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Review

Relationship between initial motor variability and learning and adaptive ability. A systematic review

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ABSTRACT

Motor variability is an intrinsic feature of human beings that has been associated with the ability for learning and adaptation to specific tasks. The purpose of this review is to examine whether there is a possible direct relationship between individuals' initial variability in their ability for learning and adaptation in motor tasks. Eighteen articles examined the relationship between initial motor variability and the ability for learning or adaptation. Twelve found a direct relationship. In reward-based tasks, greater initial variability was associated with greater learning and adaption improvement when assessed using linear measures of dispersion, however, this association was not observed with temporal structure variability. While in error-based task associations were reported with both greater amount variability and more complexity temporal structure. Nevertheless, bias in initial performance related to the amount of variability was found, so the temporal structure of initial variability seems to be a better indicator of improvement in this type of task. Further research is needed for further research to better understand the potential relationship between initial motor variability and the ability for learning or adaptation in motor tasks.

Introduction

Motor variability is a prevalent characteristic observed in human movement that refers to the inherent fluctuations in motor performance during repeated task executions (Stergiou and Decker, 2011). Consequently, even seemingly identical actions exhibit different movement patterns, despite achieving the same outcome. These different motor patterns, characteristic of motor variability, can originate from various levels within the motor pathway, encompassing planning noise in central circuits to execution noise in peripheral circuits (Dhawale et al., 2017).

In the past, motor variability was regarded as a system error or noise that should be reduced (Schmidt et al., 1979; Osborne et al., 2005). Several theories suggest that actions were planned to minimise the impact of variability on task performance (Harris and Wolpert, 1998). Conversely, it has been proposed that motor variability may possess a functional nature, considering that diverse movement patterns can yield consistent outcomes, as it has been associated with adaptive ability (Davids et al., 2003). By exhibiting variability, individuals can optimize their movements to meet the demands of diverse environments and tasks (Caballero et al., 2019). It is therefore characterised by improvements in movement performance during interactions with environmental contexts (Krakauer and Mazzoni, 2011). This plays an important role in motor learning and adaptive capacity (Mandelblat-Cerf et al., 2009; Wu et al., 2014; Zhou et al., 2013). The possible relationship between motor variability and adaptive ability has prompted examination of movement variability and its relationship with system health, injury prevention, improving performance, enhancing motor learning, etc. (Harbourne and Stergiou, 2009; Newell et al., 2001; Davids et al., 2003; Stergiou and Decker, 2011).

There is evidence that the nervous system increases rather than minimizes variability in task performance. This has been seen in studies of songbirds, where increased variability in the motor output of the bird's song was found to facilitate learning (Ölveczky et al., 2011; Tumer and Brainard, 2007). In the study Wu et al. (2014) found that the nervous system actively regulates motor performance variability in response to task demands, amplifying or reducing it. Furthermore, the researchers demonstrated that baseline motor variability is a predictor of learning rates in both individuals and tasks. The researchers observed that individuals with higher baseline variability exhibited faster

Abbreviations: DFA, Detrended Fluctuation Analysis; ApEn, approximate entropy; CNS, central nervous system; PCA, Principal Component Analysis.

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learning rates than those with lower baseline variability. This novel paradigm suggests that variability may be associated with the capacity to adapt to a task or to enhance learning processes, rather than representing a system error. This finding has prompted further investigation into the relationship between initial motor variability and motor learning (Barbado Murillo et al., 2017).

However, other studies, such as the one conducted by He et al. (2016), have examined the relationship between variability and learning ability. The findings from their study were controversial, as they indicated a lack of strong evidence that initial variability could predict adaptive and learning ability. This study does not dismiss the existence of a relationship between motor variability and learning. However, this relationship might be task-dependent, indicating that measured variability must be specific to the desired movement task. In other words, the initial variability of the task measured should be representative of the target task to be learned. It is therefore of interest to ascertain the nature of this relationship and the variables upon which it depends.

There may be different mediating variables in the relationship between initial variability and adaptive and learning ability (Moreno et al., 2023). One of these variables, can be the specific type of motor learning involved. In reward learning, aiming to reinforce successful actions, increased movement variability can enhance learning rates (Pekny et al., 2015). In this type of task, an action tends to be repeated if the result of the previous action was satisfactory (Sutton et al., 1992). It is therefore characterized by the need to explore to find the optimal solution (Wu et al., 2014). However, this type of task depends on whether the previous action was successful or not but has no other type of feedback that allows it to modify its behaviour (Pekny et al., 2015). On the other hand, error-based learning focused on reducing errors by adjusting actions based on observed outcomes and known levels of error during the action (Diedrichsen et al., 2010; Chien and Chen, 2018). Thus, there is a change in behaviour during task execution because of feedback derived from the difference between execution and task outcome. Therefore, improvement during practice is based on an increasing reduction of the perceived error during feedback (Diedrichsen et al., 2010). The benefits of higher variability are not as clear-cut as in reward learning. Unlike reward learning, error-based learning does not necessarily promote the exploration of different movement solutions (Sutton and Barto, 2018; Van Mastrigt et al., 2020).

Another mediating variable in movement variability and system adaptation is the procedure for measuring variability. Some authors propose that it is necessary to analyse not only the amount of variability but also how this variability evolves over time, i.e., its temporal structure, as it can better inform about the adaptive processes (Caballero et al., 2020). To comprehend these adaptive processes, non-linear measures have been used to investigate the self-organizing processes of a system (Barbado Murillo et al., 2017). These non-linear measures, such as Detrended Fluctuation Analysis (DFA) or Approximate Entropy (ApEn) (Stergiou, 2004) have been explored to analyse the complexity and degree of organization of the motor system (Caballero et al., 2014). To example, DFA is a method used to examine time series data, particularly those exhibiting potential long-term correlations and non-stationary behaviour. When we refer to greater variability in the context of analyzing their structure, we mean that the complexity is greater. The complementary analysis of linear and non-linear measures of variability can provide a more comprehensive picture of the role that variability plays in the adaptive ability of the motor system.

The research suggests that variability in movement can be analysed within two subspaces: task space and null space (Scholz and Schöner, 1999; Cusumano and Cesari, 2006; Latash, 2010). For redundant task learning, variability can have either beneficial or detrimental effects, depending on whether it resides in the task space (impacting task performance) or in the null space (no impact on task performance) (Scholz and Schöner, 1999; Müller and Sternad, 2009; Sternad, 2018). Cardis et al. (2018) conducted a study to determine the optimal variability space for introducing additional variability to enhance learning in redundant tasks and found that the introduction of variability had a more negative effect on motor learning than the specific space in which it was introduced.

Due to controversies in the literature about the role of variability as a mechanism employed by the central nervous system (CNS) to facilitate exploration and adaptive capacity, the aim of this study is to conduct a comprehensive review to examine the possible relationship between initial motor variability and learning, as well as adaptive capacity. Some of the studies in this review use the term adaptation (Ducharme et al., 2018; Knelange and López-Moliner, 2020) and others the term learning (Ranganathan et al., 2021; He et al., 2016; Singh et al., 2016). Although the processes "adaptation" and "learning" are distinct (Krakauer et al., 2019), we posit that both processes may benefit from the same principles of variability. Therefore, we include studies that measure adaptation and others that measure learning. In addition, we will discuss the parameters that would play a mediating role between variability, adaptability and learning outcomes, fostering a global understanding of their interconnectedness.

Method

Search strategy

For this review, the criteria of the current Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 were followed, which contains a document of the 27 items that comprise it and its elaboration procedure (Page et al., 2021). The PRISMA checklist for this review is presented in Supplementary Table 1.

The following electronic databases were searched from inception to 09 March 2024: PubMed, Scopus, SportDiscus and Web of Science. Intervention studies written in English were chosen and evaluated following the PICO procedure. Search words were defined, for which different exploratory searches with different keywords were performed. The final search used the following keywords: ("motor variability" OR "variability structure" OR "movement variability") AND ("predict" OR "predictability" OR "adaptation" OR "adaptability" OR "learning" OR "ability"). PubMed and SportDiscus databases search were "all fields". Scopus database option search was: "title, abstract and keywords". The search option in the Web of Science Core Collection database was "topic" in all databases, filtering by fields: "Neuroscience Neurology, Behavioral Science, Physiology, Sport Sciences, Engineering". The reference manager Mendeley was used to collect and manage the references found. Articles referring to the selected articles were also assessed for inclusion. Authors of selected studies were contacted via email to identify possible additional published and unpublished studies. These search strategies were used to minimize the risk of publication bias.

Inclusion and exclusion criteria

Inclusion criteria were: 1) Studies that used an experimental design to assess functional movements and motor skills. 2) Measurement of movement variability in a baseline task or at early movement times. 3) Analyses relating initial motor variability to learning or adaptation. 4) Experimental studies in humans. Exclusion criteria were: 1) Case studies and reviews. 2) Studies without measurement of motor learning or adaptation. 3) Studies using variability as a performance criterion.

Articles were initially selected by reading the titles and abstracts. Where the title and abstract did not clearly indicate whether an article should be included, the full article was read and assessed for inclusion. After reading the full text, the selection of the articles comprising this review was completed. Fig. 1 illustrates the stages adopted for selecting and including studies in this review, according to the current PRISMA Statement (Page et al., 2021).

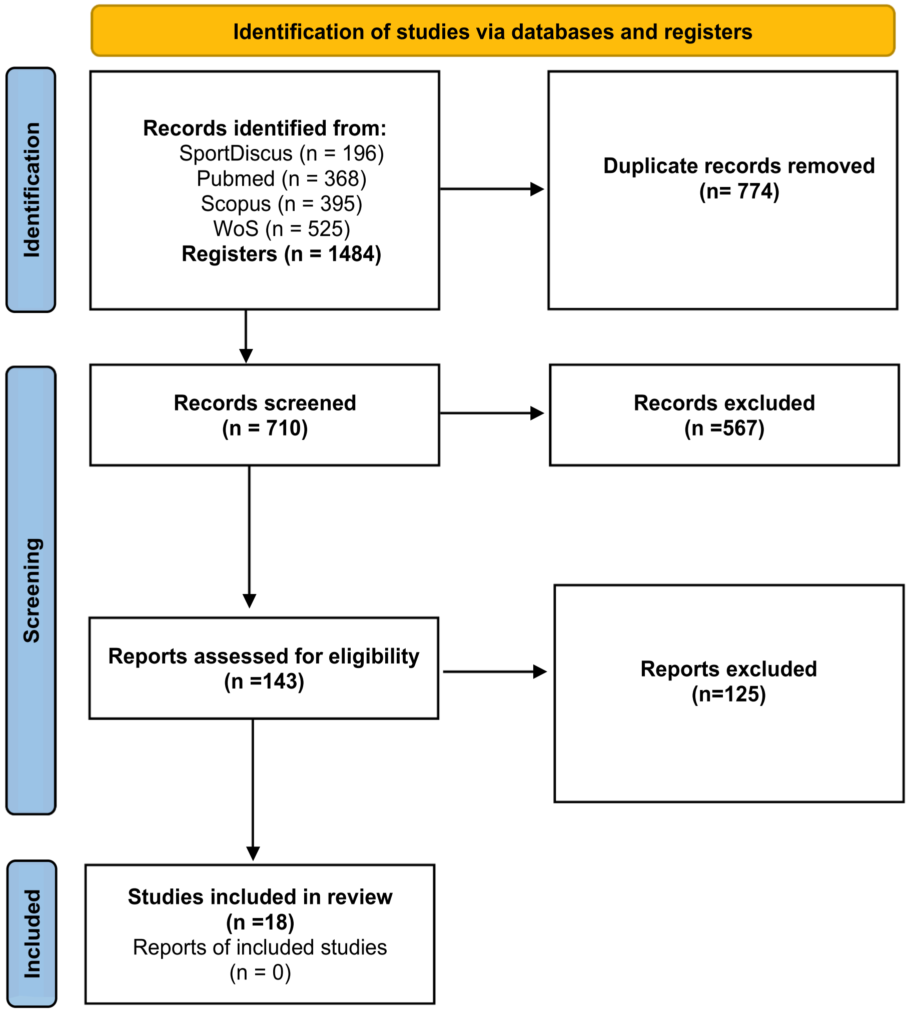

Fig. 1. PRISMA flowchart showing the selection process for systematic review.

Risk of bias and methodological quality Assessment

Two researchers (MLF and RS) carried out the selection process independently. In cases of disagreement regarding the outcomes, consensus was reached. If an accord could not be achieved, a third researcher (FM) was consulted. The level of concurrence amongst the reviewers was gauged using Cohen's kappa coefficient (κ). The degree of agreement was Near Perfect Agreement (0.92).

A protocol was developed to extract study characteristics. The characteristics of the included studies were coded by two authors. For the title and abstract screening stage, two researchers (MLF and RS) filtered the articles to be read in full. In case of a lack of consensus, a third researcher (FM) was consulted. If there was doubt about an item, it was added for review at the following stage. In the full-text reviewing stage, the consensus of three researchers (MLF, RS and FM) was necessary to decide which articles were included in the review.

Reviewers assessed the included articles according to the Study Quality Assessment Tools developed by The National Institutes of Health (Ma et al., 2020; The National Institutes of Health, 2021). Different tools were used depending on the type of study: Quality Assessment of Controlled Intervention Studies, Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies and Quality Assessment Tool for Before-After (Pre-Post) Studies With No Control Group. As these scales use different items (up to 12 or 14 items depending on the scale), the result of the assessment is expressed as the percentage of items that each study met, excluding those considered as "not applicable".

Coding study characteristics

The following information was extracted from the included studies: (a) study characteristics: authors, publication year, and study design; (b) participant characteristics: sample size, sex, age; (c) assessment characteristics: task performed (reaching movement, walking, virtual shuffleboard or others), learning/adaptation type (reward-based tasks or error-basesd tasks), variability measures, variability spaces, retention test, number of trials, signal to measure variability; and (d) main outcomes and conclusions.

Results

Study selection

A total of 1,484 articles were identified through a database search (368 in PubMed, 525 in Web of Science, 395 in Scopus and 196 in SportDiscus). After removing all duplicated articles (774 dismissed articles), the titles and abstracts of the remaining articles were reviewed, and 567 articles were discarded. The remaining 143 were eligible for full-text analysis. Articles that did not meet the inclusion criteria were eliminated, and the remaining articles were re-examined and comprehensively screened as full texts. After full-text re-evaluation of the articles, 18 fully met the inclusion criteria and were included in this review. Fig. 1 illustrates the systematic review process.

Table 1 summarizes the characteristics of the sample, the task

Table 1
Characteristics of studies.

Authors	Sample	Task performed	Retention test	Learning/ adaptation type	Variability measures	Variability space (variability dimension)	Number of trials	Signal to measure variability	Conclusions
Wu et al. (2014)	67 male and 81 female (18–58 years)	Reaching movement with joystick	Exp 1–3: no Exp 4 yes	Learning EB and RB	Amount variability (standard deviation) and variability structure (principal component analysis)	ND	Exp 1: 500 Exp 2: 1000 Exp 3: 150 Exp 4: 720–912	Linear velocity and dynamic force	They predicted learning in error- and reward-based tasks. Those with greater total baseline variability learned faster than those with less baseline variability. Those with even more variability in task space even learned faster.
Lefumat et al. (2015)	10 male and 10 female (mean age: 23.3–24.6 years)	Reaching intermittent visual targets	No	Adaptation EB and RB	Amount variability (standard deviation)	ND	100	Angular velocity	Did not predict adaptation through baseline variability. The last part of the adaptation task (training) does predict adaptive ability in the final task.
He et al. (2016)	90 participants	Reaching movements to visual targets and isometric force production with different force magnitudes	No	Learning EB	Amount variability (standard deviation)	ND	Exp 1: 200 Exp 2: 200 Exp 3: 400 Exp 4: 600	Linear velocity and dynamic force	Did not predict learning
Singh et al. (2016)	42 male and 18 female (22–70 years)	Reaching movement	No	Learning EB	Amount variability (standard deviation)	TS and NS	Exp 1: 60 Exp 2: 200 Exp 3: 200	Angular position	Null-space variability predicts motor learning
Barbado Murillo et al. (2017)	41 male and 11 female (mean age: 24.2–24.6 years)	Standing balance task and sitting balances task	Yes	Learning EB	Variability structure (Detrended Fluctuation Analysis)	ND	Exp 1: 10 Exp 2: 15	Linear position	They predicted learning rate when they took into account the initial performance of the participants; those with lower values of autocorrelation (more variability) in the COP had higher learning rates.
Selinger et al. (2019)	36 participants	Walking task with exoskeletons	No	Adaptation RB	Amount variability (coefficient of variation)	ND	12 min	Angular velocity	The high variability of the natural gait is a predictor of optimal gait adaptation initiation.
Knelange and López-Moliner (2020)	15 female (20.3 ± 2.3)	Interception task on a graphic tablet with a stylus	No	Adaptation EB	Amount variability (standard deviation)	ND	90	Linear velocity	A positive correlation was identified between the variability in movement velocity during the baseline phase and the subject's ability to adapt to a temporary disturbance.
Dal'Bello and Izawa (2021)	8 male and 16 female (mean age: 21.4 years)	Hand gesture task	No	Learning EB and RB	Amount variability (standard deviation)	TS and NS	480	Angular velocity	Predicted error-based learning, but not reward-based learning. Learning rate of the error-based component was

(continued on next page)

Table 1 (*continued*)

Authors	Sample	Task performed	Retention test	Learning/ adaptation type	Variability measures	Variability space (variability dimension)	Number of trials	Signal to measure variability	Conclusions
									positively correlated with task space and null space variability. But the rate of reward-based learning was not correlated with task space and null space variability.
Sadnicka et al. (2018)	10 Dystonia DYT1 (mean age: 43.9 years)12 Controls (mean age: 42.3 years)	Reaching movement with robotic arm	No	Adaptation EB	Amount variability (standard deviation)	ND	192	Angular position	Did not predict adaptation. High task-relevant variability correlates with lower performance on the adaptation task.
Ducharme et al. (2018)	8 male and 7 female (mean age: 28.5 years)	Treadmill walking	No	Adaptation RB	Variability structure (detrended fluctuation analysis)	ND	5 (512 steps)	Angular position	Did not predict adaptation. Preferred or semi-preferred gait was not associated with adaptation in asymmetric gait.
Van der Vliet et al. (2018)	14 male and 55 female (18–35 years)	Reaching movement with joystick	No	Adaptation EB and RB	Amount variability (standard deviation) and variability structure (lag-1 autocorrelation)	ND	450	Angular velocity	Predicted the adaptation rate with planning noise, but not with execution noise.
Ulman et al. (2019)	16 male and 16 female (mean age: 21.20 years)	Walk	No	Learning EB	Amount variability (standard deviation)	ND	3–23 (35 s completed)	Angular position and linear velocity	Measures of variability of joint kinematics, specifically variability of frontal plane coordination of hip-knee and knee-ankle joint pairs, predicted motor learning ability.
Renault et al. (2020)	13 male and 7 female (mean age: 23.5 years)	Reaching movement with prism adaptation	No	Adaptation EB	Amount variability (variance)	ND	100	Angular position, angular velocity, acceleration	Did not predict adaptation. Initial direction variability during the exposure phase (not the pre-adaptation phase) to the prism was positively correlated with inter-limb transfer to the non-dominant arm.
Haar et al. (2020)	18 male and 12 female (mean age: 24 years	Hitting a target ball in billiards	No	Learning EB	Amount variablity (scale parameter of a t-distribution)	ND	300	Angular velocity	Predicted the adaptation. Task-relevant initial variability in ball direction predicts learning and also initial variability in forearm supination (relevant variability) predicts learning.
Ranganathan et al. (2021)	10 male and 40 female (18–25 years)	Virtual shuffleboard task with joystick	No	Learning EB	Amount variability (variance)	TS and NS	200	Linear velocity	Not predict adaptation in the task. Higher baseline movement variability was associated with better initial or final performance levels when performing the task with a new solution.

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Table 1 (*continued*)

Authors	Sample	Task performed	Retention test	Learning/ adaptation type	Variability measures	Variability space (variability dimension)	Number of trials	Signal to measure variability	Conclusions
Caballero et al. (2021)	33 male and 11 female (mean age: 26,46 years)	Virtual shuffleboard task with joystick	Yes	Learning RB	Amount variability (standard deviation) and variability structure (detrended fluctuation analysis)	TS and NS	600	Dynamic force	Predicted the learning. Those who showed higher task-relevant variability in the pre-test also showed higher learning rates.
Ruano et al. (2022)	9 female and 23 male (age 26,50 ± 5,93)	Throwing task with joystick	Yes	Learning EB	Amount variability (standard deviation)	ND	440	Dynamic force	Statistically significant correlations were found between initial error variability (VE) and improvement in absolute error (AE) post-training phase (difference between pretest and post-test) and re-test 2.
Matsuda and Abe (2023)	12 female and 19 male (age 21,3 ± 3,0)	Visuomotor reaching task	No	Adaptation EB	Amount variability (standard deviation)	ND	448	Angular position	They observed a significant positive relationship between motor variability and implicit adaptation driven by a 12° absolute error but not a 3° or 6° absolute error.

Note: Exp, experiment; M, male; F, female; RB, reward-based; EB, error-based; TS, task space; NS, null space; ND, No distinction

performed, the learning/adaptation type, the method of variability analysis, the variability space analysed, whether they performed a retention test for each study, number of trials, signal to measure variability and whether there was a positive correlation between variability and learning or adaptation ability for all the studies selected. A retention test was considered a test that measured performance after an adaptation or learning test. For the 18 studies selected, the total sample was 707 participants; 303 were male, 302 were female and the remaining 102 were unidentified.

Mediating variables

Of the 18 papers, four differentiated variability space (Singh et al., 2016; Dal'Bello and Izawa, 2021; Ranganathan et al., 2021; Caballero et al., 2021). In other words, task-relevant variability and task-irrelevant variability (i.e., task-space variability and null-space variability) were analysed separately. One study differentiated between planning noise and execution noise (Van der Vliet et al., 2018). The remaining 13 did not differentiate the variability space or noise (Wu et al., 2014; Lefumat et al., 2015; He et al., 2016; Barbado Murillo et al., 2017; Ducharme et al., 2018; Sadnicka et al., 2018; Selinger et al., 2019; Ulman et al., 2019; Haar et al., 2020; Renault et al., 2020; Knelange and López-Moliner, 2020; Ruano et al., 2022; Matsuda and Abe, 2023).

Regarding motor variability analysis tools used, thirteen papers used only linear analyses of variability (Lefumat et al., 2015; He et al., 2016; Singh et al., 2016; Dal'Bello and Izawa, 2021; Sadnicka et al., 2018; Selinger et al., 2019; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Renault et al., 2020; Ranganathan et al., 2021; Ruano et al., 2022; Matsuda and Abe, 2023), two studies used non-linear analyses to measure variability (Barbado Murillo et al., 2017; Ducharme et al., 2018) and three combined linear and non-linear analyses of variability (Wu et al., 2014; Van der Vliet et al., 2018; Caballero et al., 2021).

For categorization by learning/adaptation type (reward-based or error-based tasks), eleven studies analysed learning or adaptation ability in error-based tasks only (He et al., 2016; Singh et al., 2016; Barbado Murillo et al., 2017; Sadnicka et al., 2018; Ulman et al., 2019; Knelange and López-Moliner, 2020; Renault et al., 2020; Haar et al., 2020; Ranganathan et al., 2021; Ruano et al., 2022; Matsuda and Abe, 2023), three analysed learning or adaptation in reward-based tasks (Ducharme et al., 2018; Selinger et al., 2019; Caballero et al., 2021) and four analysed it in both error- and reward-based tasks (Wu et al., 2014; Lefumat et al., 2015; Dal'Bello and Izawa, 2021; Van der Vliet et al., 2018). The tasks were three virtual shuffleboard tasks (Ranganathan et al., 2021; Caballero et al., 2021; Ruano et al., 2022), nine reaching tasks (Wu et al., 2014; Lefumat et al., 2015; He et al., 2016; Singh et al., 2016; Sadnicka et al., 2018; Van der Vliet et al., 2018; Knelange and López-Moliner, 2020; Renault et al., 2020; Matsuda and Abe, 2023), one billiard ball hitting task (Haar et al., 2020), three walking tasks (Ducharme et al., 2018; Selinger et al., 2019; Ulman et al., 2019), one hand gesture task (Dal'Bello and Izawa, 2021) and one balancing task (Barbado Murillo et al., 2017). In task type, eight studies were on motor adaptation tasks/processes (Lefumat et al., 2015; Selinger et al., 2019; Knelange and López-Moliner, 2020; Sadnicka et al., 2018; Ducharme et al., 2018; Van der Vliet et al., 2018; Renault et al., 2020; Matsuda and Abe, 2023), while ten were in motor learning tasks/processes (Wu et al., 2014; He et al., 2016; Singh et al., 2016; Barbado Murillo et al., 2017; Dal'Bello and Izawa, 2021; Ulman et al., 2019; Haar et al., 2020; Ranganathan et al., 2021; Caballero et al., 2021; Ruano et al., 2022).

Methodological quality assessment

In terms of the Quality Assessment Tool for Before-After (Pre-Post) Studies With No Control Group, all studies achieved a score of between 5 and 8 items. Similarly, for the Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies, all studies scored between 8 and 13 items. Finally, for the Quality Assessment of Controlled Intervention Studies, all studies fulfilled between 6 and 7 items. When all the NIH scales are taken into account, item compliance represents 62 % of the total number of items. The risk of bias for the quality of the included studies was categorised as: good, fair or poor. 11 of the 18 studies were of 'fair' quality, and 7 of the 18 were of 'good' quality. The results of the evaluation process are presented in Supplementary Table 2. Some items are not reported or cannot be determined because they are not specifically discussed in the text of the article.

Learning and adaptation prediction

From all the articles chosen, twelve found direct and positive correlations between initial variability and the rate of learning or adaptation (Wu et al., 2014; Singh et al., 2016; Barbado Murillo et al., 2017; Dal'Bello and Izawa, 2021; Van der Vliet et al., 2018; Selinger et al., 2019; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Caballero et al., 2021; Ruano et al., 2022; Matsuda and Abe, 2023). By predicting we mean that there were direct and positive correlations between initial variability and the rate of learning or adaptation. Six articles did not find relationships between initial variability and the rate of learning or adaptation (Lefumat et al., 2015; He et al., 2016; Sadnicka et al., 2018; Ducharme et al., 2018; Renault et al., 2020; Ranganathan et al., 2021).

Of the 12 articles that predicted learning or adaptive ability, eight articles found correlations only in error-based tasks (Singh et al., 2016; Barbado Murillo et al., 2017; Dal'Bello and Izawa, 2021; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Ruano et al., 2022; Matsuda and Abe, 2023), two of them in both error-based and reward-based tasks (Wu et al., 2014; Van der Vliet et al., 2018) and two in reward-based tasks (Selinger et al., 2019; Caballero et al., 2021). Eight articles used only linear measures to analyse variability (Singh et al., 2016; Dal'Bello and Izawa, 2021; Selinger et al., 2019; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Ruano et al., 2022; Matsuda and Abe, 2023) and three included linear measures and measures of the structure to analyse variability (Wu et al., 2014; Van der Vliet et al., 2018; Caballero et al., 2021). Barbado Murillo et al. (2017) only used a structure variability analysis. Regarding the dimension of variability analysed, only one article predicted learning or adaptation rates in the task space (Caballero et al., 2021), one predicted it only in the null space (Singh et al., 2016) and one predicted in both variability spaces (Dal'Bello and Izawa, 2021). The remaining articles predicting learning and adaptive ability did not differentiate between the two variability spaces.

Discussion

This review examined the current knowledge on how initial motor variability in individuals can predict their ability to learn or adapt to a task, collecting those articles that purported to establish such a relationship. We have therefore presented the results of each of the collected articles to try to understand a possible relationship.

It is important to distinguish between the processes of adaptation and learning, as they are not necessarily analogous. However, there may be some underlying mechanisms that are shared between the two, which could benefit from variability due to their inherent characteristics. Consequently, this text presents both adaptation and learning tasks, while acknowledging the differences between them as outlined in the literature (Krakauer et al., 2019).

In terms of risk of bias and methodological quality, the results indicate a robust and systematic assessment in this review. The assessment of risk of bias among the reviewers yielded a Cohen's Kappa coefficient of 0.92, which reflects an almost perfect agreement in the selection of studies. This improves the reliability of the study inclusion process and minimizes the possibility of bias in the selection phase. Nevertheless, an analysis of the methodological quality of the included studies revealed some variability in the results. Of the 18 studies evaluated, 11 were rated as 'fair' and 7 were rated as 'good'. This indicates that, 62 % of the selected evidence meets the established methodological criteria, there are areas where improvements can be made in terms of scientific rigor. Notwithstanding, some of the studies designated as 'fair' are merely one item away from being classified as 'good' quality studies. This indicates that the quality and risk of bias of many included studies can provide reliable information about the purpose of this review. However, a small number of studies provide a 'fair' quality, necessitating caution in the interpretation of the results. But these data do not change the interpretation of the results, so our conclusions consider this methodological information.

Generally, it has been found that motor variability can be beneficial for learning and performance of a skill (Dhawale et al., 2017). This is partly because variability could help individuals discover the most effective movements to achieve the goal of a task (Davids et al., 2003; Emmerik and Wegen, 2002). On the other hand, some authors have related movement variability to the ability to adapt to different situations, resulting in more effective skill performance across various contexts (Wu et al., 2014). If variability can indeed be related to learning and adaptation, it leads us to consider that initial variability prior to learning or training a skill may provide information about an individual's capacity to adapt or learn a task. We found 12 articles that observed relationships between participants' initial motor variability and their ability to learn or adapt (Wu et al., 2014; Singh et al., 2016; Barbado Murillo et al., 2017; Dal'Bello and Izawa, 2021; Van der Vliet et al., 2018; Selinger et al., 2019; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Caballero et al., 2021; Ruano et al., 2022; Matsuda and Abe, 2023). This relationship indicates that individuals with higher initial movement variability in a task tend to have higher rates of learning or adaptation, or simply start adapting or learning earlier in time. However, we did not find the same relationship in six papers (Lefumat et al., 2015; He et al., 2016; Sadnicka et al., 2018; Ducharme et al., 2018; Renault et al., 2020; Ranganathan et al., 2021). In this paper, we attempt to review whether the relationship between variability adaptive capacity could depend on different factors associated with the capacity to learn and the procedure used to measure variability.

Movement variability is often evaluated by measuring dispersion from the mean, where greater variability corresponds to greater dispersion. However, this measurement approach is closely associated with task performance, and higher variability is typically associated with lower performance. Analysing variability this way can lead to misleading conclusions when examining whether increased variability leads to improved learning or adaptation. While some studies have found a positive relationship between variability and learning/adaptation, there is a bias present in these studies. Participants with higher variability often exhibit lower performance, and their greater ability for improvement may explain their increased learning or adaptation mainly in error-based tasks (Anderson et al., 2021). However, in reward-based task processes, a higher level of initial variability may be associated with the ability to explore the environment and discover the most effective solution for the task (Sutton et al., 1992). It is true that in error-based task, motor variability can be not only related to worse performance but also to facilitate error correction through increased perceptual feedback during execution (Diedrichsen et al., 2010). To solve this issue and better address the possible relationship between variability and adaptation or performance, some studies not only analyse the quantity of variability but also its temporal structure (Barbado Murillo et al., 2017; Urbán et al., 2019). Analysing variability structure allows researchers to gain insights into how variability is distributed over time, reducing the bias associated with initial performance.

Finally, certain studies differentiate between task-space variability, also known as task-relevant variability, and null-space variability, also known as task-irrelevant variability (Scholz and Schöner, 1999; Dal'-Bello and Izawa, 2021). These distinctions add complexity to establishing definitive connections between initial variability and learning or adaptive abilities. Consequently, this review aims to consolidate these variables to identify the factors that could potentially influence this relationship.

Amount of variability, performance and room for improvement

After delving into the articles that perform an analysis of the amount of variability, we found that the amount of initial variability is related to the capacity to learn or adapt (Wu et al., 2014; Singh et al., 2016; Van der Vliet et al., 2018; Dal'Bello and Izawa, 2021; Selinger et al., 2019; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Caballero et al., 2021; Ruano et al., 2022; Matsuda and Abe, 2023). Other articles were collected that did not obtain the same results (Lefumat et al., 2015; He et al., 2016; Sadnicka et al., 2018; Renault et al., 2020; Ranganathan et al., 2021). Of the papers that did not find a positive relationship between the amount of initial variability and adaptive or learning ability, Lefumat et al. (2015) and Renault et al. (2020) found that subjects with higher movement direction variability showed better interlimb transfer during the adaptation task but not in the initial task. Sadnicka et al. (2018) also did not find this relationship between variability and adaptation, although it should be noted that their study used a sample with pathology such as DYT1 dystonia, which involves high levels of variability due to involuntary movements. The excessive variability resulting from DYT1 dystonia may not represent variability to adapt.

While we initially excluded articles that utilized initial variability as a measure of task performance, it is worth noting that some of the articles mentioned, particularly those involving error-based tasks, may still be subject to bias stemming from initial performance levels. To mitigate this bias, it is crucial to consider the type of learning/adaptation task, whether it is error-based or reward-based, as suggested by Barbado Murillo et al. (2017) and Friedman et al. (2022). By doing so, we can avoid confounding effects related to participants' initial performance.

Reward-based and error-based task

Wu et al. (2014), Van der Vliet et al. (2018), Selinger et al. (2019) and Caballero et al. (2021) found a positive relationship between initial variability and adaptive and learning ability in reward-based tasks. These authors argue that participants who show higher variability explore a greater number of movement combinations to effectively find a solution to the task and, therefore, show higher adaptive or learning ability than those with lower variability. However, Lefumat et al. (2015), Ducharme et al. (2018) and Dal'Bello and Izawa (2021) did not find this in reward-based tasks. We think that initial variability in reward tasks may also be influenced by the outcome obtained in each execution, so that if an action is followed by another action with a negative outcome, movement variability will be higher than if it is preceded by a successful outcome in the previous trial (Wiegel et al., 2022). However, none of the studies reviewed used procedures for analysing variability as a function of previous outcome.

We found studies that observed a positive relationship between initial variability and adaptive or learning ability in error-based tasks (Wu et al., 2014; Singh et al., 2016; Barbado Murillo et al., 2017; Van der Vliet et al., 2018; Ulman et al., 2019; Haar et al., 2020; Knelange and López-Moliner, 2020; Dal'Bello and Izawa, 2021; Ruano et al., 2022; Matsuda and Abe, 2023). However, we also found studies that did not show this relationship in error-based tasks (Lefumat et al., 2015; He et al., 2016; Sadnicka et al., 2018; Renault et al., 2020; Ranganathan et al., 2021). Notably, Lefumat et al. (2015) and Renault et al. (2020) did not observe this relationship in an interlimb transfer protocol but noted that individuals with higher initial variability demonstrated more significant improvements during the training phase. In a study by Sadnicka et al. (2018), negative correlations were found between initial variability and adaptive ability. The groups with DYT1 Dystonia, characterized by high variability due to involuntary movements, showed worse adaptation as they exhibited more variability. The authors suggested that over an upper threshold, variability no longer assists motor learning, introducing error and uncertainty in the control of movement leading to poorer adaptation. He et al. (2016) did not obtain a relationship between initial variability and learning ability. Instead, they discovered that variability correlates differently depending on the task. They proposed that the sensory uncertainty of error feedback, which affects variability, is what determines learning rate rather than variability itself. Ranganathan et al. (2021) concluded that there is no relationship between initial variability and motor learning. However, they did find a correlation between initial variability and the rate of improvement. To avoid potential bias from initial performance, Ranganathan et al. (2021) examined the correlation between initial variability and final performance rather than learning rate. In addition, it should be noted that in this study, variability in task space and variability in null space were discussed to account for other mediating factors in the relationship between initial variability and learning ability. The latter issue will be addressed later in the discussion.

Regarding error-based tasks, as mentioned earlier, initial variability may be closely linked to initial performance and, consequently, the potential for improvement (Anderson et al., 2021; Ranganathan et al., 2021). However, to mitigate any bias stemming from initial performance, several studies propose alternative approaches for variability analysis. Instead of solely considering the magnitude of variability, they examined the temporal structure of variability (Barbado Murillo et al., 2017; Friedman et al., 2022). These measures have been associated with sensitivity to error or the ability to adjust during movement.

Analysis of the variability structure

The temporal structure of variability was previously related to self-organized and adaptive behaviours that may be related to learning and adaptive ability (Lipsitz, 2002; Lipsitz and Goldberger, 1992; Stergiou et al., 2004; Stergiou and Decker, 2011). This relationship between variability structure and adaptive ability has been observed in various domains of human behaviour such as in saccadic movement tasks (Wong and Shelhamer, 2014) and vestibulo-ocular tasks (Beaton et al., 2017). In the field of motor learning, Barbado Murillo et al. (2017) argued that the temporal structure of variability (measured through DFA) could be related to adjustment mechanisms in movement or sensitivity to error.

Wu et al. (2014) and Barbado Murillo et al. (2017) reported a positive relationship between variability structure and learning ability in error-based tasks. Wu et al. (2014) used a Principal Component Analysis (PCA) to analyse variability structure, while Barbado Murillo et al. (2017) used DFA. However, Ducharme et al. (2018) and Caballero et al. (2021) did not find this relationship using fractal scale analysis. It should be noted that the studies by Ducharme et al. (2018) and Caballero et al. (2021) were conducted on reward-based tasks in which exploratory behaviours for reward-based tasks seem to be more related to the amount of variability. In fact, Caballero et al. (2021) found a relationship between the amount of variability and learning ability.

Other studies included in this review analysed the structure of variability but did not conduct a correlation analysis between the structure of initial variability and adaptive or learning ability (Van der Vliet et al., 2018; Haar et al., 2020; Ranganathan et al., 2021). It remains uncertain whether they did not mention it because they did not find a correlation or because it was not the primary objective of their studies. It is important to note that analysing variability structure using non-linear tools such as fractal analysis requires very long variance data sets to produce reliable results (Warlop et al., 2017). If the data sets analysed in some studies are insufficient, it becomes challenging to obtain reliable results. However, it is not always possible to ascertain the amount of data analysed in a given study, as this information is not always provided.

Task space variability and null-space variability

Another aspect that should be considered in the relationship between initial variability and adaptive and learning ability is the variability space in which it is examined. Null-space variability represents combinations of joint angles that do not impact the task outcome, whereas task-space variability represents combinations of joint angles that may affect the task outcome (Scholz and Schöner, 1999; Müller and Sternad, 2004).

Most of the studies in this review analysed task space variability or did not make a distinction between variability spaces. Only four studies made this distinction regarding adaptive or learning ability. Ranganathan et al. (2021) found no relationship between initial variability and the ability to learn or adapt, while Singh et al. (2016), Dal'Bello and Izawa (2021) and Caballero et al. (2021) found a relationship. Singh et al. (2016) and Dal'Bello and Izawa (2021) found that initial null space variability was related to learning ability. Singh et al. (2016) indicated that "null-space variability not only reflects the biomechanical characteristics of the arm but may reflect active control" and therefore active exploration in null-space may be essential for motor learning as it minimizes task-space variability, ensuring optimal motor performance. Dal'Bello and Izawa (2021) found a relationship between learning ability with variability in the null space and with variability in the task space, in this case the strength of the correlation was stronger than in the null space. The authors indicated that variability in both spaces serves as active exploration. It's noteworthy that Singh et al. (2016) and Dal'Bello and Izawa (2021) measured variability in error-based tasks, which may introduce initial performance bias and explain why Dal'Bello and Izawa (2021) found relationships in both spaces. On the other hand, Caballero et al. (2021), in a reward-based tasks, only found a relationship between initial task space variability and learning ability. They suggested that in reward-based tasks, participants with higher task space variability would be exploring among the range of successful motor combinations to achieve the task goal.

Moreover, the procedure by which researchers decide what constitutes the variability of the task space and what constitutes the variability of the null space is not yet agreed upon. In fact, they use different procedures to determine this variability. With the limited information available from studies that differentiate between both variability spaces, we cannot draw clear conclusions about the relevance of differentiating between task-space variability and null-space variability. Further studies are needed to ascertain the usefulness of this procedure for analysing motor variability.

Adaptation and learning task

One of the key aspects of the study is the classification of previous studies into tasks involving adaptive or learning processes, based on the descriptions provided by the authors of these studies. This classification allows us to analyse whether variability might differentially influence adaptive or learning ability, as the two processes have different characteristics.

However, on closer examination of some of these studies, we found that certain experiments categorised by their authors as learning processes might represent adaptive processes. A relevant case is the study by He et al. (2016), which discusses learning processes and concludes that there is no significant relationship between initial variability and learning. However, we believe that the tasks described in this study involve motor adaptation, as participants adjusted their movements in response to visual perturbations, which implies an adjustment of the motor system to changes in the environment (e.g. visuomotor rotation). This adaptation is characteristic of an adaptive process, suggesting that the study could be reconsidered in this category.

Another relevant example is the study by Selinger et al. (2019), which mentions both adaptive and learning processes. While we have classified their experiment as an adaptive process due to the nature of the task, it is important to note that the motor optimisation process they describe can also be considered a form of reward-based learning. This ambiguity highlights the difficulty of making a strict categorisation between adaptation and learning in certain motor tasks.

Despite these considerations, our results show no difference in the relationship between learning or adaptive ability and initial variability. This suggests that variability appears to have a common effect on both types of processes, whether adapting to a familiar task or learning a new one. This finding highlights the overarching role of variability in motor performance.

However, we recognise that more research is needed to adequately address this conceptual distinction between adaptation and learning. Some studies may describe as learning what are adaptive processes, and vice versa, which could influence conclusions about the role of variability in each case. Future research that explores these categories in more detail may provide a more accurate understanding of the interplay between variability, learning and adaptation.

Final remarks, conclusion and limitations

This review compiles the most relevant factors concerning the relationship between participants' initial motor variability and learning and adaptive ability as found in the scientific literature. We consider there may be some relationship between initial variability and learning and adaptive ability according to some of the studies in this review, although there are divergences in the factors considered between the relationship between initial variability and learning and adaptive ability. However, we have observed that this relationship may depend on the type of learning/adaptation used in the task and the method used to measure variability. In reward-based tasks, individuals who exhibit higher amount of initial variability have more exploratory behaviour whereby they explore a larger number of possible solutions to adapt to the task. It is our contention that in reward learning/adaptation tasks, a greater degree of variability is conducive to adaptability and learning processes. In error learning/adaptation tasks, we also see that most studies have identified a positive correlation between participants who initially display greater variability and those who demonstrate enhanced capabilities for adaptation and learning. However, in error learning/adaptation tasks, higher amount of initial variability may indicate worse initial performance, therefore, there may sometimes be an initial performance bias, as those who are more variable are more likely to have more room for improvement. Because of this initial performance bias, some of the reviewed studies have proposed alternative measurement procedures for error learning/adaptation tasks, such as variability temporal structure analysis. It was previously suggested that the structure of variability is related to the processes of self-organization and sensitivity to error informing variation and adaptation in a temporal space (Barbado Murillo et al., 2017; Sternad, 2018; Harbourne and Stergiou, 2009). Therefore, we believe that in order to eliminate this bias, analysing the structure of initial variability in error learning/adaptation tasks can also provide insight into the relationship between variability and learning and adaptive ability. The space or dimension of variability in relation to adaptive or learning ability has also emerged as a topic in the studies reviewed here. However, the limited number of studies that make such a differentiation and the different procedures used to analyse the space of variability make it difficult to draw clear conclusions in this regard. Nevertheless, we believe that considering variability space could hold promise for studying initial variability and its relationship to adaptive or learning capacity.

Among the limitations of this review, we found that, despite having excluded articles where variability was considered as a measure of performance, certain learning/adaptation-by-error articles included in this review still showed relationships between variability and the initial performance of the participants. The diversity of protocols used in the experiments included in this review is a limitation for generalizing conclusions. Because we included studies with very different tasks (walking tasks, throwing tasks, joystick tasks, etc.). This leaves open the possibility that each type of task could be a variable that influences the finding of the relationship we are looking for. However, we believe that if we only added studies with the same type of task, we would hardly have a sufficient number of studies to draw clearer conclusions or trends. Finally, although we collected the factors that we consider mediating the relationship between initial variability and learning and adaptive ability, there may be other influencing factors that we have not extensively studied. One such factor may be task specificity, as some authors have suggested that tasks in which initial variability is analysed and tasks in the practice process should have several similarities (He et al., 2016). Assuming that the novel task to be adapted to is different or has completely different solutions, the reference task may result in finding no relationship between initial variability and motor learning (Ranganathan et al., 2021).

In conclusion, based on the studies reviewed, we believe that there may be some relationship between the initial motor variability of individuals and their ability to learn or adapt. However, this relationship may depend on the measurement procedure and the type of learning/adaptation task utilized. Therefore, further studies employing standardized protocols are necessary to establish conclusions regarding the conditions under which greater initial variability predicts adaptative and learning ability. Identifying the cases in which this relationship occurs would enable the application of more individualized training procedures.

CRediT authorship contribution statement

Miguel López-Fernández: Writing – original draft, Methodology, Funding acquisition. **Rafael Sabido:** Writing – review & editing, Validation, Methodology. **Carla Caballero:** Visualization, Validation. **Francisco J. Moreno:** Writing – review & editing, Supervision, Project administration, Methodology.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroscience.2024.10.052.

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