



Review article

Predicting individual differences in motor learning: A critical review

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ABSTRACT

The ability to predict individual differences in motor learning has significant implications from both theoretical and applied perspectives. However, there is high variability in the methodological and analytical strategies employed as evidence for such predictions. Here, we critically examine the evidence for predictions of individual differences in motor learning by reviewing the literature from a 20-year period (2000–2020). Specifically, we examined four factors: (i) the predictor and predicted variables used, (ii) the strength of the prediction and associated sample size, (iii) the timescale over which the prediction was made, and (iv) the type of motor task used. Overall, the results highlight several issues that raise concerns about the quality of the evidence for such predictions. First, there was a large variation in both predictor and predicted variables, suggesting the presence of a large number of researcher degrees of freedom. Second, sample sizes tended to be small, and the strength of the correlation showed an inverse relation with sample size. Third, the timescale of most predictions was very short, mostly constrained to a single day. Last, most studies were largely restricted to two experimental paradigms – adaptation and sequence learning. Based on these issues, we highlight recommendations for future studies to improve the quality of evidence for predicting individual differences in motor learning.

1. Introduction

It has been long recognized that individuals who undergo the same training show differences in how much they learn during practice. These individual differences in motor learning have been the centerpiece of several long-standing theoretical issues ranging from general motor abilities (Seashore, 1930), aptitude-treatment interactions (Cronbach, 1957) and cognitive-intellectual determinants (Ackerman, 1988). Several reviews have focused on this issue (Marteniuk, 1974; Ackerman, 1987; Adams, 1987; Seidler and Carson, 2017), including a recent historical perspective (Anderson et al., 2021).

An important issue in this regard is whether these individual differences can be predicted – i.e., whether it is possible to identify how much an individual will learn based on measurements either early on or even prior to the practice period. Here, we use the term ‘prediction’ to refer to contexts where the independent variable is measured *earlier* in time relative to the measurement of the dependent variable. Making these predictions is not only important for testing theoretical ideas of individual differences but is also critical for applied domains like coaching and rehabilitation, where the ability to predict learning could have significant implications for the design and implementation of

practice strategies.

However, a challenge in synthesizing the evidence for predicting individual differences is the variability in the methodological and analytical strategies employed. These variations include differences in the types of variables measured, the time point in learning when these variables are measured, and the types of motor tasks chosen. These variations are not only important from a methodological viewpoint but also have theoretical implications as they relate to different issues in motor learning. For example, predictions made using variables measured during practice (i.e. performance ‘inside’ the same task) are relevant to the theoretical construct of ‘task specificity’ (Henry, 1968) since future performance in a task is being predicted from prior performance on the same task. On the other hand, predictions made using variables measured *before* practice (i.e., performance ‘outside’ the task) provide insight into whether there are general motor learning abilities that underlie learning (Seashore, 1930; Hands et al., 2018). Therefore, it is important to assess the variability in these choices when examining the strength of the evidence for prediction of individual differences.

The purpose of this review was to critically examine the evidence for predictions of individual differences in motor learning over a 20-year period (from 2000 to 2020). We focused on four primary factors – (i)

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the type of predictor and predicted variables, (ii) the strength of the prediction, (iii) the timescale of the prediction, and (iv) the type of task used. By analyzing these factors, we identify challenges in the current state of evidence and suggest directions for future work.

2. Methods

We examined studies published between 2000 and 2020 for the purpose of this review. We screened studies based on the following criteria: (i) the study focused on motor learning in unimpaired individuals, (ii) the study had a 'prediction' (i.e., the independent variable was measured ahead of time relative to the dependent variable), (iii) the prediction was based on a single independent variable, and (iv) the prediction was quantified in terms of a Pearson correlation coefficient. The justification for excluding studies using a 'group differences' approach (e.g., using an ANOVA to compare 'good' vs. 'poor' learners) was based on the observation that these studies typically examined groups posthoc by dichotomizing a continuous variable, which can be misleading (MacCallum et al., 2002; Altman and Royston, 2006). To capture a wide range of articles, our search strategy involved the use of Web of science and Pubmed (with the keywords "motor learning", "individual differences" and "prediction"). We also identified papers from references cited from selected articles. If a paper reported multiple experiments, each experiment was considered as an independent study. Overall, we selected 29 papers with a total of 37 studies for the purpose of this review.

3. Data analysis

3.1. Variables involved in prediction

Based on the correlation that was reported, we coded the predictor variable (i.e., the variable that was used to predict learning) and the predicted variable (i.e., the measure of learning) in each study. The predictor variable was coded based on two factors: (i) its relation to the task being learned – i.e., whether it was "inside" or "outside" the task being learned, and (ii) the type of variable – i.e., whether it was based directly on a neural measure (e.g., EEG, fMRI) or a behavioral measure.

The predicted variable was coded based on the learning measure, which we categorized into three types (i) a 'learning level' (e.g., the movement time at the end of practice), (ii) a 'change score' (e.g., the difference between movement times in the first and last block of practice) or (iii) a 'learning rate' (e.g., the exponent of an exponential fit of the movement time data across practice). Furthermore, we also examined how these learning measures were computed – e.g., if a change score was reported, we also noted if this was reported as an absolute change or a percentage change. Similarly, if learning rates were computed, we noted if this was done using a single exponential, a double exponential, a power law, or another method (Newell et al., 2006).

3.2. Strength of prediction

The strength of prediction in each study was quantified using the Pearson correlation coefficient where the dependent variable was learning-related. Because some papers had multiple correlations reported, we used the following criteria to select the specific correlation: (i) because the focus of the study was on the distinction between behavioral and neural variables, we excluded correlations with demographic variables (such as age), (ii) we focused on the primary variables related to the learning or retention of the task (as opposed to transfer, relearning etc.), and (iii) of the remaining correlations, we focused on the one with the strongest correlation (i.e., highest absolute value of the correlation coefficient) that was determined to be a primary analysis (i.e., excluding secondary analyses with subgroups etc.). Any discrepancies were resolved through discussion between the authors.

Because the focus of the study was only on the strength of the

correlation (and not the sign), we used the absolute value of the correlation (Vul and Pashler, 2017) to compare different studies. If an R^2 value was directly reported using a linear regression, we transformed it to the absolute value of the Pearson correlation by taking the square root. In addition to the absolute value of the correlation, the sample size that was used in the correlation analysis was also noted. We also noted the number and ranges of other reported correlations that were related to predicting learning, including if there was mention of non-significant correlations.

3.3. Time scale of prediction

We examined the time scale of prediction – i.e., the time gap in 'real-world' units (measured in terms of days) between when the predictor variable was measured and when the predicted variable was measured. For example, if both predictor and predicted variable were measured on the same day, the time scale of prediction was reported as 1 day.

3.4. Type of motor task

We categorized the type of motor task used in each study. The classification of tasks was done based on six categories- adaptation, applied, coordination, sequence, tracking and variability (Ranganathan et al., 2021).

4. Results

4.1. Variables involved in prediction

4.1.1. Predicted variables

There was a wide variation in types of predicted variables (Fig. 1A). Learning levels ($n = 16$, 43.2 %) and learning rates ($n = 15$, 40.5 %) were more common compared to change scores ($n = 6$, 16%). In addition, even within each category there were differences in how they were operationalized. For example, for the 15 studies that measured 'rate of learning', this was operationalized using single exponential fits ($n = 4$), power laws ($n = 3$), average of a specified number of trials ($n = 3$), state space models ($n = 2$), linear slopes ($n = 2$) and a time to criterion measure ($n = 1$). Similarly for the 6 studies using a change score, this was operationalized both as an absolute change score ($n = 3$) and a relative change score ($n = 3$).

4.1.2. Predictor variables

There was a wide variation in types of predictor variables (Fig. 1B). The use of 'outside' task predictors ($n = 33$, 89.2 %) was more common relative to those 'inside' tasks ($n = 4$, 10.8 %). There was a roughly even split between studies using neural ($n = 18$, 48.6 %) and behavioral predictor variables ($n = 19$, 51.4 %). Analysis of the predictors (Fig. 1C) indicated that the most common neural predictors were related to measures of functional connectivity either measured through fMRI ($n = 5$) or EEG ($n = 4$), and structural connectivity as indexed through fractional anisotropy ($n = 4$). The most common behavioral predictors were motor variability ($n = 9$) and working memory ($n = 5$).

4.2. Strength of prediction

We found that the sample size was typically small (median sample size = 20, interquartile range 21). Moreover, when the absolute correlation values were plotted against the sample size, we found that smaller sample sizes tended to show higher correlations (Fig. 2A). To estimate the average effect size, we ran a meta-analysis of the correlation coefficients using the MAJOR package in Jamovi. The estimated average Fisher r -to- z transformed correlation was 0.66 (corresponding to an r of 0.58) (Fig. 2B).

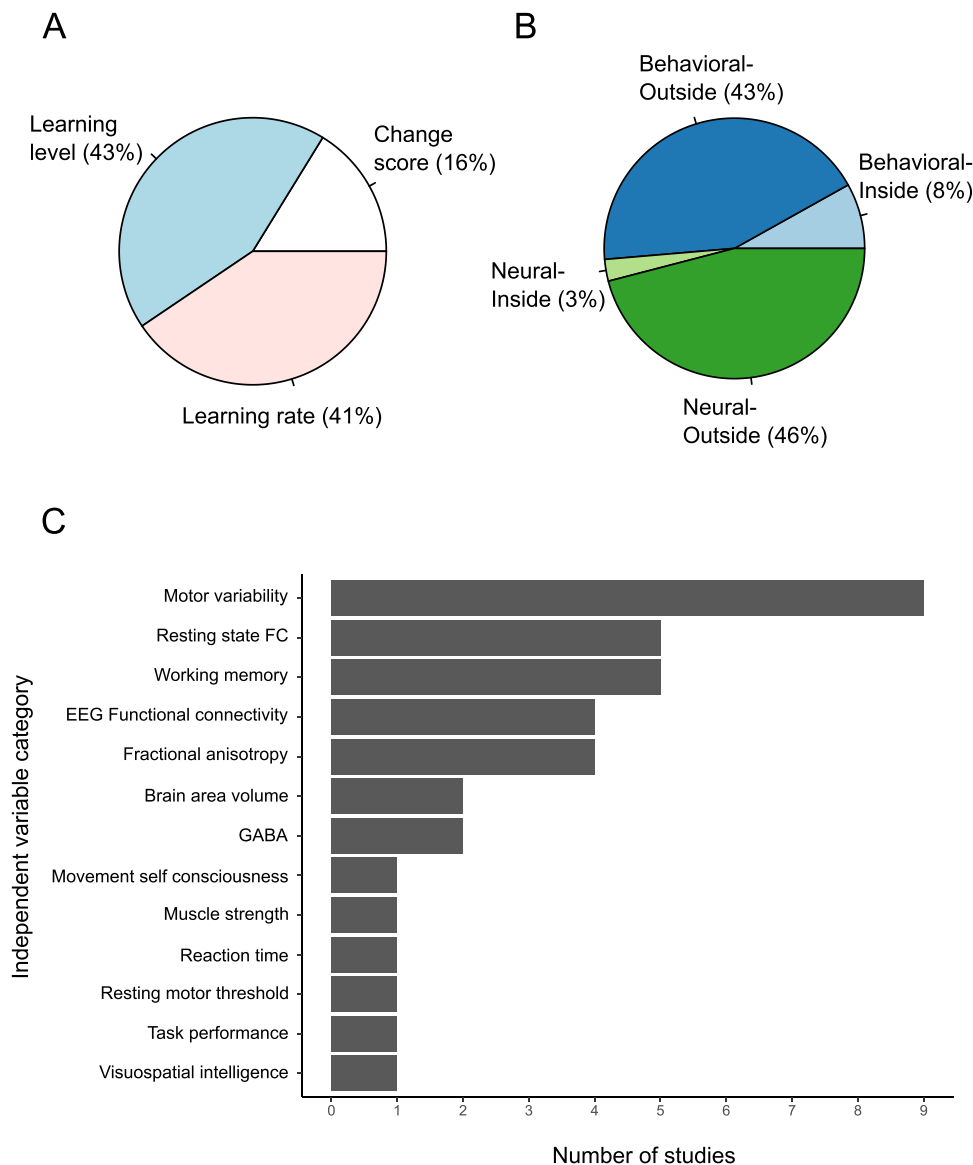


Fig. 1. Distribution of predicted and predictor variables showing large variation across studies. (A) Types of predicted variables (B) Types of predictor variables based on whether they were measured ‘inside’ or ‘outside’ the task and if they were behavioral or neural variables, (C) histogram of categories of predictor variables used across studies.

4.3. Time scale of prediction

The timescale of prediction used in studies was typically very short (Fig. 3A). Results showed that studies used a time span of 1 day ($n = 29$, 78.3 %) - i.e., both the predictor and predicted variable were measured on the same day. In fact, the number of studies that had a time span of 3 or more days was only ($n = 3$, 8.1 %).

4.4. Type of motor task

Finally, we found that an overwhelming majority of tasks ($n = 30$, 81 %) were from just two categories (Fig. 3B) – adaptation ($n = 19$, 51 %) and sequence learning ($n = 11$, 30 %). Certain categories of tasks (e.g., tasks requiring the reduction of variability or the acquisition of coordination patterns) were not used.

5. Discussion

The purpose of this review was to critically examine the evidence for

predictions of individual differences in motor learning. Overall, our results highlight four critical challenges in the evidence for predicting individual differences in motor learning. First, there was a wide variation in both predicted and predictor variables across studies even when tasks were similar, indicating there is potentially a large number of ‘researcher degrees of freedom’ available in these studies. Second, the strength of these correlations was inversely dependent on the sample size, indicating that there is a risk of these correlations being inflated. Third, the timescale of predictions was extremely short, mostly restricted to the same day. Finally, an overwhelming majority of the studies tended to focus on two types of motor tasks – sequence learning and adaptation, indicating a gap in the field for learning other types of tasks.

In view of these challenges, we suggest the following four recommendations for future research:

5.1. Adopting pre-registration and transparent reporting

Given the variation observed in both predictor and predicted

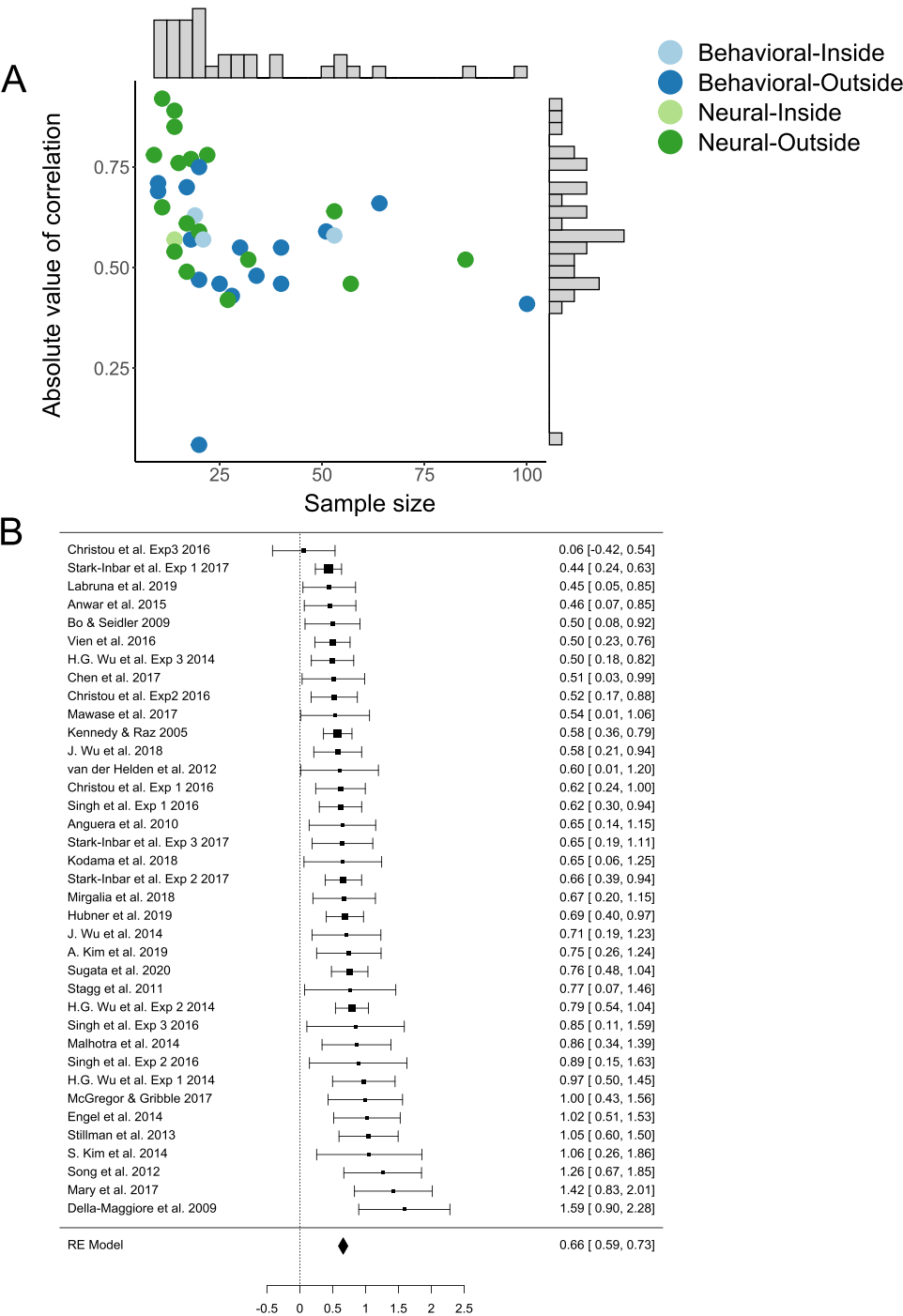


Fig. 2. (A) Absolute value of Pearson's correlation coefficient (r) versus sample size. Higher sample sizes were associated with smaller correlations. Histograms of the sample size (top) and the correlation value (right) are also shown. (B) Forest plot showing Fisher r -to- z transformed correlation coefficients of individual studies plotted in increasing order and the overall estimated effect size. (Anguera et al., 2010; Anwar et al., 2015; Bo and Seidler, 2009; Chen et al., 2017; Christou et al., 2016; Della-Maggiore et al., 2009; van der Helden et al., 2010; Engel et al., 2014; Hübner et al., 2019; Kennedy and Raz, 2005; Kim et al., 2019, 2014; Kodama et al., 2018; Labruna et al., 2019; Malhotra et al., 2014; Mary et al., 2017; Mawase et al., 2017; McGregor and Gribble, 2017; Miraglia et al., 2018; Singh et al., 2016; Song et al., 2012; Stagg et al., 2011; Stillman et al., 2013; Sugata et al., 2020; Vien et al., 2016; Wu et al., 2014a, 2014b, 2018).

variables, the results highlight the need for transparent reporting in studies of individual differences. It is worth noting that even though our selection criteria did not screen for significant results, all studies except one had at least one significant correlation in support of the prediction of individual differences in motor learning. Although we do not make any claims about the analyses in the reviewed studies, we simply highlight that there is a risk of flexible analyses when there is such a large number of potentially justifiable predictor and predicted variables to examine the hypothesis of individual differences in motor learning. Pre-registrations and registered reports can help minimize these researcher degrees of freedom and reduce the chances of using undisclosed flexible analyses to find relationships (or at least clearly label

such findings as exploratory) (Simmons et al., 2011; Chambers, 2013; Wicherts et al., 2016).

In terms of the predictor variables in motor learning experiments, given the potential for a large number of measures at different levels of analysis (e.g., movement outcome, kinematics, coordination, neural), pre-registration can help reduce selection bias in the independent variables used for prediction. Pre-registration can also reduce arbitrariness in the dependent variables related to motor learning. We found a large variation in not only the learning measure (e.g., learning level or learning rate), but even within the same type, there were differences in how they were operationalized. For example, we found especially that “rates of learning” or “change scores” were operationalized differently

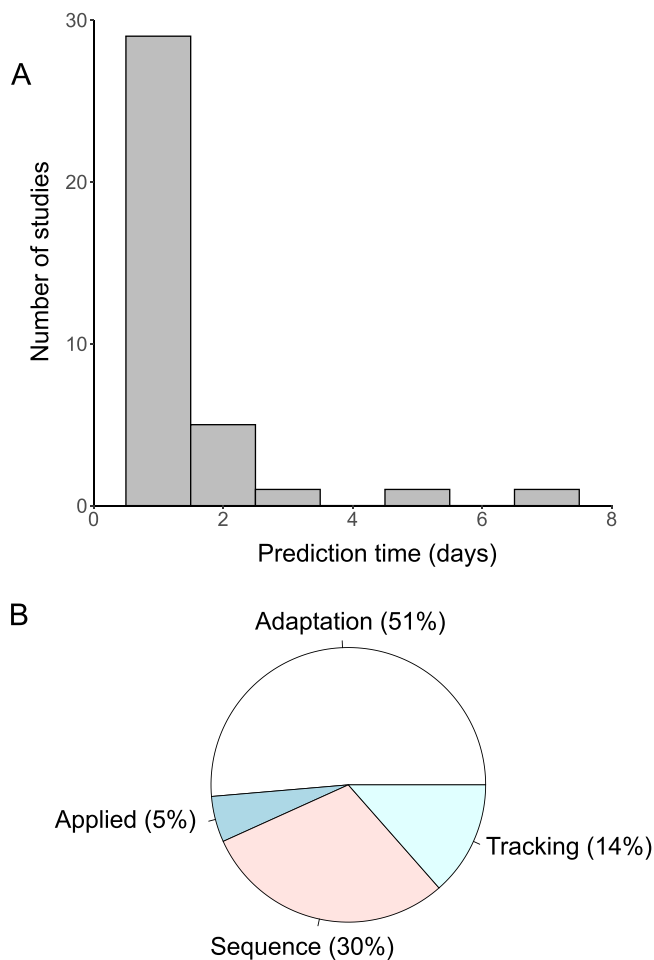


Fig. 3. (A) Prediction time span and (B) Motor task type. Prediction time spans were very short, mostly confined to a single day (i.e., both predicted and predictor variables measured on the same day). A majority of studies relied on two types of tasks – adaptation and sequence learning.

across studies. It is critical to note that some measures of learning like change scores may be misleading in certain contexts and can create correlations because of statistical artifacts (Schmidt, 1972; Hawe et al., 2018; Anderson et al., 2021). While it is important to acknowledge that learning measures are not ‘one-size-fits-all’ and that the exact learning measure or function for the learning curve will depend on the task and context (Newell et al., 2006; Liu and Newell, 2015), pre-registration can also provide greater transparency surrounding the justification for specific measures.

The need for transparent reporting is also evident in the reporting of correlations, especially when they did not reach statistical significance. While our analysis used the strongest correlations to compare across studies (since they are typically the primary focus of the paper), most of the papers typically reported several other learning-related correlations (median reported correlations = 3; range 1–25) including non-significant correlations. However, reporting of these non-significant correlations was generally not adequate. First, several papers simply reported non-significant correlations based only on the p-value (e.g., “this correlation was not significant, $p > .05$ ”) with no information about the magnitude of the correlation or the exact p-value. Second, when non-significant correlations were used as evidence to advance an argument (e.g., to make the case that a correlation was significant in group A but not in group B), these arguments were generally not accompanied by statistical procedures to test if these non-significant correlations were indeed statistically different from other significant correlations (Gelman and Stern, 2006; Nieuwenhuis et al., 2011;

Rousselet and Pernet, 2012). Therefore, in addition to specifying dependent and independent variables, pre-registration of the analysis pipeline could help in more transparent reporting of the primary analysis of interest.

5.2. Increasing sample size

Perhaps not surprisingly and consistent with other reviews on motor learning (Lohse et al., 2016; Ranganathan et al., 2021), sample sizes used for these correlations tended to be small, although to some degree, these studies tended to be somewhat larger than typical group-based studies on motor learning (median of 20 compared to 13 in group studies). More critically though, there was an inverse relation between the absolute value of the correlation and the sample size, with the highest correlations being observed in studies with the smallest sample sizes. This peculiar pattern of results indicates that small studies tend to ‘inflate’ effect sizes and mirrors similar findings in a review on social neuroscience studies (Vul and Pashler, 2017). Although there may be several causes underlying this result that depend on the specifics of the study (e.g., using non-independent analyses in fMRI studies, Vul et al., 2009), one dominant factor that can cause inflation of significant correlations across all studies is the lack of power (Yarkoni, 2009). In other words, in studies with small sample sizes, correlations will have to be large to be detected as significant (even if the underlying population correlation is low). Moreover, this inflation of significant correlations is higher for stricter levels of significance (such as those adjusted for multiple corrections typically used in neuroimaging studies). For example, using simulations, Yarkoni (2009) reported that a population level of correlation of 0.3 will become inflated to 0.73 at an $\alpha = 0.001$ when tested with 20 participants, but the degree of inflation drops with higher sample sizes (around 0.4 when tested with 100 participants). This indicates that low sample size not only decreases power (i.e., the ability to detect an effect when it is present), but that it can also generate spuriously high correlations (Ioannidis, 2008; Yarkoni, 2009; Yarkoni and Braver, 2010).

In addition, small sample sizes also influence the interpretation of the magnitude of the effect sizes because of the width of the confidence interval. Schönbrodt and Perugini (2013) provide the example that a correlation of 0.4 in 25 participants (which is below the threshold of 0.05) has a 90 % CI from 0.07 to 0.65. This wide range highlights the challenge in interpreting such correlations in support of any hypothesis. Moreover, while we selected for studies that reported a Pearson’s correlation coefficient, a challenge with relying only on the Pearson’s coefficient (especially with small sample sizes) is that it is extremely sensitive to outliers (Rousselet and Pernet, 2012; Pernet et al., 2013). Therefore, in addition to pre-registration, larger sample sizes with associated power analyses (Schönbrodt and Perugini, 2013), and robust measures for estimating correlations (Pernet et al., 2013) are needed for establishing individual differences.

5.3. Increasing time scale of prediction

The timescale of predictions here were all mostly within the same day. While we acknowledge that the timescale of prediction is not an ‘absolute measure’ and should be considered in context of the timescale of the learning process (e.g., the timescale of prediction for a task takes a few minutes to learn is not directly comparable to a task that takes days or weeks to learn), increasing the time scale of predictions is still critical from both methodological and theoretical reasons. From a methodological standpoint, increasing the time scale of predictions beyond a single day minimizes the effect of temporary confounding factors (e.g., fatigue or motivation) that can create issues in distinguishing between ‘learning’ and ‘performance’ (Salmoni et al., 1984; Kantak and Winstein, 2012). From a theoretical standpoint, expanding the timescale of learning over longer time scales may also allow the test of other hypotheses such as whether: (i) initial skill and final skill have differing

contributions of abilities (Fleishman and Rich, 1963), (ii) individual differences can be separated into component processes that are related to the rate of learning and final levels of performance (Jones, 1970) and (iii) individual differences tend to diverge or converge with learning (Ackerman, 1987).

5.4. Broaden range of tasks

Finally, the fact that the majority of tasks used were adaptation and sequence learning may be a consequence of their popularity in the motor learning literature, especially in terms of their convenience for neuroimaging paradigms. However, using convenience as the sole metric for the choice of tasks can lead to a distorted picture of how these results have relevance to real-world learning. Several commentaries have emphasized that motor tasks are not interchangeable and that there may be fundamental differences in how certain types of tasks are learned (Newell, 1991; Bastian, 2008; Krakauer and Mazzoni, 2011). Therefore, the use of tasks that capture other core aspects of motor learning (e.g., acquiring novel coordination patterns or reducing motor variability) may be important to test the generalizability of these ideas (Anderson et al., 2021).

However, it is important to note that the goal of broadening the types of tasks has to be balanced with the concern for ‘task fragmentation’ (Ranganathan et al., 2021), where too many different tasks are used making it difficult for comparing results across studies. In our view, tasks have to be chosen carefully so that they can be representative of several different types of learning, and where the properties of learning can be assessed carefully. For example, in our review, we found only a single study that quantified the reliability of the learning measures used in the task (Stark-Inbar et al., 2017) which is critical for establishing individual differences. These competing demands highlight the need for developing ‘model tasks’ for different domains of learning where the diversity in experimental paradigms can also be coupled with experimental rigor (Ranganathan et al., 2021).

6. Conclusion

In summary, the issue of predicting individual differences remains a core issue for motor learning. The search for general predictors of motor learning spans a wide range of variables from behavioral measures such as working memory and motor variability to neural measures such as those identified by fractional anisotropy and functional connectivity. However, we believe that this search is currently hampered by several challenges that affect the quality of the evidence for predicting individual differences. Although many of the issues raised have been highlighted in other reviews (Seidler and Carson, 2017; Vul and Pashler, 2017; Anderson et al., 2021), it is clear that the recommendations needed to address these challenges (e.g., increasing sample size, developing model tasks etc.) require the need for large scale collaborative efforts like those that have started in other domains – e.g., Psych Science Accelerator (Moshontz et al., 2018) and ManyLabs projects (Klein et al., 2014). We anticipate that addressing these steps as a field can help provide a more robust evidence base for the study of individual differences in motor learning.

Supplementary Data

The table of individual studies used for this review and the associated references can be found at <https://osf.io/3j2zu/>.

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