Consistent Individual Tendencies in Motor Speed-Accuracy Trade-Off

Matheus M. Pacheco[1,2]*, Charley W. Lafe[3], Che-Hsiu Chen[4], Tsung-Yu Hsieh[5,6,7]*

[1] Motor Control and Neural Plasticity Research Group, KU Leuven, Belgium
[2] School of Physical Education and Sport at Ribeirão Preto, University of São Paulo, Brazil
[3] VA Pittsburgh Healthcare System, Pittsburgh, PA, USA
[4] Department of Sport Performance, Natuonal Taiwan University of Sport, Taichung, Taiwan
[5] Department of Physical Education, Fu Jen Catholic University, New Taipei, Taiwan.
[6] Research and Development Center for Physical Education, Health and Information Technology, Fu Jen Catholic University, New Taipei, Taiwan.
[7] Physical Education Office, Fu Jen Catholic University, New Taipei, Taiwan.

* The authors contributed equally to this work

Corresponding Author:
Tsung-Yu Hsieh
yu691207@gmail.com

Abstract

The literature of Speed-Accuracy Trade-Off (SAT) in motor control has evidenced individuality in the *preference* to trade different aspects (mean, variance) of spatial and temporal errors. Nonetheless, to the best of our knowledge, how robust this preference is has not been properly tested. Thirty participants performed nine conditions with different time and spatial criteria over two days (scanning). In-between these scanning conditions, individuals performed a practice condition that required modifications of the individuals' preferences in SAT. Through Bayesian analyses, we found that, despite individuals demonstrating changes during practice, decreasing movement time, they did not modify how they performed the scanning conditions. This is evidence for a robust SAT individual tendency. We discuss how such individuality could modify how individuals perform within/between SAT criteria, and what this means for interpretation of results.

Keywords: intrinsic dynamics; aiming; reaching; adaptation

Introduction

There are, at least, two phenomena in motor control that are acknowledged by the whole community: increasing movement speed degrades spatial movement accuracy (1–3), decreasing movement speed degrades temporal movement accuracy (4). However, the exact relation between movement speed and movement accuracy (the speed-accuracy trade-off [SAT]) is still elusive. There are at least five different model accounts of SAT (e.g., (1,3,5–7)); none holds for all variations imposed.

Collectively, the development of these accounts helped to provide important insight on the SAT phenomena – each highlighting other models' limitations. Hancock and Newell (6) was the only one that encompassed both temporal and spatial error. Furthermore, these authors demonstrated that not only variability (temporal and spatial accuracy) changed as a function of movement speed, but also other moments of the error distribution: constant error (mean), skewness and kurtosis. Guiard and Rioul (5) account was also the only one that understood the issue that individuals *could* perform worse than their best. What this means is that, while the outcome will be influenced by the SAT condition, participants are not necessarily performing to optimizing the parameters of the given criteria. In more general terms, they provided the first arguments that SAT has the potential to demonstrate large individual bias.

Interestingly, if one complements (and integrates) the aforementioned insights, we find a direction of inquiry that, to the best of our knowledge, was not taken yet. Hancock and Newell (6) discussed the issue of all moments of error distribution (in space and time) varying as a function of movement speed, and posited that this implied a complementarity between space and time (i.e., the complementarity principle). This would mean that to fully understand mean spatial error, for instance, one would need to be aware of all other moments of error in both space and time. This makes sense as time and space are inherently interconnected; a phenomenon that involves speed will influence both space and time. However, when stating their position, they provided functions for each moment of error that would be independent of each other, contradicting the complementarity argument (see (8)). Thus, their operationalization of the complementarity principle failed to encompass the strength of the idea.

Recently, researchers on motor learning and motor control revisited the fact (see (9,10)) that there is individuality in strategies when performing SAT paradigms (e.g., (5)). Different than Guiard and Rioul (5), that only considered the fact that individuals *might* show worse performance than their best in these experiments, these new studies demonstrated that individuals *are* distinct in their whole tendency to perform, emphasizing either spatial or temporal accuracy (11,12).

Considering the complementarity principle, these individual preferences (tendencies to favor either space or time in SAT) would, logically, affect how the SAT relation is demonstrated in both space and time for a given individual. For instance, if an individual decreases movement time in a task (increasing movement speed) to decrease temporal variance, it would inevitably increase mean temporal error (as there was a change in movement time) and decrease spatial accuracy (as there was an increase in movement speed). Because of distinct individual preferences, changes in task conditions (changes in either spatial or temporal criteria) would affect individuals uniquely. The only way to understand the individual SAT relation would be by considering also the other moments of both spatial and temporal errors. Indeed, this was what Pacheco et al. (13) demonstrated (see also (14)).

Thus, integrating the complementarity principle postulated by Hancock and Newell (6) and the clear influence of individuality pointed out by Guiard and Rioul (5), we can postulate that individuals demonstrate preferences to emphasize given moments of distribution of spatial and temporal errors. If this preference accompanies the individual throughout the spectrum of SAT manipulations, then this preference is a strong factor that would predict deviations from a general SAT law – that is still to be unraveled. That is, if an individual consistently emphasizes, for instance, spatial accuracy (variance) over all other moments of errors, then large deviations in spatial bias as well as temporal bias and variance would be observed throughout range of SAT conditions. This would alter how SAT is observed for this individual. Nonetheless, this tendency to emphasize one error moment over others would need to be relatively robust (consistent) so as to be measured and used as covariate in understanding SAT trends. To test whether such preference is robust for each individual is the goal of the present paper. As we are aware, Pacheco et al. (13) could only provide evidence for the complementarity principle – there was no evidence that the same individual *always* emphasize a given SAT strategy through all SAT manipulations.

Previous studies demonstrated that individuals *can* change their way of acting in a given condition if it is required to do so (11,12). That is, if an individual emphasized temporal accuracy rather than spatial accuracy, one can modify the task constraints to induce changes in how this individual performs the task (i.e., emphasize more spatial accuracy). Nonetheless, there is no evidence that such change in preference for space or time in SAT is permanent. It could be that individuals are able to adapt their strategies for new task requirements transiently, *returning* to their original preference whenever such requirements cease to be (something that can be called as a *shift*, see (15)). In fact, this is a strong possibility. In Pacheco et al. (12) (see also (16)), participants had to decrease an error function combining spatial and temporal error in an aiming task. Different conditions weighted more temporal than spatial errors on the performance score (and vice-versa) requiring changes in their preference. While for some individuals the change in preference took time but occurred, others never changed. Additionally, individuals that showed a given preference in one condition were likely to show the same preference in another.

If there are strong individual biases on SAT, we will only understand how speed and accuracy relate to each other after understanding the generalities that emerge *from* these tendencies. Thus, the present study investigates whether preferences to favor given moments of distribution of spatial and temporal errors are robust *signatures* of individuals when performing SAT tasks. For this, we followed the same paradigm of previous studies that introduced task constraints that would emphasize spatial and temporal relations different than the individuals' initial tendency. On the first day of practice, we scanned individual preferences in nine SAT conditions modifying temporal and spatial criteria and, after, asked participants to perform a task that would require changes in their preferences. On the second day, participants performed the same nine SAT conditions to observe whether previous practice modified their preferences.

Methods

Participants

Thirty one healthy (ages 23.36 ± 3.75, 8 females), right-handed (self-reported) individuals, with normal (or corrected-to-normal) vision capacities, volunteered for this experiment. One participant did not complete all conditions and, for this reason, was removed from the sample. This experiment was approved by the ethics committee of the Fu Jen Catholic University and all participants read and signed an informed consent form.

Task and Equipment

The task was to draw a line from a pre-specified home position to a target on a WACOM Cintiq 27 digital tablet (Model DTK-2700/K0-CX, 130 Hz, 770mm x 465mm with active surface area of 596.7mm x 335.6 mm) by using a handheld stylus (Pro pen, Model KP-503E) with a weight of 18 g. The digital tablet monitor was connected to a PC computer (the pixel range was set at 1680 x1050) and angled 15º forward on the tabletop and placed in front of participants.

Participants performed two different conditions: scanning and practice. The Scanning condition was performed in the first and second day and contained 9 movement time x distance criteria. Each movement time x distance criterion was performed as a whole (50 trials) before moving to the next condition and the order of conditions was randomized. A break was provided after every two time x distance criteria blocks. The three movement time criteria were "as fast as possible", 550 ms, and 1000 ms. The three distance criteria were 10, 20 and 30 cm. Participants were instructed to be as accurate as possible in both space and time. These conditions were chosen as they encompass criteria that induce increases in either temporal or spatial errors (see (14)).

The practice condition was similar to Hsieh et al. (16). Participants performed an aiming task, for 100 trials, in a condition with no explicit time criteria and a distance from home position to target of 20 cm. Their goal in this condition was to achieve an error score (composed of temporal and spatial criteria) of 1.00. The score (s) followed the equation

$$s = (w_t * p_t + w_s * p_s)/(w_t * c_t + w_s * c_s)$$

where s and t subscripts represent spatial and temporal parameters, w represents the weight for space and time, p is the performed movement time or spatial error, and c represent the criteria for both time and space. For the current study, w_t was 500, w_s was 1, c_t was 0.25 s, and c_s was 2 cm. Given the weighing, this practice condition emphasized an increase in movement speed by decreasing movement time. For instance, if an individual was performing the task in 500 ms and missed the target by 4 cm (twice the criteria for both space and time), the score would be 2. An improvement of 100 ms (decreasing the movement time to 400 ms) would lead to a score of 1.6063 while an improvement in movement accuracy to 0.1 cm of error would only improve the score to 1.9693.

For each trial, participants would place the stylus on the home position (a small square of 2 x 2 mm) on the left of the screen. The target position was displayed as a small circle of 2 mm diameter and would be visually available for the whole movement time x distance criteria block or practice condition. After this, the tablet would make a beep sound indicating that the participant could start the trial. Participants were informed that this was not a reaction time task and, thus, they could take as long as they wanted to start the movement after the beep sound. The start of the movement was defined by the stylus tip crossing the velocity threshold of 3 mm/s. The trials were finished when the velocity of the cursor was less than threshold of 3 mm/s for more than 4 frames (~ 30 ms).

Data Analysis

For the scanning condition, we measured the mean and standard deviation of spatial error in the *x*-axis (horizontal) and movement time. Movement time was preferred here instead of the temporal error since the "as fast as possible" criterion has no specific comparison to make. Thus, it would only be possible to have an error score from two of the three 'time' conditions, so for continuity in the analysis we chose to use movement time. Given the main variable of the analysis is the standard deviation of error in space, analyzing movement time instead of temporal error does not have any implication on our results or interpretation. For the practice condition, we measured the mean of movement time, standard deviation of the radial axis error (the one used in the equation of the score) and the mean score for the first and last 20 trials.

The first analysis was to demonstrate that individuals did modify their initial tendency during the Practice condition. For this, we performed three Bayesian paired Wilcoxon tests in terms of movement time, spatial error, and score. The second analysis was to test whether such changes during practice modified the overall SAT tendency from the first to the second day of practice. For this, we performed a Bayesian Repeated Measures ANOVA considering day, movement time, and distance as independent variables and standard deviation of spatial error as dependent variable. The Bayesian analysis was preferred to the frequentist approach to qualify the argument on the evidence in favor (or against) of including the variable "day" to explain the data. Evidence in favor of inclusion implies changes in the individual preferences in SAT and vice-versa. The data demonstrated a distribution far from normal and, thus, we also performed robust analyses (17) using Rallfun-v38 package to "confirm" whether non-significant *p*-values matched those when BF_{null} were higher for repeated measures.

Finally, provided the argument on complementarity between error measures, we also investigated whether the individuals' response (average and standard deviation of spatial error, standard deviation of movement time) would change over days. For this, we performed a MANOVA with day, movement time, and movement distance as independent variables. We did not include average movement time as this was not (and could not be) corrected by the movement time criteria (see above). The post-hoc analysis of the MANOVA were corrected with Bonferroni's procedure. Provided the data deviated from parametric assumptions, the post-hoc ANOVAs were performed using robust repeated measures comparisons (17). All the *p*-values for the robust analyses were corrected by Benjamini & Hochberg false discovery rate.

To understand how each type of error covaried with the other, we performed, as an exploratory analysis, principle component analysis (PCA) and, using parallel analysis, found the number of components that significantly explained the variance in the data. Parallel analysis identifies how many components explain more variance than expected from shuffled data. The data was standardized – we calculated the z-scores of each one – before running PCA. To characterize the variables that composed each PC, we used a threshold of at least 0.40.

For all Bayesian analyses, we consider moderate evidence in favor of the alternative (or the null) a Bayes Factor (BF) of at least 3 (18). BF reflects the amount of evidence provided by the data (or the probability of the data given the hypothesis – e.g., alternative versus null) – or, more generally, the strength of evidence provided by the data. When BF_{null} is presented, it refers to the amount of evidence favoring the null hypothesis – when this is higher than the $BF_{alternative}$. All analyses were performed in Matlab 2020b, SPSS 17.0, R and JASP 0.16.0.

All the data and codes can be accessed directly at https://osf.io/zwcgy/

Results

Practice Condition

Figure 1 shows the performance score, spatial and temporal measures over time (one versus the other, and a ratio between them) from three exemplary participants. It is clear that, regardless of the dependent variable, we see that individuals explored different combinations and improved performance over practice. The Wilcoxon signed-rank paired analyses (2000 samples) showed that individuals increased their spatial variability ($BF_{alternative}$ = 6.28), decreased their movement time ($BF_{alternative}$ = 414.64) and, with this, improved their performance score ($BF_{alternative}$ = 119.59).

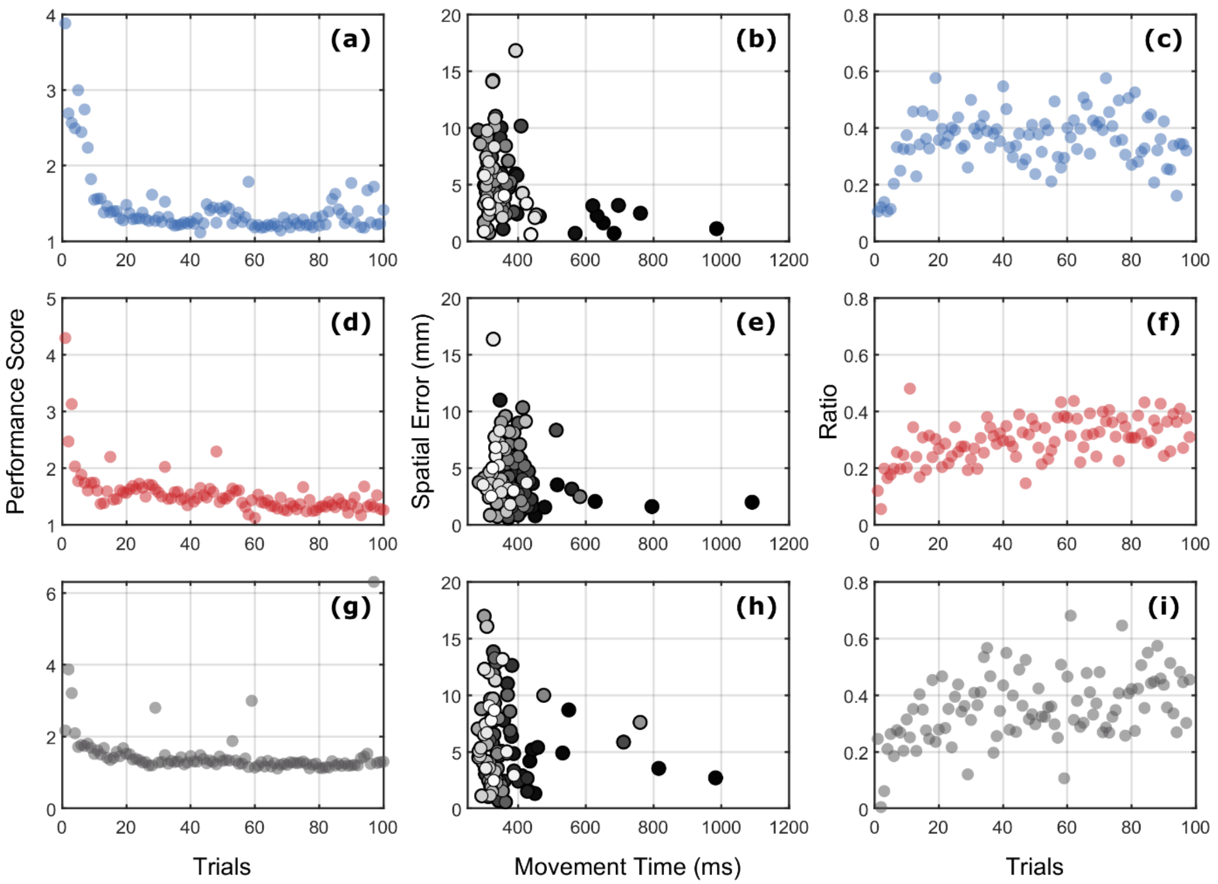

Figure 1. Three exemplary participants (one per row) in terms of their performance score across trials ((a), (d), and (g)), spatial error as a function of movement time ((b), (e), and (h)), and the ratio between spatial error and movement time over trials ((c), (f), and (i)). The color of the circles in the second column represent trials (with lighter color representing later trials). The ratio was calculated as in Pacheco et al. (12): $r = log(MT)/log(S)$ with movement time in ms and spatial error in dm.

Scanning Condition

Figure 2 shows the standard deviation of spatial error as a function of movement time, distance and days. Despite a large between subject variation that seemed to have occurred for the 30 cm distance criterion on the first day, there is a tendency to decrease spatial variability with increased time and decreased distance – a traditional speed-accuracy trade-off relation.

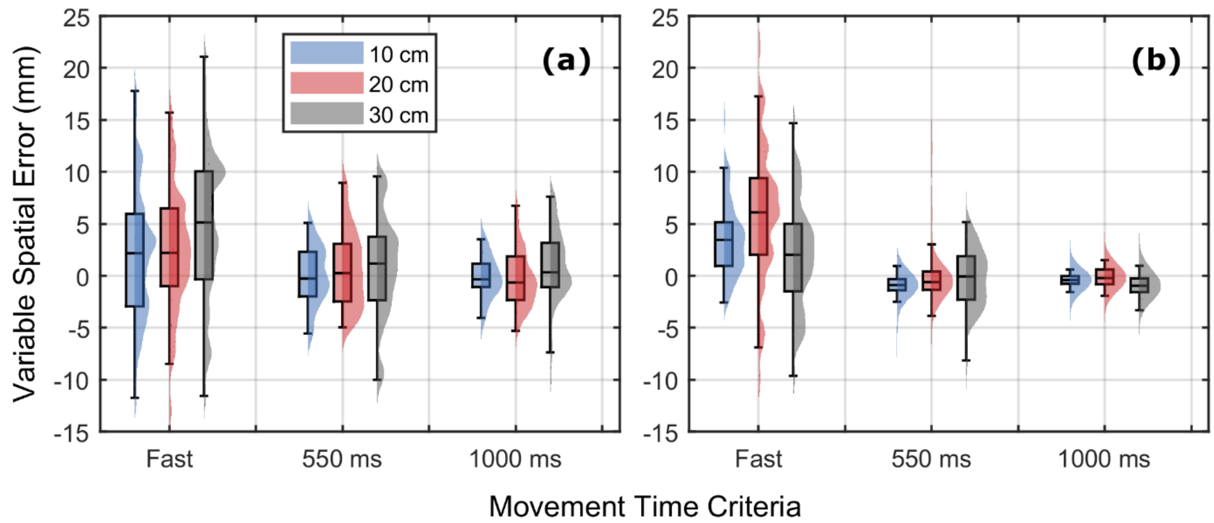

Figure 2. Variable spatial error (boxplot and distribution) as a function of distance and movement time criteria.

.

The Bayesian Repeated Measures ANOVA showed that the best model was the model that included only movement time and distance, with no interaction. This model had a $BF_{alternative}$ of $4.17 * 10^{26}$ and had 3.83 more evidence than the second best model (that would only include movement time). The best model including day as an independent variable was the one that included day, movement time and distance – with no interaction as well. However, the best model (not including day) had 7.74 more evidence than this one.

If we are to consider the inclusion of the variable day against all other models without it, the BF for models excluding day was 18.36 – which is higher considering exclusion of "day" interacting with any other variable (day * movement time: BF_{null} = 33.53; day * distance: BF_{null} = 72.42; day * movement time * distance: BF_{null} = 1404.51). Thus, we seem to have enough evidence, given the present data, that there was no change in terms of how individuals showed their standard deviation of spatial error across the scanning conditions after practice.

The post hoc analyses of the best model (including movement time and distance, no interaction) showed that the differences occurred given the "as fast as possible" conditions elicited higher standard deviation in spatial error than the other two conditions (fast vs 550 ms: $BF_{alternative} = 4.74 * 10^{10}$; fast vs 1000 ms: $BF_{alternative} = 2.45 * 10^{19}$) while the 550 ms conditions also showed more variable spatial error than the 1000 ms conditions ($BF_{alternative}$ = 37.75). Additionally, the 10 cm conditions showed less variable spatial error than both 20 cm conditions ($BF_{alternative}$ = 7.90) and 30 cm conditions ($BF_{alternative}$ = 18.49).

The trimmed mean bootstrapped repeated measures robust analysis showed results in accordance to the Bayesian Analysis. We found a non-significant effect of day (Q = 1.10; p = .298), main effects of movement time (Q = 77.05; p < .001) and distance (Q = 9.07; p < .001), no significant interactions with day (p's > .642), and an interaction between movement time and distance (Q = 1.45; p = .015).

Change of SAT Considering the Complementary Between Moments in Space and Time

From the principal component analysis and parallel analysis, two main components explained the data more than the simulated data (variance accounted for = 74%). We found that the first component was positively related to variability in spatial error (loading: 0.76) and average spatial error (0.78), while negatively related to average movement time (-0.76). The second component was positively related to variability in movement time only (0.90); no other variable was above the 0.4 threshold. That is, those who overshot the target (spatially), increased variability in spatial error and finished the movement faster. Variability in time seemed unrelated to these. Figure 3 shows how four exemplary individuals varied in terms of each component for day 1. We see that each participant combined these variables differently. For instance, one participant (red) always showed large values of PC2 – being somewhat separated from the other exemplary participants in the figure. One participant (gray) showed not much change over the six conditions (a grouping around -0.5 PC2 and 0 PC1) while others showed clear groupings of three (probably indicating similar average movement times for each time criteria).

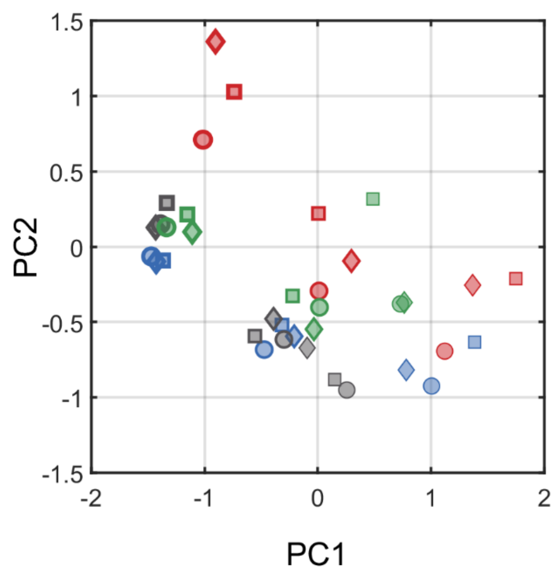

Figure 3. Individual combination of spatial and temporal errors represented by the scores of the resultant first and second principal components for four participants on day 1. The first component (PC1) has large loading from variable spatial error, average spatial error and average temporal error. The second component (PC2) has large loading from variable temporal error only. Each color represents a different participant. Circles reflect 10 cm distance, squares represent 20 cm distance, and diamonds represent 30 cm distance. Symbols with thicker lines represent longer movement time conditions.

Considering all measures, the MANOVA (after the false discovery rate procedure) showed that there was a main effect of measures (*Roy's Largest Root* = 7.96; $p < .001$; $\eta_p^2 = 0.89$), two-way interactions between movement time and distance (*Roy's Largest Root* = 0.63; $p = .011$; $\eta_p^2 = 0.39$), measures and movement time (*Roy's Largest Root* = 0.70; $p = .006$; $\eta_p^2 = 0.41$) and measures and distance (*Roy's Largest Root* = 0.83; p = .003; η_p^2 = 0.45), and a three-way interaction of measures, distance and movement time (*Roy's Largest Root* = 1.10; p = .019; η_p^2 = 0.53). Of relevance, provided there was no effect of day in the MANOVA, we did not perform any extra post hoc analyses.

Discussion

The speed-accuracy trade-off is one of the most robust phenomena in the area of motor control. Interestingly, its underlying processes and influential factors are far from being totally unraveled. In the present manuscript, we encompassed the views from Guiard and Rioul (5) and Hancock and Newell (6) to understand the individual intrinsic tendencies in SAT (see also (13)). A main issue is that such tendencies would not be easy to identify if they were simply a "bias" due to recent experiences (transient changes). Thus, we aimed to investigate whether such intrinsic tendencies in SAT would be affected by a single session of practice that required individuals to decrease spatial accuracy via decreasing movement time. Our results demonstrated, through several analyses, that, despite individuals being able to shift their current spatial/temporal speed/accuracy tendencies if a given task condition requires them to do so, they do not change their tendencies in SAT – the same space/time criteria lead to the same outcome.

The current results, which show that individuals perform similarly after practice, are relevant as they might contribute to understanding not only how individuals emphasize either speed or accuracy but also to *why* this is the case. For instance, a common feature in aging is that old adults become more conservative – they decrease speed to accommodate the increased variability in their movements (9,19). Additionally, recent investigations have demonstrated that children with developmental coordination disorder can maintain similar compensatory joints/end-point as healthy individuals *if* they decrease their movement speed in reaching (20). Clearly, such emphasis between speed and accuracy might not need to be explained in terms of capacity limits, but also individual preferences that emerge over practice that favored more one (e.g., speed) rather than the other (e.g., accuracy) aspect of SAT.

The question is why would individuals be so "rigid" in terms of SAT tendencies? Considering the previous discussion, the outcome in a SAT task will depend on both individuals physiological capacities (e.g., processing limits, inherent variability) and intrinsic preferences (e.g., previous experience, *modus operandi*). Such combination of many factors leads to a *sweet spot* where, potentially, variability is at the minimum. We strongly believe that pushing individuals away from this balance between speed and accuracy might increase overall difficulty in performing the task – something that could be grasped through the concept of sample entropy ((14,21) but see below). Previous studies that used such concept found a specific condition on which individuals would reach its minimum, in the average. Clearly, when analyzing each individual one would find that, for each, the sweet spot between conditions was slightly different (between conditions) (14). We are, however, arguing that the emergent error (variability) arising from a given condition is the sweet spot *within that given condition*. Thus, it is our argument that this emergent sweet spot might be the basis of individual consistency or “rigidity” in the SAT paradigm. This argument has not been, to the best of our knowledge, appropriately tested in the literature.

Note that such sweet spot might not be easily measured from the sample entropy applied in Hsieh et al. (14). This is the case because they only considered variability of the data, not how much individuals deviate from target (the average spatial and temporal errors). Despite such variability potentially implying how individual capacities are being defied – how difficult is it for the system to be consistent in the task – it fails to consider how individuals adjust other moments of errors to compensate variability (13) and how much they act to correct such errors (22). Thus, despite an interesting possibility, future research should focus on how to quantify and test the possibility of SAT sweet spots. From the present results, we have evidence that, *at least*, there is a spot to where individuals return to after adapting it for given task requirements.

Despite not being the main question of our paper, an important question is whether our results support or challenge previous models in SAT literature. In demonstrating a large (and robust) individuality between individuals, we can argue that all models are challenged by the present results. This is the case provided most models assume that individuals respond similarly to changes in SAT conditions. That is, if one requires one individual to perform with a decreased movement time in a given condition, then all individuals would change the other moments of spatial error similarly. The reported individuality, nonetheless, is consistent with the current state of many other areas of motor control, as researchers are abandoning the idea that people behave similarly and are instead being discussed as non-ergodic systems (23). Our results (see Figure 3) show that this is not the case. Also, the fact that one needs to consider temporal accuracy (variance) is something beyond most models. The question is which model holds after controlling for these individual preferences – something that is still an open question.

An important final point of discussion is that changes in SAT relation given short term practice – if they were to occur – would largely hurt the estimates of the SAT relation itself. That is, if practicing condition *x* with given spatial/ temporal criteria creates a bias in the SAT relation, the next practiced condition, let us say *y*, would measure the SAT relation *plus* the influence of *x*. This would also occur for all subsequent conditions. Thus, the SAT relation at the end of the assessment would not be the same as the SAT relation at the beginning of the assessment; an issue of the measurement altering the measure. The present experiment provides initial evidence that this is not the case, but future studies await for longer practice effects.

The current study, however, has some limitations or concerns that must be acknowledged. The first is that we based ourselves in “average-based” analyses to infer whether individuals would modify their intrinsic tendencies. As the name states, this can be problematic as intrinsic tendencies are individual and adaptations could have occurred differently for each individual (see (23,24)). Clearly, we based our analyses on the idea that the same task requirements were imposed in all individuals. Thus, if the task constraints are similar and constrain individuals towards more speed and less accuracy, we are to expect *similar* changes even between individuals. We acknowledge the issue that a *proper* analysis of the task space was not performed and, thus, we cannot affirm that this would be the case. The second issue is that the resultant data did not demonstrate parametric assumptions. Bayesian analyses and the MANOVA do require parametric assumptions to be met. Yet, the Bayesian analyses were necessary to argue in favor of the null hypothesis as this was a main aspect of this investigation. We also performed robust analyses to make sure that if results were found through one analysis, this should be similar when performing frequentist (robust) analyses.

In summary, we found that individuals show a robust intrinsic tendency in SAT. This is maintained even after modifying it to attend to specific task demands. Such result allows further research to identify how such intrinsic tendencies are demonstrated when the full spectrum of speed-accuracy trade-off conditions are tested. It is important to highlight that there is great chance that averaging might confound or suppress important information in how speed and accuracy relate – something demonstrated elsewhere (24–26). We believe that, only after understanding what is individual in SAT, can we understand what is general.

References

1. Fitts PM. The information capacity of the human motor system in controlling the amplitude of movement. J Exp Psychol. 1954;47(6):381–91.
2. Meyer DE, Abrams RA, Kornblum S, Wright CE, Smith JEK. Optimality in Human Motor Performance: Ideal Control of Rapid Aimed Movements. Psychol Rev. 1988;95(3):340–70.
3. Schmidt RA, Zelaznik H, Hawkins B, Frank JS, Quinn Jr. JT. Motor-output variability: A theory for the accuracy of rapid motor acts. Psychol Rev. 1979;86(5):415–51.
4. Newell KM, Hoshizaki L, Carlton MJ, Halbert JA. Movement time and velocity as determinants of movement timing accuracy. J Mot Behav. 1979;11(1):49–58.
5. Guiard Y, Rioul O. A mathematical description of the speed/accuracy trade-off of aimend movement. In: 2015 British Human Computer Interaction Conference. Lincoln, UK; 2015. p. 91–100.
6. Hancock PA, Newell KM. The movement speed-accuracy relationship in space-time. In: Heuer H, Kleinbeck U, Schmidt K-H, editors. Motor behavior: Programming, control, and acquisition. Berlin, Germany: Springer; 1985. p. 153–88.
7. Plamondon R, Alimi AM. Speed/accuracy trade-offs in target-directed movements. Behav Brain Sci. 1997;20(2):279–349.
8. Schmidt RA. Movement time, movement distance, and movement accuracy: A reply to Newell, Carlton, and Kim. Hum Perform. 1994;7(1):23–8.
9. Welford AT, Norris AH, Shock NW. Speed and accuracy of movement and their changes with age. Acta Psychol (Amst). 1969;30:3–15.
10. Woodworth RS. The accuracy of voluntary movement. Psychol Rev Monogr Suppl. 1899;3(3).
11. King AC, Ranganathan R, Newell KM. Individual differences in the exploration of a redundant space-time motor task. Neurosci Lett [Internet]. 2012;529(2):144–9. Available from: http://dx.doi.org/10.1016/j.neulet.2012.08.014

12. Pacheco MM, Hsieh T-Y, Newell KM. Search strategies in practice : Movement variability affords perception of task dynamics. Ecol Psychol [Internet]. 2017;29(4). Available from: http://dx.doi.org/10.1080/10407413.2017.1368354
13. Pacheco MM, Hsieh T-Y, Newell KM. Movement speed and accuracy in space and time : The complementarity of error distributions. J Mot Behav. 2019;51:100–12.
14. Hsieh T-Y, Pacheco MM, Newell KM. Entropy of space-time outcome in a movement speed-accuracy task. Hum Mov Sci. 2015;44:201–10.
15. Kostrubiec V, Zanone P-G, Fuchs A, Kelso JAS. Beyond the blank slate: Routes to learning new coordination patterns depend on the intrinsic dynamics of the learner—experimental evidence and theoretical model. Front Hum Neurosci [Internet]. 2012;6(August):1–14. Available from: http://journal.frontiersin.org/article/10.3389/fnhum.2012.00222/abstract
16. Hsieh T-Y, Liu YT, Mayer-Kress G, Newell KM. The movement speed-accuracy relation in space-time. Hum Mov Sci [Internet]. 2013;32(1):257–69. Available from: http://dx.doi.org/10.1016/j.humov.2012.12.010
17. Wilcox RR. Introduction to robust estimation and hypothesis testing. New York, NY: Academic Press; 2017. 777 p.
18. Jeffreys H. Theory of Probability. Oxford, England: Clarendon Press; 1961. 459 p.
19. Seidler RD, Bernard JA, Burutolu TB, Fling BW, Gordon MT, Gwin JT, et al. Motor control and aging: Links to age-related brain structural, functional, and biochemical effects. Neurosci Biobehav Rev [Internet]. 2010;34(5):721–33. Available from: http://dx.doi.org/10.1016/j.neubiorev.2009.10.005
20. Golenia L, Bongers RM, van Hoorn JF, Otten E, Mouton LJ, Schoemaker MM. Variability in coordination patterns in children with developmental coordination disorder (DCD). Hum Mov Sci [Internet]. 2018;60:202–13. Available from: https://doi.org/10.1016/j.humov.2018.06.009
21. Hsieh T-Y, Pacheco MM, Newell KM. Matching and Minimizing Movement Time in Speed-Accuracy Tasks. Motor Control [Internet]. 2016;20(4):444–58. Available from: http://journals.humankinetics.com/doi/10.1123/mc.2015-0036
22. Wolpert DM, Miall RC, Winter JL, Stein JF. Evidence for an error deadzone in compensatory tracking. J Mot Behav. 1992;24(4):299–308.
23. Mangalam M, Kelty-Stephen DG. Point estimates, Simpson's paradox, and nonergodicity in biological sciences. Neurosci Biobehav Rev [Internet]. 2021;125(February):98–107. Available from: https://doi.org/10.1016/j.neubiorev.2021.02.017
24. Newell KM, Mayer-Kress G, Liu Y-T. Human learning: Power laws or multiple characteristic time scales? Tutor Quant Methods Psychol. 2006;2:66–76.
25. Newell KM, Mayer-Kress G, Hong SL, Liu Y-T. Adaptation and learning: Characteristic time scales of performance dynamics. Hum Mov Sci [Internet]. 2009;28(6):655–87. Available from: http://dx.doi.org/10.1016/j.humov.2009.07.001
26. Newell KM, Liu Y-T, Mayer-Kress G. Time scales in motor learning and development. Psychol Rev. 2001;108:57–82.