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# Task difficulty promotes tactical learning but supresses the positive learning effects of autonomy and cognitive effort

Dave Bright[a,*], Jenny Smith[a], Philip Kearney[b], Oliver Runswick[c]

[a] Institute of Applied Sciences, University of Chichester, College Lane, Chichester PO19 6PE, UK
[b] Sport & Human Performance Research Centre, Health Research Institute, University of Limerick, Limerick V94 T9PX, Ireland
[c] Department of Psychology, Institute of Psychiatry, Psychology and Neuroscience, King's College London, London SE1 1UL, UK

A R T I C L E I N F O

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A B S T R A C T

Learning conditions that provide task-relevant autonomy, and those that encourage cognitive effort through manipulations of difficulty, have been reported to enhance skill development. However, research is yet to directly compare these two manipulations to establish their relative contribution to enhancing motor learning. This study used an on-screen target interception task to compare an autonomous group (self-selection of racquet size), a Challenge Point group (performance-contingent racquet size), a yoked group, and a fixed racquet size control group. Task accuracy and self-report measures of intrinsic motivation and cognitive effort were recorded at multiple time points across acquisition and at immediate, 24-h, seven-day, and 30-day retention and transfer tests. Results showed that task accuracy improved over acquisition, and remained robust across all retention tests, but no between group differences were seen. Intrinsic motivation levels decreased over acquisition, but with no between group differences observed. Participants (83, mean age 40(±12) years, 50 % male) within all groups reported consistently high cognitive effort scores, and made tactical learning choices, suggesting that high task difficulty may have suppressed the more subtle effects of autonomy and performance contingent practice. Conclusions are made regarding the variability of individual approaches to a novel task and the need to build experiments that can detect these idiosyncrasies.

## 1. Introduction

Motor learning research aims to establish which methods of practice are most fruitful for learning and developing skills. Evidence has been developed to support a variety of training paradigms that manipulate variables such as practice structure (Ramezanzade et al., 2022) and focus of attention (Singh & Wulf, 2020). Bringing together several lines of research, the OPTIMAL theory (Optimizing Performance Through Intrinsic Motivation and Attention for Learning; Wulf & Lewthwaite, 2016) proposes that a combination of learner autonomy, an external focus of attention, and enhanced performance expectancies creates a strong platform for learning, predominantly via increases in intrinsic motivation. Support for the theory has been seen in various fields including development of fundamental movement skills (Simpson et al., 2021), and learning with compromised motor abilities (Khalaji et al., 2024). However, the work in this area has not clearly established the nature or direction of the relationship between autonomy, motivation and

* Corresponding author.
*E-mail addresses:* d.bright@chi.ac.uk (D. Bright), jenny.smith@chi.ac.uk (J. Smith), philip.kearney@ul.ie (P. Kearney), oliver.runswick@kcl.ac.uk (O. Runswick).

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performance (Parma et al., 2024), nor has it investigated how these elements may interact with other factors such as cognitive effort. Applying direct measures of these psychological factors over the course of acquisition may help to develop a clearer understanding of how these elements interact (Carter & Ste-Marie, 2017).

The intrinsic motivation component of OPTIMAL theory was developed based on findings suggesting that autonomy provided via choice over task-relevant factors yields greater learning or performance effects in motor tasks such as on-screen object manipulation (Andrieux et al., 2012; Andrieux et al., 2016), balance (Hartman, 2007), force production (Iwatsuki et al., 2017), and lassoing skills (Wulf et al., 2018). The theory proposes that the effects of autonomy are strong enough to produce positive learning results even when the choice is over factors that are seemingly not relevant to the task such as dart colour (Wehlmann & Wulf, 2020) or arbitrary changes to the lab environment (Lewthwaite et al., 2015). Drawing upon self-determination theory (Deci & Ryan, 2012), the research attributes the group learning differences to autonomy's positive effect on intrinsic motivation; that is, any choice results in participants carrying out the tasks with a greater sense of interest and enjoyment than their peers who had less autonomy. While a direct causal link between autonomy, intrinsic motivation, and learning is difficult to establish there has been supporting evidence in studies giving task-relevant choice that also apply measures of intrinsic motivation (Leiker et al., 2016; Levac et al., 2017), but these effects are not always seen (Ste-Marie et al., 2016). Where positive effects are observed, the OPTIMAL theory suggests that autonomy causes raised intrinsic motivation which results in better performance and learning (Wulf & Lewthwaite, 2016) but this direction of causality has yet to be established. Although current literature suggests this causal relationship exists, that same literature provides no rationale for why motivation is required as a mediator. Throughout this body of work, autonomy may be having some other (less directly observable) effect on performance, and it is the perceptions of this improved performance that may be causing the measured changes in intrinsic motivation (Abbas & North, 2018; Badami et al., 2011; Chiviacowsky et al., 2012).

As the findings for the effects of intrinsic motivation are varied, some researchers suggest that the positive learning effects are secondary to those of frequency of feedback (Drews et al., 2021, 2024) or increased cognitive processing (Barros et al., 2019; Carter et al., 2014; Carter & Ste-Marie, 2017; Woodard & Fairbrother, 2020), specifically engagement with identifying performance errors and processing of task relevant feedback (Barros et al., 2019). Carter et al. (2014) provided autonomy by allowing participants to choose which trials they would receive feedback on in a force production task. Results showed that despite autonomy being equally available across all three groups participants that could choose to receive feedback after a task repetition showed significantly better performance than those without that option at retention and were also significantly more accurate in their performance estimations. The authors ascribed the improved learning of those groups to the processing of more salient performance information, negating the motivational effects of autonomy (if present) as that should have had the same impact on all three groups. While plausible, this explanation lacks direct measures of motivation or cognitive processing to support it. The application of direct measures of motivation at multiple timepoints during acquisition would potentially give a clearer picture of any interplay or effects of these psychological factors. Despite this limitation, the idea of improved learning via higher levels of task specific processing finds support in the Challenge Point Framework (Guadagnoli & Lee, 2004).

The Challenge Point Framework (CPF) (Guadagnoli & Lee, 2004) suggests that for any individual learning a skill there is an ideal level of difficulty that will provide the optimum level of performance information (and therefore concurrent cognitive processing) to allow for efficient learning to take place. As skill improves the level of difficulty required increases, and so the point of optimal challenge is constantly in flux. While research has been scarce the findings have been supportive (Akizuki & Ohashi, 2015; Wadden et al., 2018), and the improved learning outcomes from difficulty manipulation seem to run parallel with the effects of autonomy on cognitive processing mentioned above. While the optimum levels of cognitive effort for learning will be individualised, the CPF does suggest levels should be stable if changes in difficulty are made in line with participant performance (Guadagnoli & Lee, 2004). This could be monitored by observing levels of cognitive effort at multiple timepoints during acquisition. Application of this measure will also provide data on whether the performance contingent changes in difficulty demanded by the CPF result in different levels of cognitive effort when compared to the suggested motivational benefits of the OPTIMAL theory. The CPF does not explicitly consider the effects of intrinsic motivation, but it is reasonable to assume that naturally occurring task errors seen when difficulty is increased may have a negative motivational affect (Hodges & Lohse, 2022), although this yet to be investigated experimentally. Applying measures of intrinsic motivation while the CPF is used as a practice structure could begin to reveal if there are effects present that were not predicted by Guadagnoli and Lee (2004), but are predicted by OPTIMAL theory (Wulf & Lewthwaite, 2016), allowing for more direct comparisons between two frameworks that make differing claims regarding what constitutes an effective learning environment.

While research continues in efforts to find support for either intrinsic motivation or cognitive processing as the more impactful factor when autonomy is present, these two variables have not been implemented under identical experimental conditions where direct comparisons of learning outcomes can be made. The varied approaches in choice of task in previous research also makes direct comparison of results difficult (Ranganathan et al., 2020). Motor learning protocols that can not only be accurately replicated, but also have scope to change parameters or experimental groups to expand upon previous findings or directly compare different models of learning will give a platform from which the generalisability of those models can be tested and expanded. Andrieux et al. (2012) and Andrieux et al. (2016) provide a good example of such a protocol with the second study allowing an increase in the specificity of what was under investigation as an informed progression from the first, but both using the same task. As technology and internet access continue to progress, Andrieux et al. (2012, 2016) also provide an excellent example of a motor learning task that can be distributed and run online, giving scope for efficient access to large samples for data collection.

Both models discussed have received comment that their use during acquisition causes superior or more efficient and robust learning to occur (Guadagnoli et al., 2012; Wulf & Lewthwaite, 2016). To the authors knowledge comparison of the two learning models within the same task has not yet been carried out, nor have there been direct measures of intrinsic motivation during use of the CPF, or direct measures of cognitive effort during use of the OPTIMAL theory. Applying these measures as well as examining learning outcomes may reveal not only which model is the more effective for learning within the context of that task, but also the psychological underpinnings by which that learning occurs. Where multiple time point measures of motivation or engagement have been applied in motor learning there is evidence to suggest that measurable changes occur over time (Abbas & North, 2018; Pathania et al., 2019) which has the potential to give a more descriptive picture of why and where those changes occur under autonomous, yoked, or CPF conditions. The current study provided a protocol that could facilitate real time performance-contingent and autonomous difficulty changes when learning a novel skill, while concurrently measuring intrinsic motivation and cognitive processing. The addition of a yoked practice group (to give an identical practice structure but remove the autonomy) and a fixed difficulty control group allowed for direct comparison of the cognitive and motivational impacts across theory based and constrained/fixed practice structures, and observation of the resulting effects on performance and retention.

It was hypothesised that:

1) The CPF and autonomous groups will display larger performance improvements between the first and last acquisition blocks, and better learning at retention and transfer than fixed difficulty and yoked groups.
2) The autonomous practice group will report higher levels of intrinsic motivation than the CPF, fixed difficulty, and yoked groups over acquisition and at retention and transfer.
3) The CPF group will report higher levels of cognitive effort than autonomous, fixed difficulty, and yoked groups over acquisition and at retention and transfer.

## 2. Method

The study used a repeated measures design, and was preregistered via the Open Science Framework; https://osf.io/sj29b/

A schematic of the method is provided as a supplement (Supplement 1).

### 2.1. Sample size

Using the task that was replicated here, Andrieux et al. (2012) reported $\eta_p^2$ of 0.14 for absolute error on immediate retention, and 0.19 and 0.11 for variable error on immediate and delayed retention respectively. These represent (or are very close to) large effect sizes (Pallant, 2020), but given the restrictions on how the task was administered (outlined below) it was concluded that powering for a moderate effect size would be appropriate. Across the four experimental groups G*Power (Faul et al., 2007) estimated a sample size of 72 (18 per group) to be able to identify a moderate effect ($\eta_p^2 = 0.06$, $\alpha = 0.05$, power = 0.8). Eighty-three participants were included in the initial data across the four experimental groups, mean age 39.04 (±13.21) years, dropping to 73 participants at the seven-day retention, and 47 participants at the 30-day retention (see Table 1).

### 2.2. Participants

Due to the restrictions of the COVID-19 pandemic the study was designed to be carried out online via the Gorilla platform (https://gorilla.sc/), which has been shown to give equivalent results for studies whether carried out online or in person (Anwyl-Irvine et al., 2020). This allowed for recruitment locally via email to staff and students at the institute, and more widely via the Prolific recruitment platform (www.Prolific.com). Participants were required to give their age (they had to be over 18 years of age to take part) and were screened out of the study if they played more than six hours a week of mouse-controlled video games. This ensured the final sample were at or below average gaming use (Buono et al., 2020) and were therefore learning a relatively novel task. Participants were also asked to confirm that they were sitting at a desk and using a mouse as control device (rather than a touchpad). Following this process participants were asked to provide informed consent via an online form. Ethical approval for the study was given by the institute.

### 2.3. Task

The task replicated that used by Andrieux et al. (2012, 2016) as it was appropriate for online data collection while also offering opportunities for manipulation of task difficulty and autonomy. It also allowed additional groups and psychological measures to be applied without a negative effect on the task to be learned. For online distribution via the Gorilla platform the task was built in JavaScript.

**Table 1**
Participant numbers ad demographic per retention/transfer phase.

| | Participants per group Imm/24 h | Age *M(±SD)* | Gender *% Male* | Participants per group 7 day/30 day | Age *M(±SD)* | Gender *% Male* |
|---|---|---|---|---|---|---|
| Autonomous | 21 | 38(±13) | 43 | 14 | 37(±11) | 48 |
| CPF | 19 | 39 (±13) | 47 | 10 | 37(±12) | 50 |
| Fixed | 22 | 41(±12) | 69 | 14 | 41(±12) | 69 |
| Yoked | 21 | 39(±10) | 39 | 9 | 39(±10) | 43 |

Participants were required to intercept three targets that fell from the top of the screen set 105 mm apart horizontally, that took 694 ms (Target 1, far right), 1042 ms (Target 2, far left), and 1562 ms (Target 3, centre) to travel to the interception line (30 mm from the bottom of the screen) from their start point 175 mm above. The targets were intercepted by a "racquet" that, starting from the far left furthest from Target 1, moved along the interception line controlled by mouse movement across a single axis (Fig. 1). The length of the racquet was dependant on which group the participant was in (see below) and was used to control the difficulty of the task. Following the three target drops feedback was provided on screen describing whether the targets were intercepted successfully by the racquet (e.g.: "Target 1 – Missed, Target 2 – Intercepted, Target 3 – Intercepted"). Three target drops and the resultant feedback constituted one trial.

#### 2.3.1. Performance/learning dependant variables

The number of successful interceptions were recorded for each trial, as well as the distance of the target from the centre of the racquet (regardless of a successful interception or not) so that absolute and variable error (standard deviation) could be calculated. For each participant in each three-target trial the absolute error (number of pixels from racquet centre (RC) to target centre (TC) when it crossed the interception line) was calculated as root mean square error (RMSE), giving a single error score for each trial:

$$\mathrm{RMSE} = \sqrt{\frac{(\mathrm{RC}-\mathrm{TC1})^2 + (\mathrm{RC}-\mathrm{TC2})^2 + (\mathrm{RC}-\mathrm{TC3})^2}{3}}$$

This replicated the method used by Andrieux et al. (2016) using the same task, and has been recommended as an appropriate measure for performance in motor learning studies (McKay et al., 2022). The RMSE score was calculated as a 10 trial block mean per participant. To assess variability standard deviations of RMSE scores were calculated for each participant in each block, and group means per block produced.

#### 2.3.2. Psychological dependant variables

To measure cognitive effort and intrinsic motivation participants were presented with two scales following every block of 10 trials. Cognitive effort was measured using the mental effort rating scale (Paas, 1992), whilst intrinsic motivation was measured using a similar single Likert- scale (numbered from 1 to 10) which had previously been shown to be effective in finding between group motivational differences in motor learning research involving on-screen stimulus (Leiker et al., 2019; Pathania et al., 2019). Both these scales required the participants to use an on-screen slider to provide their answer before moving on to the next block of 10 trials. For cognitive effort the question was "Please use the slider to show how much mental effort you had to invest in the previous block of 10 tasks" with the extreme left of the scale reading "Very, very low mental effort" and the extreme right reading "Very, very high metal effort". For motivation the question was "We're interested in how much you want to keep playing, please use the slider to show how motivated you are to continue" with the extreme left of the scale read in "Not at all motivated" and the extreme right reading "Very highly motivated". Participants were required to move the slider before they could continue to the next screen, and attention checks via different instructions (e.g. "Please move the slider all the way to the left") were implemented following acquisition blocks three, five, and eight. Participants could not move on to the next screen until those instructions were successfully followed.

### 2.4. Procedure

Following their informed consent participants were required to use a credit/bank card as a universal size reference to calibrate the Gorilla system to their screen size. They were then presented with instructions and a single screen shot of the task to familiarise them with the environment and requirements, and asked to close all non-essential applications, maximise the browser window in use (this

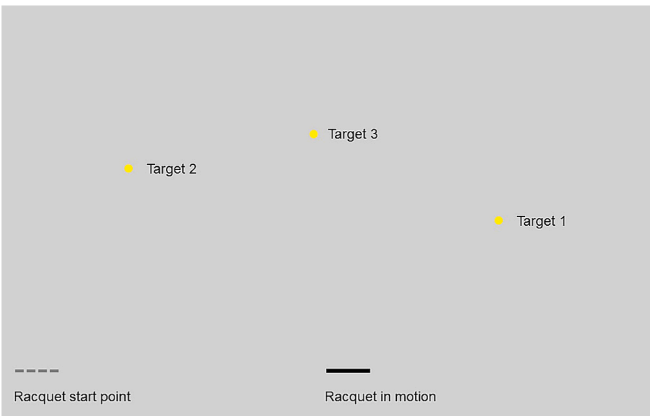


**Fig. 1.** Main play screen of task showing racquet and the right (1), left (2), and centre (3) dropping targets.
N.B. Labels are for clarity and were not present during experiment.

did not impact the calibration), and ensure they had clear desk space to allow for uninterrupted movement of the mouse, etc. System factors (such as mouse DPI) were not controlled for as lab-based motor learning results have been successfully replicated online without these measures being in place (Tsay et al., 2021).

Participants were then given two familiarisation trials using the smallest racquet size of 20 mm, larger than the minimum size used by Andrieux et al. (2012, 2016) but which pilot testing had shown to be the smallest size with which to achieve any success. This was possibly attributable to the use of mouse control as opposed to the stylus used in the original studies. Following these trials participants had an opportunity to rearrange their physical and on-screen environment for more comfortable performance. Two further trials followed using a 20 mm racquet, and participants were informed that this would be the racquet size for the final test so they should aim to be as accurate as they could. Pilot testing had shown that initial reduction in task error was rapid, so the performances of the participants in the second pair of familiarisation trials were recorded as the pretest. Engagement with the task and instructions was established via a measure of how many target interceptions were attempted in each trial. All groups completed 100 acquisition trials with cognitive effort and intrinsic motivation measures taken after every 10 trials. Reminders to try to intercept all three targets were also given after every 10-trial block. Immediately following this there were 20 retention trials with the racquet set at 20 mm, and 20 transfer trials in which the task was mirrored meaning the racquet started on the right with the first target descending on the far left. All timing and distance parameters remained the same on the transfer test, and measures of cognitive effort and intrinsic motivation were taken at the same frequency during both retention and transfer. The transfer test allowed for measurement of accuracy when travelling the opposite direction to that trained during acquisition, giving some indication of its generalisability. To investigate the longevity of any effects participants were contacted via email to repeat the retention and transfer tests at 24 h, seven days, and 30 days.

### 2.5. Experimental groups

Following familiarisation participants were randomly assigned to one of four groups: fixed (all trials with 20 mm racquet), CPF (interception of all three targets caused the racquet to reduce by 5 mm on the next trial down to a minimum of 20 mm, any missed targets caused a 5 mm increase up to a maximum of 50 mm), autonomous (participants could select their racquet size between 20 mm and 50 mm in 5 mm increments between each trial), yoked (participants followed the racquet size changes of a participant from the autonomous group). The yoked group replicated the practice structure of the autonomous group but without the element of choice, allowing the data to be examined for the effects of autonomy in isolation. The CPF group did not have a yoked counterpart as a group with no choice and changes to difficulty outside of their control was already provided by the yoked group described above. The 5 mm increments replicated the changes used in the work of Andrieux et al. (2012, 2016).

### 2.6. Pre-planned data analysis

Despite pre-registered plans for analysis initial visual inspection of the data suggested that predicted statistical group differences in success would be slight if they had occurred, and so the RMSE and standard deviation data were selected for analysis to examine accuracy (which was more variable than interception success) and unpredicted changes in participant behaviour. Due to drop out by some participants at the seven day and 30 day retention tests (Table 1) the pre-planned mixed ANOVA across all phases would be underpowered, so the initial ANOVAs on the RMSE, standard deviation of RMSE, intrinsic motivation, and cognitive effort data included the pretest, acquisition phase, and immediate and 24 h retention and transfer tests. Alpha level was set at 0.05 for all tests.

### 2.7. Exploratory data analysis

Separate exploratory mixed ANOVAs were run for the pretest, seven-day retention data, seven-day transfer data, 30-day retention data, and 30-day transfer data for the variables mentioned in the section above. Descriptive and visual exploratory analysis was carried out to investigate participant behaviour with regards to racquet size selection and indications that participants may have taken a tactical approach to learning the task that fell outside of the given instructions.

## 3. Results

### 3.1. Pre-planned analysis

Interception success data is provided as a supplement (Supplement 2).

### 3.2. RMSE

Results up to the 24 h retention and transfer phase showed a main effect for block $F(14, 1106) = 49.584$, $p < 0.001$, $\eta_p^2 = 0.386$, but no interaction effect $F(42, 1106) = 0.928$, $p = 0.603$, $\eta_p^2 = 0.034$, or between subject effects $F(3, 79) = 1.298$, $p = 0.281$, $\eta_p^2 = 0.047$. Post hoc ANOVAs were run including all groups to compare change in RMSE from the pretest to individual retention and transfer blocks. From pretest to immediate retention all groups improved in accuracy (main effect $F(1, 79) = 133.543$, $p < 0.001$, $\eta_p^2 = 0.628$) but that improvement was similar across all groups (between subjects $F(3, 79) = 0.692$, $p = 0.560$, $\eta_p^2 = 0.026$). Relative to the pretest this pattern remained for the immediate transfer test (main effect $F(1, 79) = 73.429$, $p < 0.001$, $\eta_p^2 = 0.482$, between subjects $F(3, 79) = 0.994$, $p = 0.400$, $\eta_p^2 = 0.036$), 24 h retention test (main effect $F(1, 79) = 78.912$, $p < 0.001$, $\eta_p^2 = 0.500$, between subjects $F(3, 79) =$

$1.545, p = 0.209, \eta_p^2 = 0.055$), and 24 h transfer test (main effect $F(1, 79) = 74.195, p < 0.001, \eta_p^2 = 0.484$, between subjects $F(3, 79) = 1.541$ $p = 0.210$, $\eta_p^2 = 0.055$).

No between subjects effects were observed in the retention and transfer tests at seven days $F(3, 69) = 1.184, p = 0.332, \eta_p^2 = 0.049$, or at 30 days $F(3, 43) = 1.604, p = 0.202, \eta_p^2 = 0.101$, although all groups still displayed improved accuracy from the pretest; seven day retention $F(1, 69) = 88.829, p < 0.001, \eta_p^2 = 0.566$; seven day transfer $F(1, 69) = 83.539, p < 0.001, \eta_p^2 = 0.548$; 30 day retention $F(1, 43) = 27.059, p < 0.001, \eta_p^2 = 0.386$; 30 day transfer $F(1, 43) = 17.270, p < 0.001, \eta_p^2 = 0.287$. Overall, each group improved from the pretest during acquisition, and that improvement remained at each retention and transfer phase, but no group differences were observed at any time point (Fig. 2, panel 1).

### 3.3. Standard deviation

As per the RMSE data the standard deviation was analysed via an ANOVA on the pretest, acquisition phase, and immediate and 24 h retention and transfer tests (with Greenhouse-Geisser correction applied for sphericity) and showed a main effect for block $F(7.999, 631.940) = 30.214, p < 0.001, \eta_p^2 = 0.277$, but no interaction effect $F(23.998, 631.940) = 0.928, p = 0.416, \eta_p^2 = 0.038$, or between subject effects $F(3, 79) = 1.733, p = 0.167, \eta_p^2 = 0.062$. Post hoc ANOVAs including all groups showed that all lowered their standard deviation from pretest to immediate retention (main effect $F(1, 79) = 60.486, p < 0.001, \eta_p^2 = 0.434$), but that no group showed more reduction than any other (between subjects $F(3, 79) = 0.614, p = 0.608, \eta_p^2 = 0.023$). Relative to the pretest this pattern remained true for the immediate transfer test (main effect $F(1, 79) = 21.930, p < 0.001, \eta_p^2 = 0.217$, between subjects $F(3, 79) = 1.125, p = 0.344, \eta_p^2 = 0.041$), 24 h retention test (main effect $F(1, 79) = 27.196, p < 0.001, \eta_p^2 = 0.256$, between subjects $F(3, 79) = 1.626, p = 0.190, \eta_p^2 = 0.058$), and 24 h transfer test (main effect $F(1, 79) = 22.249, p < 0.001, \eta_p^2 = 0.220$, between subjects $F(3, 79) = 1.792$ $p = 0.155, \eta_p^2 = 0.064$).

No between subjects effects were observed in the retention and transfer tests at seven days $F(3, 69) = 1.190, p = 0.320, \eta_p^2 = 0.049$, or at 30 days $F(3, 43) = 1.450, p = 0.241, \eta_p^2 = 0.092$, although all groups still displayed lowered standard deviation over the pretest at seven days (seven day retention $F(1, 69) = 34.951, p < 0.001, \eta_p^2 = 0.336$; seven day transfer $F(1, 69) = 35.284, p < 0.001, \eta_p^2 = 0.338$). At the 30 day tests standard deviation was no longer significantly different from the pretest (30 day retention $F(1, 43) = 3.922$, $p < 0.054, \eta_p^2 = 0.084$; 30 day transfer $F(1, 43) = 2.041, p < 0.160, \eta_p^2 = 0.045$). Overall, standard deviation lowered across acquisition and remained below pretest levels in the retention and transfer phases up to seven days, but the effect was not found at 30 days. No between group differences were observed at any time point (Fig. 2, panel 2).

### 3.4. Psychological measures

As per the error scores, for each psychological measure an ANOVA was run across the acquisition period and the immediate and 24 h retention and transfer tests (no psychological measures were taken during the pre-test). For each 20-trial retention and transfer test the two scores given by the participant following 10 and then 20 trials were calculated to a block mean, resulting in a single score per block across all phases.

For the intrinsic motivation scores Greenhouse-Geisser correction was applied for sphericity on all tests. There was a main effect for block $F(4.435, 350.368) = 32.417, p < 0.001, \eta_p^2 = 0.291$, but no interaction effect $F(13.305, 350.368) = 1.183, p = 0.288, \eta_p^2 = 0.043$, or between subject effects $F(3, 79) = 0.057, p = 0.982, \eta_p^2 = 0.002$. There was an overall decline in reported intrinsic motivation across acquisition (Fig. 3), but an increase from the immediate retention test was seen at the 24 h retention test $F(1, 79) = 33.909, p < 0.001, \eta_p^2 = 0.300$.

A separate ANOVA was run for the intrinsic motivation scores for the seven day and 30 day retention and transfer tests, which revealed no main effect $F(2.265, 97.395) = 1.942, p = 0.143, \eta_p^2 = 0.043$, no interaction effect $F(6.795, 97.395) = 0.938, p = 0.479, \eta_p^2 = 0.061$, and no between subject effect $F(3, 43) = 0.131$, $p = 0.941$, $\eta_p^2 = 0.009$.

For the cognitive effort scores Greenhouse-Geisser correction was applied for sphericity on all tests. There was a main effect for block $F(4.911, 387.950) = 6.598, p < 0.001, \eta_p^2 = 0.077$, but no interaction effect $F(14.732, 387.950) = 0.717, p = 0.765, \eta_p^2 = 0.027$, or between subject effects $F(3, 79) = 0.824$, $p = 0.485$, $\eta_p^2 = 0.030$. Overall, the cognitive effort scores showed a small decline across the acquisition blocks (see Fig. 4).

A separate ANOVA was run for the cognitive effort scores for the seven day and 30 day retention and transfer tests, which revealed no main effect $F(1.985, 85.353) = 1.456, p = 0.239, \eta_p^2 = 0.033$, no interaction effect $F(5.955, 85.353) = 1.227, p = 0.301, \eta_p^2 = 0.079$, or between subject effect $F(3, 43) = 1.216$, $p = 0.316$, $\eta_p^2 = 0.078$.

### 3.5. Exploratory analysis

#### 3.5.1. Tactical task attempts

Initial inspection of the data showed that many participants, regardless of group, chose to focus on only two targets in some trials. To locate these attempts the mean absolute error and standard deviation across the acquisition blocks were calculated for each group. Any targets that were missed by a figure of the mean plus two standard deviations for that group were marked as a non-attempt to intercept all three targets in that trial. If there were 5 or more such trials in any ten-trial block then the block was flagged as sitting outside of the requirements of the study; three or more flagged blocks for any individual participant in the second half of acquisition (blocks 6 to 10) resulted in that individual's data being removed from the group prior to any of the a priori and follow up analysis. This resulted in the removal of seven participants, leaving 83 included in initial data analysis (Pre-test to 24 h). The same protocol was used

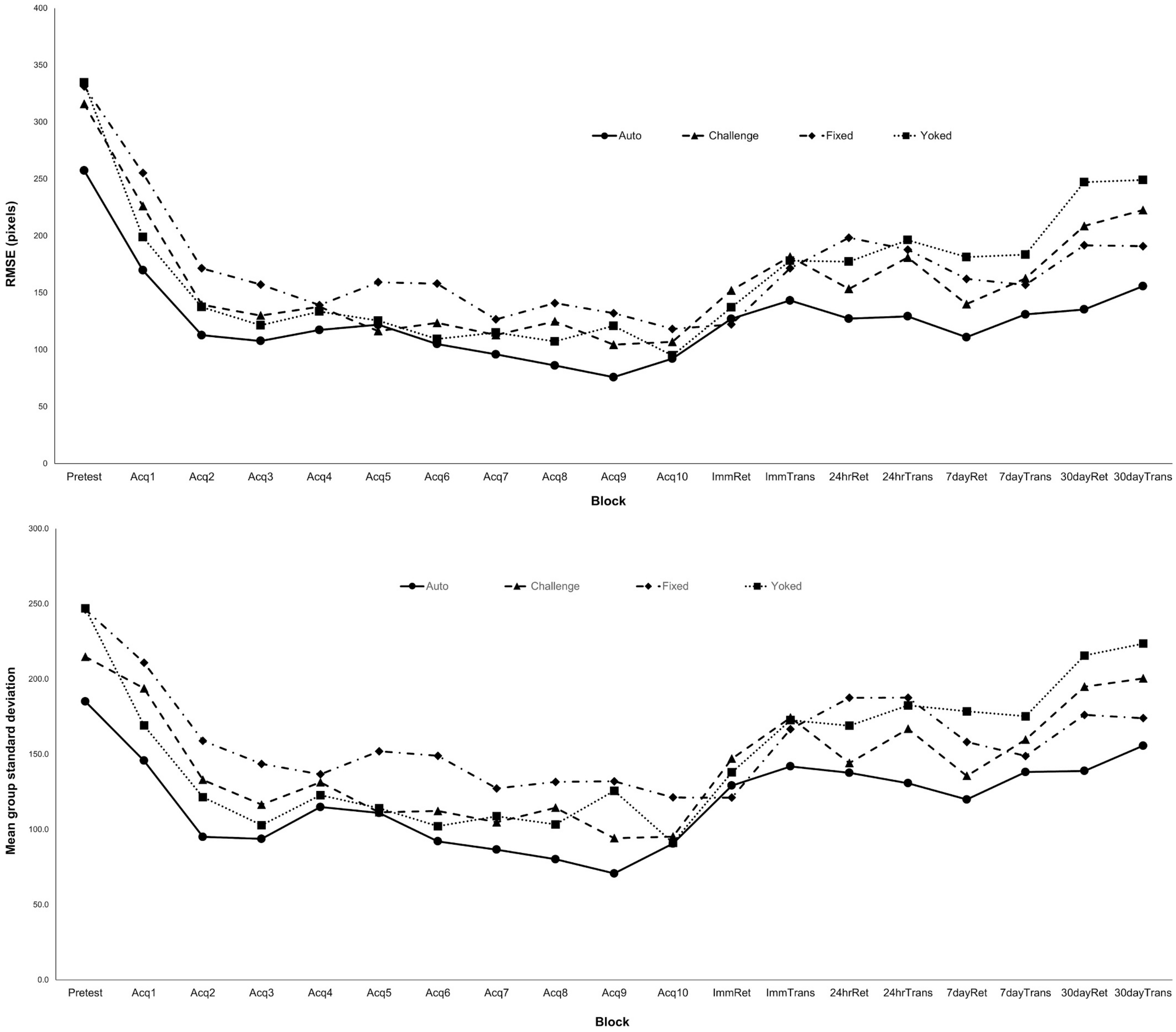


**Fig. 2.** Panel 1 Group root mean square error (pixels) per group/block. Panel 2 Standard deviation of RMSE per group/block.

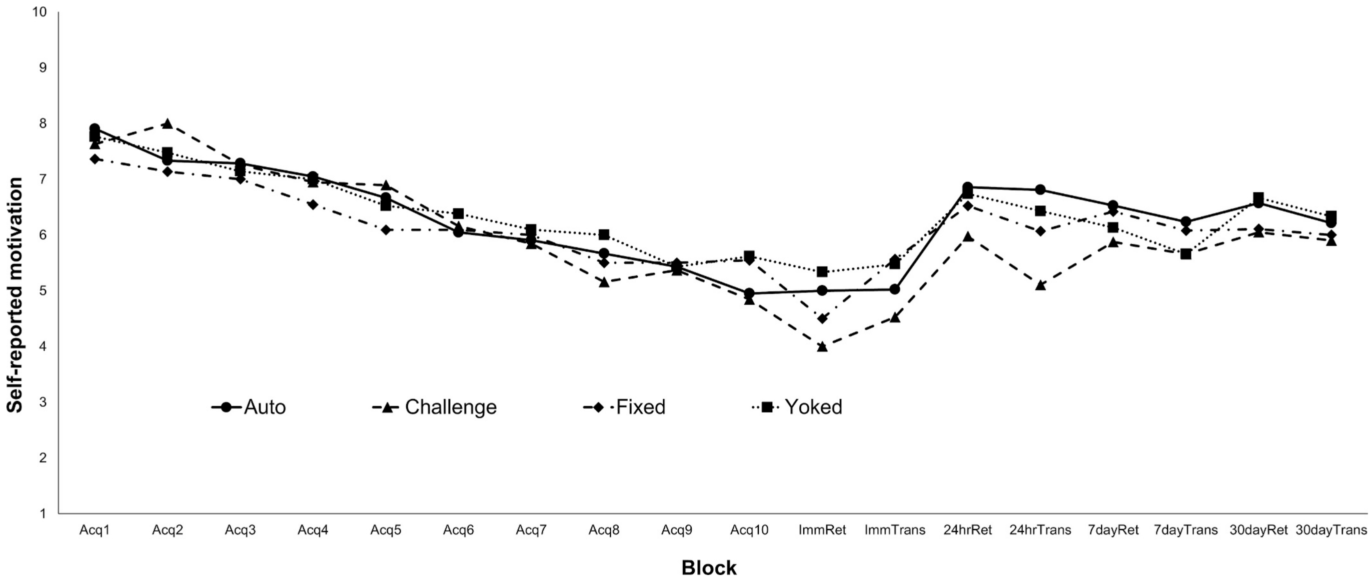


**Fig. 3.** Self-reported intrinsic motivation per group/block.

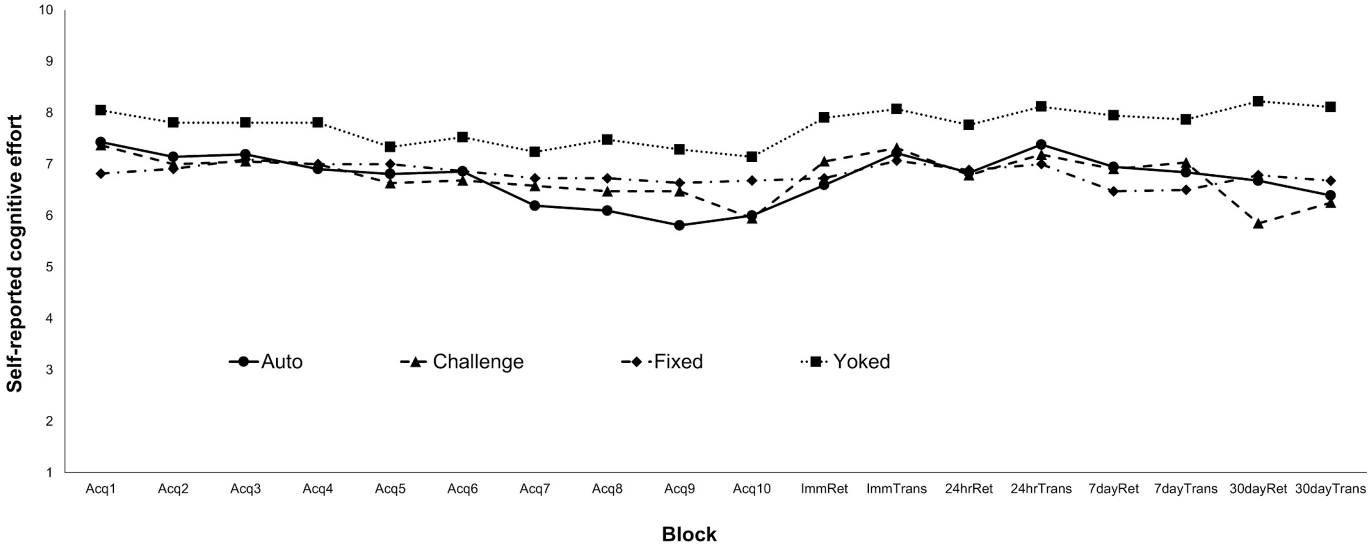


**Fig. 4.** Self-reported cognitive effort per group/block.

to establish the percentage of attempted interceptions (regardless of success) for each group in each acquisition block (Fig. 5), which indicated that a tactical approach was present across all four groups.

### 3.5.2. Racquet size selection

Group means of racquet sizes suggest the autonomous group tended to select a smaller size (and therefore more difficult task) for themselves than the externally controlled CPF group (see Fig. 6, panel 1). However, examination of the individual racquet selection data (see Fig. 6, panel 2) suggests a much more varied approach to the task, and that the group mean is not representative of the behaviour of that group.

## 4. Discussion

### 4.1. Hypotheses

The aim of the study was to investigate the effects of autonomy and performance contingent difficulty changes on the learning of a novel task. Predictions from OPTIMAL theory and the Challenge Point Framework suggest that autonomous and performance contingent groups should have shown superior learning to the yoked (no autonomy) and fixed difficulty groups. Additionally, OPTIMAL theory suggests there should be higher levels of intrinsic motivation observed for the autonomous group, and the CPF suggests there should be higher cognitive effort observed for the performance contingent difficulty group. None of these predictions were supported.

### 4.2. Task effect

While the experimental data did not lend support to any of the hypotheses this does not seem to be because of any failure of the task to provide an adequate platform for learning a novel motor skill. All groups showed a sharp drop in error and variability across the early acquisition phase, a continued trend for lowering of these factors across the remainder of acquisition phase, and retention and transfer that (with the exception of variability in the final tests) remained robust at 30 days. This was achieved without any floor or ceiling effects present (i.e., no participants data showed performance close to 100 % success or failure) suggesting there was engagement with the task and continued scope for improvement (Guadagnoli & Lee, 2004). These observations provide evidence that the task is convergent, and that the repetitions within that environment are the factor causing the changes in ability rather than any individual differences or prior learning (Anderson et al., 2021). Any possible limitations in how the task was administered (such as small variations in calibration, or lack of control over mouse DPI) do not seem to have had a detectable effect. The convergent nature of the task finds further support in the consistently high cognitive effort reported by all groups across all phases, giving indication that the task requires substantial investment of resources to achieve and maintain the improvements seen. For many participants this also resulted in the choice to switch to a tactical approach to achieve success, suggesting engagement and desire to improve was present.

### 4.3. Task accuracy

All groups successfully learned the task and with large observed effect sizes ($\eta_p^2 > 0.14$) for the reduction in error and standard deviation from the pretest in all but the 30-day standard deviation measure. Despite this, no statistically significant group differences

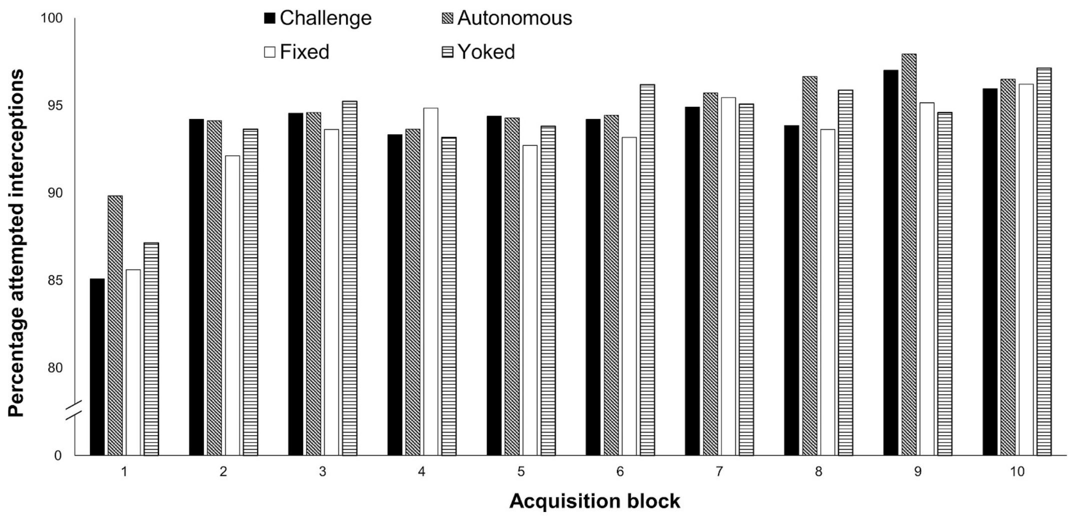


**Fig. 5.** Percentage of target attempts in each acquisition block.

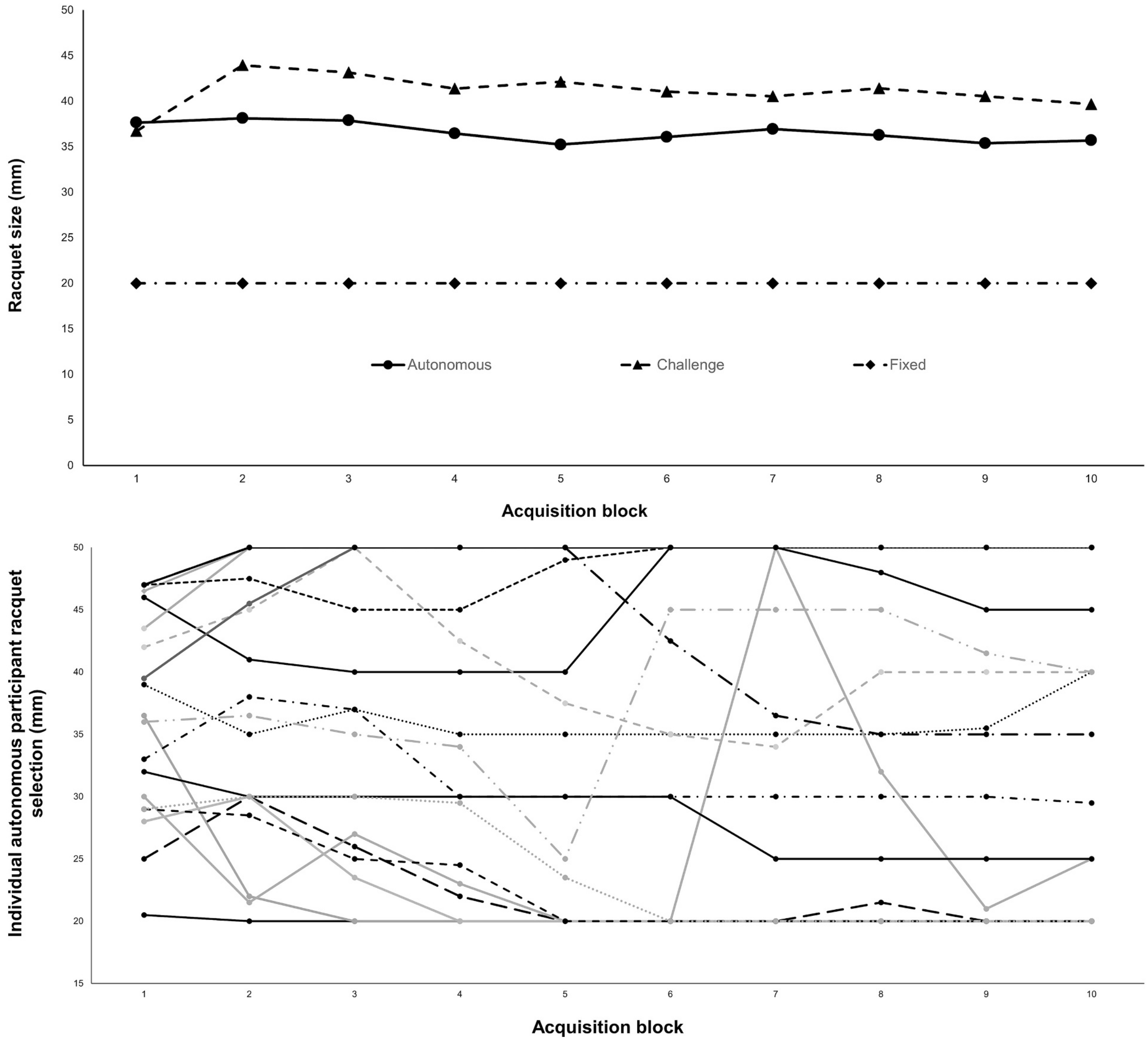


**Fig. 6.** Panel 1 Mean racquet selection size per group/block. Panel 2 Mean individual autonomous participant racquet size selection per block.

were apparent at any stage, failing to immediately support the predictions made by both the OPTIMAL theory and the CPF. One plausible explanation for this finding is that the task, even when parameters are controlled autonomously or externally, is difficult to master within the confines of repetitions required in the protocol used here. High difficulty can introduce a level of challenge that is not facilitative for learning (Akizuki & Ohashi, 2015), and have a negative effect on perceptions of competence (Wulf & Lewthwaite, 2016). The high difficulty of the task is supported by the consistently high cognitive effort reported (with group means reported that are substantially higher the maximum figure reported by Paas (1992) of 5.6), and in the observed choice to move to a tactical, two targets only approach outside of the task requirements. This choice was made by participants in all groups including those where changes in difficulty (either autonomous or performance contingent) were already taking place.

Further support for an explanation being found via the level of task difficulty is found in the racquet size selection for the autonomous group, which while highly varied, does predominantly sit above the minimum racquet size that was the known criteria for the post acquisition phases. Even with this autonomy present, and measurable changes in intrinsic motivation happening over time, the levels of cognitive effort required to engage with and improve at the task may be overriding the more subtle effects of motivation (McKay et al., 2023). To give a specific example, the significant rise in intrinsic motivation at the 24-h retention test did not coincide with a rise in performance, with all groups showing similar scores between the immediate and 24-h retention tests, and the immediate and 24-h transfer tests. Meanwhile, cognitive effort remained consistently high, suggesting that task engagement was still in place but that intrinsic motivation was having no measurable effect on performance.

The autonomous, CPF, and yoked groups had an easier interception task throughout acquisition due to their choice of or constraint to a larger racquet size. Despite this, in the retention tests they had similar accuracy to the fixed group who went through acquisition with a more difficult task. When this is viewed in conjunction with the lack of between and within group differences seen in the transfer tests it can be concluded that, regardless of group or difficulty, the learning of the task creates a generalised ability within the parameters of the software. In short, learning of the task occurred equally for all groups, but as has been shown in other work the high difficulty of the task meant that any positive effects of the manipulations were not observable (Elghoul et al., 2022; Jaquess et al., 2018; Leiker et al., 2016; Wulf et al., 2007).

### 4.4. *Cognitive effects*

The CPF group did not report different levels of cognitive effort to any other group, and as with the lack of learning advantage, this finding may be as a result of the inherently high task difficulty. Previous work has shown that any positive effects of task switching or changes of parameters seen in the acquisition of an easy task may disappear when task difficulty is increased (Akizuki & Ohashi, 2015; Keetch & Lee, 2007). Additionally, the average racquet size achieved during acquisition by the CPF group remained high, supporting the contention that the task cannot be easily mastered.

### 4.5. *Intrinsic motivation effects*

The lack of group differences in intrinsic motivation and learning outcomes do not align with the predictions of OPTIMAL theory for the autonomous group (Wulf & Lewthwaite, 2016), and the observations provided above regarding task difficulty and its more dominant effects than motivation under some learning conditions may partially explain this finding (Carter et al., 2014), alongside previous findings that suggest high frequencies of feedback may reduce the positive learning effects of autonomy (Drews et al., 2024). There is a further factor that should be considered; the tactical approach taken by many participants regardless of their group may have taken place in an effort to achieve better rates of partial success (i.e., ensure interception of two targets by only trying for two) and reduce uncertainty in what they are trying to achieve (Hodges et al., 2021). This self-selection of the requirements of the task to make success more achievable allows them to establish an autonomous challenge point, a level of difficulty at which they are more comfortable progressing and improving, while presumably maintaining perceptions of competence against a self-selected criteria.

Whatever the rationale for participants making these choices it must be conceded that it does provide them with a level of autonomy regardless of their allocation to a non-autonomous group, meaning that all groups may have been exposed to the motivational effects of autonomy. However, the impact of this self-selected autonomy on the current experiment may be minimal as changes in success criteria (i.e. what is regarded by the individual as an acceptable outcome regardless of the given instructions or perceptions of others performance) have been shown to have no effect on motor learning when externally controlled even when positive changes in intrinsic motivation and perceptions of competence are induced (Parma et al., 2023). Given the decrease in intrinsic motivation seen across acquisition for all groups, it is difficult to concede that the self-selected autonomy, and any concurrent changes in perceived competence, had any of the effects predicted by OPTIMAL theory, or any impact on the data collected.

### 4.6. *General discussion*

The lack of support for both learning theories under investigation adds to existing cautions about the strength and generalisability of other significant findings (McKay et al., 2022) within a body of literature that is prone to utilising very niche or simple skills in efforts to introduce tasks that are novel (e.g. Carter et al., 2014; Wulf et al., 2018). The current study also suffers from the same limitations by using a simple (albeit challenging) motor skill but has done so in an effort to introduce additional measures to gain a better understanding of the phenomena under investigation. If changes of task or increases in difficulty nullify the positive effects of autonomy or performance-contingent changes then recommending these strategies broadly, to learners of a wide range of skills in different fields, could result in scenarios where other learning methods are just as (or possibly more) effective. The results of the current study suggest that more task specific research is required before these recommendations can be made, and that even then the needs and strategies of individual learners must be considered. It may be necessary to repeat studies or include multiple groups to see at what point changes in experimental parameters or difficulty allow the advantages of the theories tested here to become observable and meaningful. As used here, the application of multiple time point measures of motivation and cognitive effort will allow for a clearer understanding of how these phenomena occur and interact.

Establishing a bandwidth of task complexity, difficulty, and type under which these theories of learning can more confidently be applied may be necessary to start to make more positive steps towards moving these studies out of the lab and into the hands of coaches and practitioners. While researchers often recommend models or practices following positive research results, it must be borne in mind by both researchers and applied practitioners that the positive findings may be weaker or cease to appear dependant on task (Barreiros et al., 2007), and the ability and creative flexibility of those charged with learning it. A "one size fits all" approach to applying positive research findings to practice is limiting, and practitioners and coaches should take research evidence on board in parallel to their own understanding of their field and, possibly more importantly, their understanding of their learners.

The tactical choices of some participants, despite repeated visual reminders of the requirements being embedded in the task environment, occurred regardless of group allocation. These choices suggest that even the groups who had an easier task due to a larger racquet size were still looking for ways to adapt and personalise their progress. The task and data from this particular study makes those approaches easy to identify, but it does raise the question as to how often this is occurring in motor learning research but going undetected. Researchers must be mindful that human participants may misunderstand or simply decide not to follow instructions (Ranganathan et al., 2022), and may make tactical choices that fit whatever they perceive to be an effective approach to any given task. Where repetitions are high (as is often case in motor learning studies) those tactics may vary over time and, as seen in the data presented here, vary more widely between participants. Setting the task that is in the researcher's mind, with all possible controls in place, may still not result in participants carrying out that task as intended, and so checks of adherence to the requirements of the task should be default practice for researchers where possible (Hoewe, 2017; Yamada et al., 2021). Responses such as the deliberate tactics observed in this study require further investigation to try to establish the rationale for these behaviours, and to ascertain if they occur within a bandwidth of difficulty or are more individualised. The racquet selection data from the autonomous group gives an example of this individuality, and also provides strong evidence that, depending on the variable, using group means to describe the findings may be unrepresentative, or at least miss some of the nuances of what is being observed. Researchers must be mindful of capturing the behaviours that actually occur and not simply measuring the responses they are hoping to observe. Further studies may wish to investigate if there are common points of difficulty or complexity at which learners begin to establish unique and personalised approaches to a task regardless of the guidance given.

### *4.7. Limitations & strengths*

Given the remote administration of the task, and the limitations of the software to capture and adjust for all system factors and calibration of equipment (e.g. mouse DPI) there may be small differences in the magnitude of motor movement required by the task between participants. The lack of experimenter presence while the task was carried out may have promoted higher disregard for the instructions (and therefore more of the observed tactical behaviour) in a reverse of the Hawthorne effect (Chiesa & Hobbs, 2008). This potential phenomenon requires specific investigation to establish the size of effect if it is present, although previous work has shown results between online and in-person data collection to be comparable (Tsay et al., 2021). The above factors are predominantly a result of the data being collected under COVID conditions, making these limitations unavoidable. Despite these limitations, the high number of participants, and the consistency of behaviours observed both within and between groups suggest that comparable outcomes would be seen in a more traditional, lab-based setting. The inclusion of multiple time-point measures of psychological factors successfully allowed for tracking of these variables over time and should be considered for inclusion in motor learning studies that are suggesting that intrinsic motivation or cognitive effort are responsible for any observed effects.

## 5. Conclusions

Contested theories in motor learning require direct comparison to give maximum validity to claims regarding their effectiveness or one's dominance over another. These comparisons should also be coupled with, where possible, direct measures of the mechanisms said to underpin these frameworks, and at multiple time points during pre-test, acquisition, and retention tests. As observed in the current study, this can be successfully applied to allow for some understanding of why group differences occur (or not) under the specifics of the task being administered. With those measures in place the data presented here suggests that the proposed positive learning effects of both autonomy and performance contingent changes may be quite subtle in certain tasks and may be suppressed when task difficulty is high. Difficulty can also provoke tactical behaviour in participants who may set their own criteria for successful engagement, and studies should be built to both limit the scope for this to happen and be able to detect it when it occurs.

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## CRediT authorship contribution statement

**Dave Bright:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jenny Smith:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Philip Kearney:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Oliver Runswick:** Writing – review & editing, Supervision, Software, Methodology, Conceptualization.

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## Declaration of competing interest

None.

## Data availability

Link to data via OSF is included in the article

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