in real-life sport. However, the optimal difficulty level varies, with performance-oriented athletes responding best to difficult goals (Burton & Weiss, 2008).

An early meta-analysis by Kyllo and Landers (1995) of experimental studies found that, overall, goals improved performance by an average of 0.34 standard deviations (*SD*) and were most effective when of moderate difficulty ($SD = 0.53$). They also found less widespread evidence for the effectiveness of goals specifying absolute standards ($SD = 0.93$), publicizing goals ($SD = 0.79$), involving athletes in goal-setting ($SD = 0.62$), and goals with both short- and long-term proximity ($SD = 0.48$). This overall effect size of $SD = 0.34$ is lower than found in non-sporting goal-setting studies (Burton et al., 2010), however, which may reflect sport's more complex skills and performances approaching physical limits (Burton et al., 2001). Sport psychology research has generally distinguished between goal types related to performance (e.g., times), outcome (e.g., winning), and process (e.g., technique) (Burton & Weiss, 2008). However, few studies have measured their unique effects, which may reflect their inter-relatedness (Jeong et al., 2021).

The effect of goals on performance specifically is rarely studied, however, particularly among elite athletes (Burton et al., 2010; Burton & Weiss, 2008). Accordingly, Jeong et al. (2021) conducted a recent systematic review of research in real-life sports, focusing solely on competitive athletes and excluding recreational exercisers. Investigating goal difficulty, specificity, proximity, source, and type, they found goal-setting theory inconsistently applied, defined, and measured in applied sport settings. Furthermore, like the earlier meta-analysis (Kyllo & Landers, 1995), they found small sample sizes ($N < 30$) were still widespread, limiting statistical power and inferences. So, while goals generally improved performance, they found scarce and mixed evidence for the efficacy of different goal characteristics, and definitive conclusions therefore remain elusive for competitive athletes in applied settings.

The current research addresses these methodological issues and heeds previous recommendations to examine performances of a very large sample of elite athletes (Burton & Weiss, 2008; Jeong et al., 2021), at major championships (Burton & Weiss, 2008; Jeong et al., 2021; Weinberg & Weigand, 1996), with specific, performance goals of verifiably high difficulty (Jeong et al., 2021; Weinberg & Weigand, 1996). To do so, the transient and artificially enhanced superior performances of the supersuit season are conceptualized as extremely difficult goals, with their effects on subsequent swimming performances examined. Specifically, these targets should improve athletes' future performances, by recalibrating their expectations upwards when training for championships.

Indeed, there is evidence that elite athletes use world records, and even performances beyond these, as performance goals. Most famously, the quest to run a mile in under four minutes preoccupied elite male middle-distance athletes until Roger Bannister's barrier-breaking run in 1954 (Krüger, 2006). While breaking world records can motivate elite athletes during competitions (Jones et al., 2007), they are primarily used as goals to structure training in the preparation phase (Krüger, 2006). Within swimming, specifically, elite athletes have long used world records to motivate training effort (Chamblis, 1989; Lord, 2019). While, explicitly, such records (i.e., times) represent performance goals (Burton & Weiss, 2008), athletes also recognize that such performances would likely deliver victories in championships (Sachs, 2020), so they also implicitly represent outcome goals (Jeong et al., 2021). Furthermore, athletes also identify the underlying training progression and technique improvements to achieve these performances (Sachs, 2020), so they would also yield accompanying process goals (Jeong et al., 2021).

In theoretical terms, then, these transient and artificially enhanced superior performances of the supersuit season represent goals that are optimally configured to improve performance as they are: (a) performance goals, specifying absolute performance levels (i.e., target times in each event) (Burton et al., 2001; Burton & Weiss, 2008; Kyllo & Landers, 1995); (b) offering feedback that is both short-term (i.e., training and competition performances during the year) and long-term (in the championship itself) (Jeong et al., 2021; Kyllo & Landers, 1995); and (c) highly difficult (i.e., above non-supersuited world-leading levels), which should benefit performance-oriented elite athletes (Burton & Weiss, 2008; Locke & Latham, 2006). The first contribution of this research, therefore, is to use these methodologically-optimal conditions to establish: (a) that these goals improve performance, and (b) the size of this effect. Accordingly, the first hypothesis is:

Hypothesis 1: Performance following transient, artificial improvement will be higher than predicted from performance prior to the artificial improvement.

While evidence indicates goals improve performance, there is ongoing debate in the wider literature about whether this positive relationship between goal difficulty and performance is linear (e.g., Latham et al., 2008), or curvilinear whereby performance improvements plateau or even decline beyond the point at which goals are perceived as impossible (e.g., Baron et al., 2016). Within sport psychology, around half of studies suggest a positive linear relationship (Burton & Weiss, 2008), and while a positive, curvilinear relationship has not been examined explicitly, it is often implied. For instance, the meta-analysis by Kyllo and Landers (1995) found goals of moderate difficulty to be most effective, implying a curvilinear inverted-U relationship. Furthermore, while endurance performance responds similarly to both attainable and unattainable goals (Bueno et al., 2008; Weinberg et al., 1987), the latter can induce feelings of helplessness (Bueno et al., 2008), implying the performance curve levels-off for highly difficult goals. Indeed, even if a curvilinear relationship is found here, performance improvements will likely plateau, rather than decline, for seemingly impossible goals, as elite athletes are highly motivated and uniquely talented (Issurin, 2017). This research will test these competing explanations, as its second contribution, to illuminate goal-setting theory, as indicated in Hypotheses 2a and 2b, below:

Hypothesis 2: The positive relationship between transient, artificial improvement (i.e., goal difficulty) and subsequent performance will: (a) be curvilinear, with performance increasing at a decreasing rate following higher transient, artificial improvement; and (b) plateau, rather than decline, when the apex of this curve is reached.

In timed racing sports, like track athletics and swimming, it has been suggested that even a 1% performance improvement may be near that tipping point beyond which short-term goals are perceived as too challenging and unrealistic (Weinberg & Butt, 2014), and performance improvements therefore plateau or decline. However, this research will identify the apex of this curve precisely, as part of its second contribution, to illuminate goal-setting theory. Furthermore, this knowledge will enable elite athletes and their coaches to set optimally challenging goals—at the precise, performance improvement percentage-level identified—to elicit maximum performance improvements.

Method

Participants

The research examined the swimming performances of 867 elite athletes at the Olympic Games (2000–2016) and World Championships (2001–2017). These athletes represented 58 countries, had a mean age of 22.74 years (*SD* = 3.50), and comprised 454 men and 413 women. Additional age data were obtained from a database (Kaufmann, n.d.).

Data from the 26 individual, pool-based Olympic swimming events in each of these championships were examined, comprising 13 men's events and 13 women's events (see FINA, 2019; Omega, 2019). These events ranged in distance (in meters, m) and spanned all four swimming strokes: freestyle (50m, 100m, 200m, 400m, and 800m for women or 1500m for men), butterfly (100m, 200m), backstroke (100m, 200m), breaststroke (100m, 200m); and one multi-stroke discipline, individual medley (200m, 400m). Only the results of the final for each event were used, comprising eight swimmers in each event, as some leading swimmers do not exert maximum effort in the preceding qualifying rounds (heats and semi-finals) to conserve energy for the final.[1] Overall, 2,912 elite swimming performances were examined, divided equally between men's and women's events, comprising 208 performances at each of the 14 global championships from 2000 to 2017. However, six missing values were identified, leaving a final sample of 2,906 performances (see *Results*).

[1] For instance, in the 2017 World Championships, the mean speed in the final of each of the 26 events (*M* = 1.74 meters per second; *SD* = 0.21) was faster than the mean speed for the same athletes in the respective, immediately-preceding, qualifying round (i.e., semi-finals of events of 200m and shorter, and heats of longer events) (*M* = 1.73 meters per second; *SD* = 0.21), $t(206) = 6.97$, $p < .001$.

Design

The research design was an interrupted time-series natural experiment (Craig et al., 2017). The artificial, supersuit-enhanced performances in the 2009 season acted as a naturally-occurring intervention of transient, artificial improvement midway between the periods of regular performances before (2000–2007) and after (2011–2017) the intervention. Consequently, the artificial, supersuit-enhanced performance improvements constituted the independent variable, while post-supersuit performances constituted the dependent variable relative to pre-supersuit performances.

Inevitably, there was no control group in this research as swimmers in all events used supersuits during the 2009 season. However, the longitudinal time-series data provided confidence in the causality by demonstrating the stability of the regular performance improvement trend over time (Craig et al., 2017) within each of the periods before (2000–2007) and after (2011–2017) the anomalous intervention (see *Results*). Furthermore, interrupted time-series natural experiments obtain highly similar results to randomized experiments (St. Clair et al., 2014).

As stated in the *Participants* section, the 2,906 performances analyzed were delivered by 867 athletes, so a mean of 3.35 performances each. The data are not therefore fully independent. For time-series data, where the same participants are tracked over time at every time-point, a statistical correction for autocorrelation can be applied (e.g., Craig et al., 2017). However, this correction was not applied here because: (a) where data were from the same athletes this was restricted to just a few years, not the whole 2000–2017 period; (b) including further controls reduces statistical power (Bernerth & Aguinis, 2016); and (c) the Durbin-Watson statistic indicated no autocorrelation issues (see *Results*).

Consideration of alternative causal explanations

As with all natural experiments outside of laboratory conditions, it was not possible to control extraneous variables. So, it is possible that another variable (or other variables) caused the performance increases attributed to the supersuit-enhanced targets (i.e., goals). However, this is unlikely for the following two broad reasons.

First, there is theoretical support for this explanation—that the supersuit-enhanced targets acted as performance goals—as discussed in the earlier literature review (see *Introduction*). In particular, there is general literature about athletes using performance goals (e.g., Burton & Weiss, 2008) and specific literature about elite athletes using world records as performance goals (e.g., Sachs, 2020).

Second, there is no evidence for plausible alternative explanations. The mean post-supersuit performance improvement across all events, once regular improvements over years had been controlled, was a substantial 1.19 seconds (s) (see *Results*). While there were three major technical rule changes in elite swimming during the study period, the resultant performance improvements were negligible compared with this: (1) breaststroke events after 2005 permitted a single propulsive dolphin kick after each start and turn which improved performance by 0.19s per 50m pool length (McLean et al., 2008), but non-breaststroke events (i.e., 22/26 events, see *Participants*) were unaffected; (2) a wedge at the rear of starting blocks introduced in 2010 improved performance by 0.04s per race (Honda et al., 2010); (3) an underwater foot-ledge attached to starting blocks after 2013 improved backstroke performance by 0.06-0.08s per race (de Jesus et al., 2016).

It was also unlikely that any residual improvements in swimsuit technology retained after the supersuit ban in 2010 caused the subsequent improvements, as even prior to the supersuit era (2008–2009) elite swimmers were already using full bodysuits made from regular textile materials (Foster et al., 2012) that would have also been prohibited by the 2010 supersuit ban due to limb coverage (FINA, 2010). Finally, the consistent improvement across events, of different strokes (with different techniques) and different distances (using different energy systems), by athletes from 58 different countries (see *Participants*), in such a sudden way, suggests this was not due to widespread changes in coaching, particularly in swimming where coaching science is an advanced, mature discipline (Maglischo, 2003).

Measures

Initially, annual world ranking data (i.e., fastest times per event) from before, during, and after the 2009 supersuit season were sought, but accurate and complete ranking data were not available from before 2009. While FINA's world ranking data did extend back to 2000, a large number of omissions were identified. So, instead, the accurate and complete results from elite swimming's two periodic, global, long-course championships were used: the biennial FINA World Championships and the quadrennial Olympic Games. Data were collated from the official results of these two championships (FINA, 2019; Omega, 2019).

Unlike track athletes, swimmers compete in individual lanes for all pool events and environmental conditions are standardized (FINA, 2017), so performances in elite competitions represent the swimmers' maximum capabilities at that time. Consequently, swimmers' seasonal best times and world records are usually achieved at these championships (Omega, 2019), for which swimmers target and taper their training (Papoti et al., 2007).

The key season in which the supersuits caused the transient, artificial performance improvement was 2009, so this was the midpoint in the required time-series data. The FINA World Championships moved from a quadrennial to biennial cycle in 2001 (FINA, 2019), so this was the chosen start-date eight years before 2009 and, for symmetry, the chosen end-date was the championship eight years after in 2017. For the Olympic Games, data were used for the five championships centered on 2008, the first year of the supersuit era. So, overall, the data extended from 2000 to 2017, with six global championships before the supersuit era of 2008–2009, two during, and six after, for symmetry and consistency, with data from a total of 14 championships. Information about the swimming events analyzed is provided in the *Participants* sub-section.

The raw results data from these global championships were in time units (minutes, seconds, and hundredths of seconds) so were initially converted to speed in meters per second (m/s) so that higher performances were shown intuitively as higher data-points on graphs. Next, to control for natural differences in swimming speed as a result of gender, distance, and stroke, the speed data were converted into standardized Z-scores (i.e., [x – mean] / standard deviation; e.g., Field, 2013) within each of the 26 events—referred to below as intra-event Z-score of speed—so that speed improvements were directly comparable across diverse events.

Data analysis procedures

To test Hypothesis 1, it was necessary to account for the fact that performances were improving over time naturally, both overall and within each period, even without the supersuit intervention. To do so, piecewise regression (also known as segmented regression) was used, a specialist technique for identifying break-points in otherwise linear relationships between variables; that is, points at which the regression line ‘breaks’ and changes gradient and/or rises above or falls below the path of the preceding line section (UCLA, n.d.; Wagner et al., 2002).

So, here, piecewise regression was used to establish and compare the regression models from the pre-supersuit (2000–2007) and post-supersuit (2011–2017) periods, to test whether the regression intercept increased between these periods (i.e., that the performance trend had shifted upwards) while the gradient remained unchanged (i.e., that this was a stable and enduring shift). So, for Hypothesis 1's specific piecewise regression, year of championship (i.e., date) was the predictor variable and swimming speed the outcome variable.

To test Hypothesis 2, it was necessary to examine the effect of the changes—between speed in the pre-supersuit period (2001–2007) and speed in the supersuit season (2009)—on speed in the post-supersuit period (2011–2017). To do so, polynomial regression was used, a specialist technique for examining the effects of changes between two predictor variables on an outcome variable (Edwards, 2002). The changes and their effects are modelled as a three-dimensional interaction surface, which is more reliable and represents the full variance of the predictor variables unlike the alternative of difference scores (see Edwards, 2002, for a detailed overview, summarized here). Specifically, hierarchical polynomial regression was used to examine the interaction between intra-event Z-score of speed in the pre-supersuit period (2001–2007) and intra-event Z-score of speed in the supersuit season (2009), when collectively predicting intra-event Z-score of speed in the post-supersuit period (2011–2017), to determine whether there is a curvilinear effect.

However, as polynomial regression analyzes changes between just two data-points, it was necessary to use the single mean of the multiple data-points in each period. So, to prepare the data, the mean intra-event Z-score of speed was calculated for swimmers in each final position (1st to 8th), in each event, across (a) the six championships in the pre-supersuit period, and (b) the six championships in the post-supersuit period.

Results

Data screening and preparation

Six missing values were identified, corresponding to five disqualifications and one non-starting competitor, leaving a final sample of 2,906 performances. Data screening found minimal levels of skew and kurtosis in either the speed in m/s (0.87, 0.64) or intra-event Z-score of speed (−0.06, −0.53) data, enabling parametric statistical analyses.

The descriptive statistics and correlations for all research variables and potential control variables are shown in Table 1, for the period 2000–2017 excluding the 2008–2009 supersuit seasons (n = 2490) as these were the data for the main analyses (see below). As well as the predictor variable, year of championship, and outcome variable, intra-event Z-score of speed, some potential control variables (variables 2–8 in Table 1) were considered, in two ways.

< Insert Table 1 here >

First, there were three control variables with small-to-medium correlations (Cohen, 1992) with raw swimming speed in m/s, as Table 1 shows, namely gender (men's events were faster than women's events), distance (shorter events were faster than longer events), and stroke (freestyle events were fastest, followed by butterfly, backstroke, individual medley, and breaststroke events; collectively represented here by the four dummy-coded stroke variables). However, converting raw swimming speed in m/s into standardized Z-scores of speed within each event for the analyses (see *Method*) controlled for these three variables. This can be seen in Table 1 where these correlations were effectively eliminated by the conversion ($r \leq |.02|$). This data conversion was required here—as this research was examining improvements in intra-event speed over time rather than inter-event speed—to make improvement data from diverse events directly comparable and enable aggregated analyses across all events.[2]

[2] For instance, while there was substantial improvement in raw swimming speed over time across all events from the Olympic Games in 2000 (M = 1.69 m/s, SD = 0.20) to the World Championships in 2017 (M = 1.74 m/s, SD = 0.21), the men's 50m freestyle in 2000 (M = 2.25 m/s, SD = 0.02) was still faster than the men's 400m freestyle in 2017 (M = 1.78 m/s, SD = 0.01), as despite the improvements over time shorter events are still faster. So, the intra-event Z-score data conversion controlled for the large inter-event differences in speed between events of different distances to enable the intra-event speed improvements over time (2000–2017, excluding the 2008–2009 supersuit seasons) to be compared in an equivalent and meaningful way.

Second, potential control variables were also examined relative to intra-event Z-score of speed in Table 1. It is important to note here that FINA implemented a rule change in breaststroke events in 2005 to permit a propulsive dolphin kick during the underwater pull-out following the starting dive and each turn (Reuters, 2005). This could have disproportionately increased the intra-event Z-score of speed after 2005 in breaststroke events relative to other strokes, so it was necessary to check this here. However, there was no evidence of such an effect sizable enough to affect these analyses as the dummy-coded breaststroke variable was not correlated with intra-event Z-score of speed (r = .01).[3] Finally, championship type (World Championships or Olympic Games) had only a very small correlation with intra-event Z-score of speed (r = − .05) so was not controlled for here.[4]

Intervention check

The mean intra-event Z-score of speed for each of the 14 global swimming championships in the 2000–2017 period are shown in Figure 1, with the error bars indicating standard deviations. The transient, artificial improvement in speed during the supersuit era at the 2009 World Championships, and to a lesser extent the 2008 Olympic Games, is clearly visible. However, to verify this statistically, and confirm the intervention of the natural experiment (i.e., conduct an intervention check), the *actual* mean intra-event Z-score of speed in 2009 was compared with the *predicted* mean intra-event Z-score of speed in 2009 from an equation generated from a regression predicting speed from year of championship, using all data from 2000–2017 except the 2008–2009 supersuit era, corresponding to Step 1 of the piecewise regression in Table 2 but with unstandardized coefficients and non-centered variables (described below). The size of the difference between these two values for 2009 (i.e., actual

[3] Furthermore, the results of the main analyses did not differ in significance when breaststroke events were excluded.
[4] The piecewise regression testing Hypothesis 1 was also run controlling for championship type (World Championships or Olympic Games) in Step 1, but the significance of the results did not differ.

and predicted) was then divided by the standard deviation of the actual value for that year to calculate the Cohen's *d* effect size (Cohen, 1992). The actual mean speed in 2009 was substantially higher (d = 1.39, a very large effect) than the predicted mean speed, thereby verifying both the anomalous nature of the improvements in the supersuit era and the natural experimental intervention.

< Insert Figure 1 here >

Hypothesis 1: Performance increase following transient, artificial improvement

To test Hypothesis 1, a hierarchical piecewise regression was conducted following the recommended procedures (UCLA, n.d.; Wagner et al., 2002) described below and shown in Table 2. First, to prepare and aid interpretation, years were centered on the 2009 supersuit season (by subtracting 2009 from each year). In Step 1, year of championship (2000–2017, excluding the 2008–2009 supersuit seasons) was entered. This represented the overall (non-segmented) regression model and predicted a significant and sizable 45.27% of the variance in intra-event Z-score of speed. The regression equation derived from this stage, but using unstandardized coefficients and non-centered variables, was also used for the intervention check above: (a) $y = 0.114x - 229.85$ (for the period 2000–2017, excluding 2008–2009 supersuit seasons). The accompanying Durbin-Watson statistic for this first step was 1.31, so between 1 and 3 thereby indicating no autocorrelation issues (Field, 2013).

Step 2 tested whether there was a difference in the gradient of the regression lines between the pre-supersuit period (2000–2007) and post-supersuit period (2011–2017). To do so, the first piecewise variable was entered, which recoded year of championship into 0 for the pre-supersuit period but retained the original year values (centered on 2009) for the post-supersuit period, to represent the change in gradient after 2009. However, this new variable explained no incremental variance at all in intra-event Z-score of speed, indicating the gradient of the regression lines did not differ between these periods.

Step 3 tested whether there was a difference in the y-axis intercept between the pre-supersuit period (2000–2007) and post-supersuit period (2011–2017). To do so, the second piecewise variable was entered, which recoded year of championship into 0 for the pre-supersuit period and into 1 for the post-supersuit period, to represent the upwards shift in intercept after 2009. This new variable explained a significant 0.86% of incremental variance in intra-event Z-score of speed, indicating that the y-axis intercept of the regression line was higher for the post-supersuit period.

Taken together, Steps 2 and 3 therefore provide strong support for Hypothesis 1, as the performance improvement trendline had shifted upwards in the post-supersuit period while the gradient had remained unchanged. This effectively yields parallel regression lines as shown in Figure 1. Following standard procedures (UCLA, n.d.), the piecewise regression was plotted with separate regression equations for each segment, using unstandardized coefficients and non-centered variables: (a) $y = 0.080x – 160.45$ for the pre-supersuit period (2000–2007), and (b) $y = 0.074x – 147.68$ for the post-supersuit period (2011–2017).

< Insert Table 2 here >

To analyze the upward shift in post-supersuit performances further and establish its magnitude, Cohen’s *d* effect sizes (Cohen, 1992) were used again. Specifically, the difference between the *actual* mean intra-event Z-score of speed for each year of the post-supersuit period (2011–2017) and the *predicted* mean intra-event Z-score of speed for each of these same years—generated from the regression equation for the earlier pre-supersuit period (2000–2007)—was divided by the standard deviation of the actual intra-event Z-score of speed for each year. The following results were found for each year: (1) 2011: $d = 0.58$; (2) 2012: $d = 0.89$; (3) 2013: $d = 0.53$; (4) 2015: $d = 0.47$; (5) 2016: $d = 0.73$; and (6) 2017: $d = 0.64$. In each case, the effect size was essentially medium ($d \geq 0.50$) to large ($d \geq 0.80$) (Cohen, 1992), with a mean of $d = 0.64$ across these six post-supersuit championships.

To contextualize these results for elite swimming, this improvement was converted back into the original times units (s). To do so, for each event the standard deviation of speed (m/s) for the post-supersuit period (2011–2017) was first multiplied by $d = 0.64$, to obtain the mean speed improvement (m/s), which was then converted into the mean time improvement (s) using the actual mean time (s) for the post-supersuit period (2011–2017). The calculated mean time improvement across all 26 events in the post-supersuit period was 1.19s ($SD = 1.51$), or 0.70% ($SD = 0.13$). So, in a typical, two-minute, elite swimming event (i.e., most 200m events), this would correspond to an improvement of almost one second. Finally, it is important to note that these are the improvements due *solely* to the goals—recalibrated following the transient, artificially enhanced, supersuit performances—and are *in addition* to any improvements in performances that also occur naturally over years (see Figure 1).

Hypothesis 2: Curvilinear relationship between goal difficulty and performance

The polynomial regression procedures advocated by Edwards (2002) were followed, as described below, with the results shown in Table 3. First, the two predictor variables were mean-centered to aid interpretation, namely mean intra-event Z-score of speed in the pre-supersuit period (2000–2007) (polynomial variable X) and intra-event Z-score of speed in the supersuit season (2009) (polynomial variable Y), by subtracting the respective means from each value. Second, both predictor variables (X and Y) were entered in Step 1 of the regression predicting the outcome variable mean intra-event Z-score of speed in the post-supersuit period (2011–2017) (polynomial variable Z). These two variables significantly predicted 80.48% of the variance in the outcome variable in this first step (see Table 3 for full results). In Step 2, the X^2, XY, and Y^2 polynomial terms were entered, collectively representing the curvilinear interaction surface. These three terms significantly predicted an incremental 1.52% of the variance in the outcome variable in this second step, for a total of 82.00% of variance explained overall. The resultant curvilinear interaction surface is shown in Figure 2 (graph macro: Edwards, n.d.). The standardized Beta for the Y^2 term was also approaching significance (p = .076) and had the highest absolute value of the three polynomial variables entered at Step 2. Collectively, then, these results partially support Hypothesis 2a, as the change in variance explained in Step 2 was significant but the standardized Beta for the Y^2 term was not quite significant (see Edwards, 2002).

< Insert Table 3 & Figure 2 here >

Further visual inspection was used to examine this curvilinear effect in detail, and to test Hypothesis 2b. Figure 3 shows the two-dimensional cross-section of the three-dimensional polynomial interaction surface from Figure 2, at the plane where the centered variable X = 0.00, namely mean intra-event Z-score of speed for the pre-supersuit period (2000–2007). This is the cross-section of the interaction surface as viewed from the right-hand wall of Figure 2, so the curvilinear effect in Figure 3 appears inverted relative to the view in Figure 2 although the axes and curve are the same. Figure 3 therefore represents the graph of the curvilinear relationship between intra-event Z-score of speed in the supersuit season (2009) and mean intra-event Z-score of speed in the post-supersuit period (2011–2017), having controlled for mean intra-event Z-score of speed in the pre-supersuit period (2000–2007).

< Insert Figure 3 here >

In simple terms, and in the context of goal-setting theory, Figure 3 therefore represents the relationship between goal difficulty and performance. The curvilinear nature of this relationship between intra-event Z-score of speed in the supersuit season and mean intra-event Z-score of speed in the post-supersuit period is clearly visible. The latter increases at a decreasing rate as the former increases, as Hypothesis 2a predicted, with the curve starting positively before plateauing, rather than declining, in support of Hypothesis 2b. Through visual examination of Figure 3, the point at which the upward curve begins to plateau is where the centered variable Y = 1.00, namely intra-event Z-score of speed in the supersuit season (2009).

Finally, to contextualize these results in terms of elite swimming performances again, the relevant intra-event Z-scores of speed were first converted back into equivalent swimming times using the mean and standard deviation data for speed (m/s) for each event. Specifically, the times were calculated for when centered variable X = 0.00 (equivalent to the cross-sectional plane represented by Figure 3 and corresponding to the mean intra-event Z-score of speed in the pre-supersuit period), and for when centered variable Y = 1.00 (equivalent to the plateau-point in Figure 3 and corresponding to intra-event Z-score of speed in the supersuit season). The percentage difference between these two times is therefore the point at which the target performance improves post-target performances most, or where the upwards curve plateaus, which was a mean of +4.17% (*SD* = 0.53) across all 26 events, relative to pre-target performances.

Discussion

This research used the transient, artificial performance improvements of elite swimming's supersuit era as a natural experimental intervention to examine the effects on subsequent performances, through the lens of goal-setting theory (Burton & Weiss, 2008; Jeong et al., 2021; Kyllo & Landers, 1995; Weinberg & Weigand, 1996). The supersuit era offered a unique context in which to study this issue, as the temporary performance improvements that occurred were unprecedented in magnitude, their scope across an entire elite sport, and the subsequent revocation of the technology. The mean swimming speed in the 2009 supersuit season demonstrated a substantial, upwards spike in performance (*d* = 1.39) relative to what would have been predicted from the overall trend for the 2000–2017 period, excluding the 2008–2009 supersuit seasons, thereby verifying the natural experimental intervention.

Hypothesis 1: Performance increase following transient, artificial improvement

In strong support of Hypothesis 1, swimming speed in the post-supersuit period was significantly higher than would have been predicted from the earlier pre-supersuit period, with the intercept difference test significant and the gradient difference test nonsignificant in the piecewise regression. The substantial, transient, artificial performance improvement of the supersuit era effectively disconnected the overall performance trendline between the pre-supersuit (2000–2007) and post-supersuit (2011–2017) periods, and moved the latter upwards to create parallel trendlines as shown in Figure 1.

These findings constitute the first contribution of this research, indicating that: (a) these goals improved performance; and (b) the mean goal-related improvement across the six post-supersuit championships was *d* = 0.64, a medium-to-large effect size (Cohen, 1992). This effect is almost twice as large as the overall *SD* = 0.34 improvement found by Kyllo and Landers' (1995) meta-analysis, and, of relevance here, comparable to their effect sizes for absolute goals (*SD* = 0.93) and those of moderate difficulty (*SD* = 0.53). However, the meta-analysis was of experiments often involving untrained non-athletes performing simple physical exercises unrelated to sport (Kyllo & Landers, 1995), in which improved performance was possible simply through increasing effort from moderate baseline levels (see e.g., Burton et al., 2001). In contrast, this research examined the upper echelon of the world's elite athletes—among the most highly motivated, physically fit, and talented humans (Issurin, 2017)—who improved on performances that were already at the perceived limits of human potential (i.e., at or near world record pace). Clearly, then, even elite athletes still have room for substantial improvement if their targets are recalibrated upwards. In real terms, this level of improvement corresponds to event times 0.70% faster on average (see *Results*). In elite swimming, this can be the difference between winning and missing medals, and sometimes even between medaling and failing to qualify for the final (see e.g., FINA, 2019).

Hypothesis 2: Curvilinear relationship between goal difficulty and performance

The nature of the relationship between the transient, artificial improvement in the supersuit era and performances in the post-supersuit period was then examined further. The results of the polynomial regression indicated that the curvilinear interaction between mean speed in the pre-supersuit period (2000–2007) and speed in the supersuit season (2009) predicted mean speed in the post-supersuit period (2011–2017) significantly. However, the standardized Beta for the square of speed in the supersuit season (2009) was not quite significant, so there was only partial support for Hypothesis 2a.

As Figure 2 shows, the level of the artificial improvement in the supersuit season was positively related to speed in the post-supersuit period, having effectively controlled for speed in the pre-supersuit period, and this relationship was curvilinear with the relationship plateauing at higher levels of artificial improvement, supporting Hypothesis 2b. It therefore appears that the relationship between goal difficulty and performance is curvilinear, with performance increasing at a decreasing rate, before improvements plateau, rather than decline, for highly difficult goals.

This finding illuminates current debates in wider goal-setting theory, suggesting that the positive relationship between goal difficulty and performance is curvilinear (Baron et al., 2016) rather than linear (Latham et al., 2008). Within sport psychology, while half the research suggests a positive linear relationship (Burton & Weiss, 2008; Jeong et al., 2021), contrary to these findings, a curvilinear relationship has yet to be examined explicitly. Nevertheless, research suggesting that moderately difficult goals are most effective (Kyllo & Landers, 1995) implies a curvilinear inverted-U relationship, while research suggesting attainable and unattainable goals are equally effective (Bueno et al., 2008; Weinberg et al., 1987) implies a curve with a plateau more similar to that found here. This study measured goals over a range of difficulty, however—by using continuous data rather than few discrete categories—thereby explicitly and precisely identifying the curvilinear relationship between goal difficulty and performance. In doing so, this research addressed previous methodological issues and solidified theory to guide future research (see Jeong et al., 2021).

Further analysis found that transient, artificial improvements from the pre-supersuit period to the supersuit season of up to +4.17% led to increasingly improved performances in the post-supersuit period, effectively acting as a target beyond which improvements plateaued (see Figure 3). According to championship dates, the mid-point of the pre-supersuit period (2000–2007) was 5.70 years before the mid-point of the 2009 supersuit season, so this would correspond to the effective time-horizon for the target. The identification of this optimal percentage improvement level for goals of +4% has not previously been examined empirically, so this is a novel contribution of the current research. However, it has been previously speculated that a 1% performance improvement was the optimal goal level (Weinberg & Butt, 2014), so this research would suggest that was an underestimate and that elite athletes can respond to more of a challenge.

Before generalizing, however, it should be recognized that progress in elite swimming has exceeded that in comparable timed racing sports—as swimming improvements are largely due to improved technique, not only improved fitness (Maglischo, 2003)—so adjustments to this target level may be required for other sports if used for goal-setting purposes. For instance, between 1990 and 2020, world records in Olympic events improved 3.31 times more in swimming (M = 4.51%, SD = 1.20) (USA Swimming, n.d.) than in track athletics (M = 1.36%, SD = 1.24) (World Athletics, 2020). So, the +4.17% optimal goal level found here for swimming would equate to +1.26% for track athletics, given this conversion factor.

Practical implications

Given the substantial performance improvements found here, it is important to understand the nature of the goals that enabled them. To do so, the transient and artificially enhanced targets which acted as goals here are now described in terms of their goal-setting properties, drawing on the literature, as a series of practical recommendations.

Accordingly, when developing goals for elite athletes, coaches and athletes should do the following. First, goals should specify absolute performance levels (Burton et al., 2001; Burton & Weiss, 2008; Kyllo & Landers, 1995), such as times, distances, weights, or repetitions. Second, these long-term performance goals should also be divided into progressive, short-term performance and process goals (Burton & Weiss, 2008; Kyllo & Landers, 1995), to guide ongoing training and performance at interim competitions before the major championships. Third, for elite athletes, these performance goals should be highly difficult (Burton & Weiss, 2008; Locke & Latham, 2006), to challenge existing expectations about what is possible. Specifically, when training for competitions around five years away (e.g., similar to an Olympic cycle), this research suggests that setting goals around 4% above their current elite performance levels can lead to performance improvements of 0.70% (in addition to natural improvement over years) in elite athletes already competing in global championship finals. While performance may improve more dramatically than this, goals more difficult than this appear not to have additional benefits.

Finally, it is important to recognize that the percentage levels for goal difficulty and expected improvement identified here are derived from, and appropriate for, timed racing sports (e.g., swimming). However, while highly related, times and speeds do not correspond perfectly linearly with other performance units such as weight lifted (e.g., Maglischo, 2003) and distance jumped (e.g., Bridgett & Linthorne, 2006). So, further research should establish and calibrate such percentage levels for other sports.

Limitations and future research

The unique circumstances yielding this natural experiment enabled goal-setting theory to be examined systematically in elite athletes competing in global championships, as discussed. Nevertheless, despite these methodological benefits, the research had several limitations.

First, there was no control group, as supersuits were used by swimmers in all events in 2009. Although it was highly likely that the transient, artificially enhanced, supersuit performances caused the subsequent improvement—as goal-setting theory supports this (see *Introduction*) and there were no plausible alternative explanations (see *Method*)—it is not therefore possible to state this with certainty. Such future research could therefore analyze situations where changes benefitting performance are implemented, and then revoked, in some events but not others. The current situation in elite athletics where new “super shoes” are enhancing performances (Taylor, 2021) could offer one such opportunity, with some athletics events acting as a potential control group (e.g., track versus road running).

Second, athletes did not confirm explicitly that the transient, artificially enhanced, supersuit performances acted as goals. Rather, this was inferred from evidence that elite athletes do use world records as goals to structure their training (see *Introduction*), and from the absence of plausible alternative explanations (see *Method*). Consequently, it would be useful for such future research to examine their specific motivations and goals explicitly using interviews (Burton & Weiss, 2008) or questionnaires (Burton et al., 2010) also. Furthermore, such future studies could untangle the relationships between these explicit performance goals, the implicit outcome goals they also represent (i.e., such performances deliver victory), and the shorter-term process goals (e.g., technique improvements) required to deliver them (Burton & Weiss, 2008; Jeong et al., 2021).

Finally, as this study focused on elite athletes competing in global championships, the results may not generalize fully to other populations. For instance, junior athletes, who are still developing, will likely experience more dramatic improvements that those found here. Consequently, they may therefore benefit from even more difficult goals, particularly if they are targeting future global competitions (Chamblis, 1989). Conversely, difficult goals may discourage recreational athletes and exercisers who instead benefit from less challenging, nonspecific goals such as "do your best" or "as well as possible" (Swann et al., 2020).

Conclusion

In conclusion, then, on the rare occasions when anomalous events serendipitously recalibrate goals upwards, it appears that human performance will increase beyond expectations, as what was previously thought impossible now appears attainable. However, these results also have clear implications for more routine and planned scenarios, where goal-setting theory can be used to design processes to deliver similar performance improvements. Specifically, for motivated, elite athletes, highly difficult goals beyond perceived existing limits, that specify absolute performance levels and offer interim feedback, can help them improve to new levels of excellence. Glimpsing the impossible may therefore enable the impossible to be achieved, which is the quintessence of human progress.

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Figure 1: Mean speeds at global swimming championships 2000–2017, with regression lines for pre-supersuit (2000–2007) and post-supersuit (2011–2017) periods

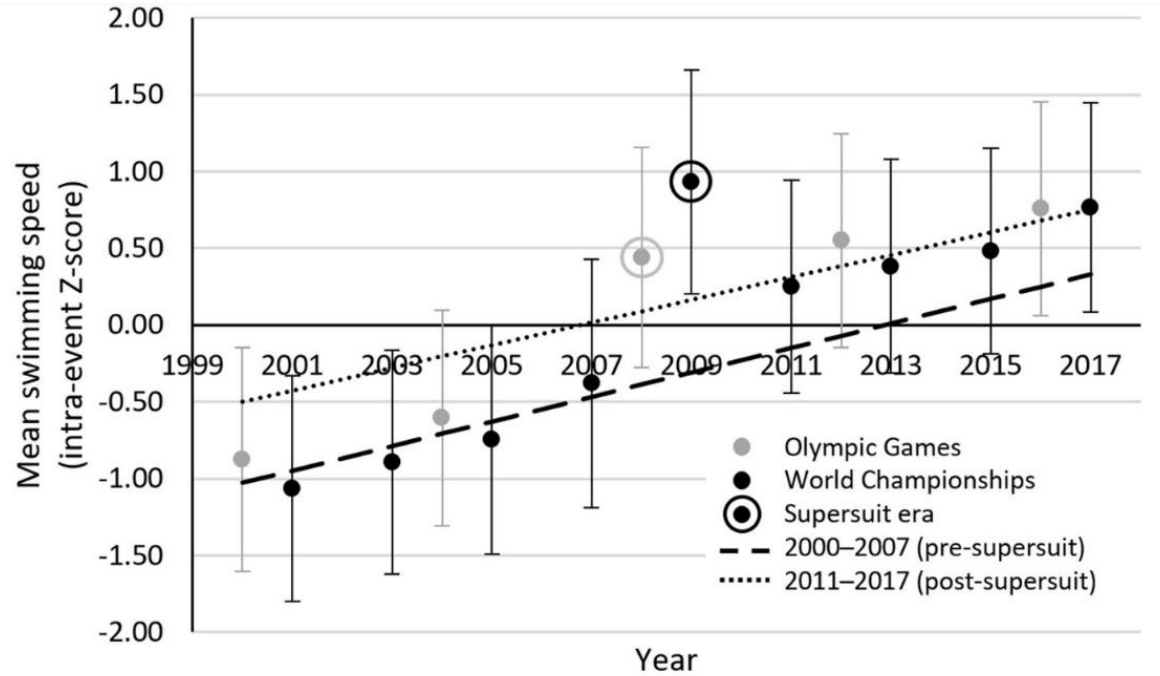

Figure 2: Polynomial interaction surface between mean speed in the pre-supersuit period (2000–2007) and speed in the supersuit season (2009) predicting mean speed in the post-supersuit period (2011–2017) at global swimming championships

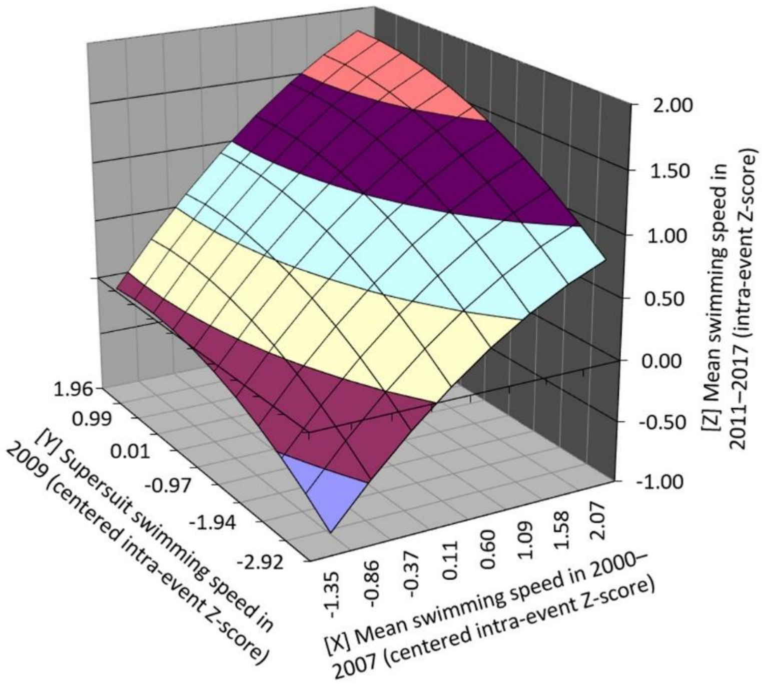

Figure 3: Cross-section of polynomial interaction surface from Figure 2 when centered mean swimming speed in 2000–2007 (intra-event Z-score) is zero [X = 0]

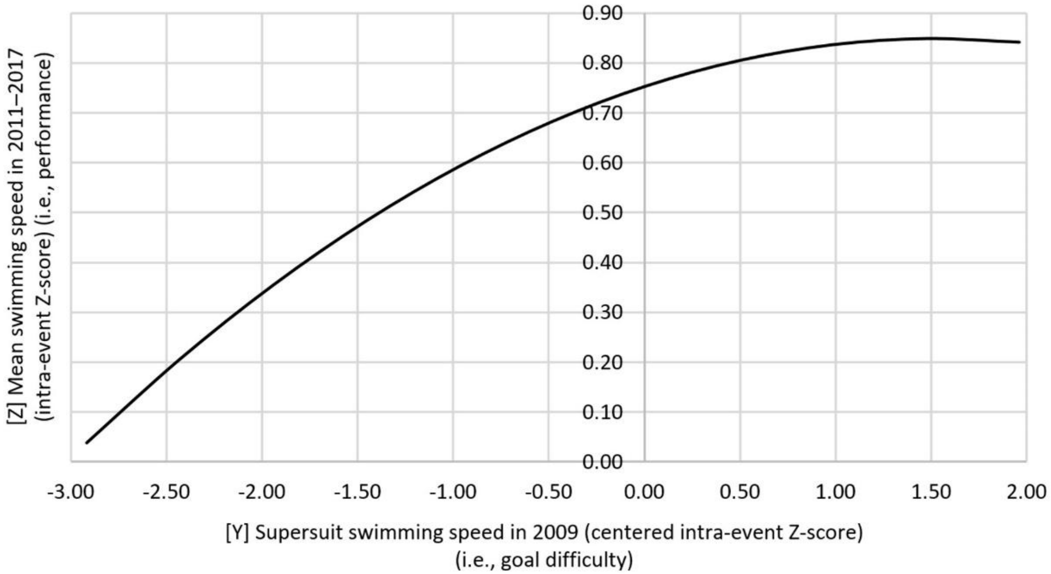

Table 1: Descriptive statistics and Pearson correlations

	Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	Year of championship	2008.66	5.79	—											
2	Gender	0.50	0.50	.00	—										
3	Event distance (meters)	261.16	292.60	.00	.09**	—									
4	Stroke 1 (dummy-coded): Butterfly	0.15	0.36	.00	.00	−.16**	—								
5	Stroke 2 (dummy-coded): Backstroke	0.15	0.36	.00	.00	−.16**	−.18**	—							
6	Stroke 3 (dummy-coded): Breaststroke	0.15	0.36	.00	.00	−.16**	−.18**	−.18**	—						
7	Stroke 4 (dummy-coded): Individual medley	0.15	0.36	.00	.00	.06**	−.18**	−.18**	−.18**	—					
8	Championship type	0.67	0.47	.08**	.00	.00	.00	.00	.00	.00	—				
9	Gradient difference test (pre-2008 = 0; post-2009 = year)	2.50	2.93	.92**	.00	.00	.00	.00	.00	.00	.00	—			
10	Intercept difference test (pre-2008 = 0; post-2009 = 1)	0.50	0.50	.92**	.00	.00	.00	.00	.00	.00	.00	.85**	—		
11	Intra-event Z-score of speed	−0.11	0.98	.67**	−.01	.02	−.01	.00	.01	.01	−.05**	.62**	.66**	—	
12	Speed (in meters per second)	1.71	0.20	.09**	.42**	−.26**	.06**	−.03	−.40**	−.32**	−.01	.08**	.09**	.11**	—

n = 2490. * $p < .05$. ** $p < .01$.

Table 2: Piecewise regression of year predicting speed at global swimming championships in the pre-supersuit (2000–2007) and post-supersuit (2011–2017) periods testing differences in gradient and intercept

Predictor variable	Outcome variable: Intra-event Z-score of speed		
	Step 1	Step 2	Step 3
Year of championship	.67***	.68***	.47***
Gradient difference test (pre-2008 = 0; post-2009 = year)	—	−.01	−.02
Intercept difference test (pre-2008 = 0; post-2009 = 1)	—	—	.24***
Adjusted $R^2 \times 100$	45.27***	45.25***	46.11***
Adjusted $\Delta R^2 \times 100$	45.27***	−0.02	0.86***

n = 2490. * $p < .05$. ** $p < .01$. *** $p < .001$. Standardized Betas are shown.

Table 3: Polynomial regression examining the interaction between mean speed in the pre-supersuit period (2000–2007) and speed in the supersuit season (2009) predicting mean speed in the post-supersuit period (2011–2017) at global swimming championships

Predictor variable	Outcome variable: Mean intra-event Z-score of speed in the post-supersuit period (2011–2017) [Z]	
	Step 1	Step 2
Mean intra-event Z-score of speed in the pre-supersuit period (2000–2007) (centered) [X]	.55***	.62***
Intra-event Z-score of speed in the supersuit season (2009) (centered) [Y]	.40***	.35***
X^2	—	−.07
XY	—	.02
Y^2	—	−.12†
Adjusted $R^2 \times 100$	80.48***	82.00***
Adjusted $\Delta R^2 \times 100$	80.48***	1.52***

n = 208. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$. Standardized Betas are shown.