

LEARNING THROUGH JOINT ACTION:
The role of haptic information and movement
variability

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Declaration of Authorship

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or which have been accepted for the award of any other degree or diploma at Central European University or any other educational institution, except where due acknowledgment is made in the form of bibliographical reference.

The present thesis includes work that appears in the following articles:

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A handwritten signature in black ink, appearing to read 'Simily Sabu', is written over a horizontal line.

Simily Sabu

Abstract

Learning motor skills while physically interacting with other people is a fundamental aspect of our social life. Joint action learning allows us to master a broad range of activities, from manipulating objects together, to performing arts or sports, to assisted motor rehabilitations, to physical interactions with artificial agents. Haptic interactions are different from interaction using other sensory channels when coordinating actions with a partner. The haptic channel transmits rich kinematic information regarding the partner's movements, from which additional task information could be retrieved, while establishing physical dependency between co-actors' movements. This poses an interesting case for the study of joint motor learning: on the one hand, action exploration represents a core mechanism at the basis of individual motor learning, as it involves exploring action possibilities for a motor outcome, until the actor identifies the optimal solution. On the other hand, in joint action performance, actors produce consistent movements by reducing their variability to facilitate action prediction and to support coordination. Therefore, when learning a motor task through haptic coupling with a partner, at least two contrasting mechanisms – action exploration and reduction of movement variability - could be at play.

In this dissertation I investigate how people *learn* motor tasks while haptically interacting with another individual through a series of empirical studies. I hypothesize that dyadic haptic interaction should benefit learning in individuals, as the kinematic cues regarding the task and the variability from the partner will support broader action exploration and thus, lead to internal models that reflect a higher degree of generalization. Such internal models would subsequently foster skill generalization, as they encompass multiple movement solutions that could be attuned for future performance.

To test these hypotheses, I developed a novel joint learning task in which a participant and a confederate learned to produce aiming movements together, while being haptically connected through an elastic band. The haptic coupling between the actors implied a translation of partner's movement variability into a force perturbation. I measured the actors' spatial accuracy and the temporal asynchrony between the partners as a measure of their individual learning and their joint performance, respectively. In my first study, actors were trained to produce sequential movements while the confederate exerted either a high or low variability on the participants movements. I tested how partner's variability, delivered at different degrees of predictability, influenced learning in individuals during dyadic haptic interaction. The results indicate that individuals involved in a joint action selectively rely on either their own or their partner's variability (or both) for achieving successful individual and joint action performance, depending on the predictability of the partner's movements. My second study explored how skills acquired through haptic interaction with a partner are transferred to novel task contexts. Participants learned to produce discrete aiming movements with a highly or less variable partner, and they were then tested on their ability to generalize to sequential movements, while encountering varying range of force perturbations. Depending on the difficulty of the novel task, actors modulated the spatiotemporal features of their movements, to successfully transfer the learned skill. Partner's variability led to a performance benefit when the task was easy.

Taken together, the results indicate that individuals exploit the kinematic cues transmitted through haptic interaction to achieve learning and transfer during joint action. For some task parameters, a partner's variability may positively influence performance in individuals. In the concluding chapter of this thesis, I discuss the implications of the present findings for theories of joint action learning and their applications in social motor interactions.

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Chapter 1. Introduction

Humans show an impeccable ability to coordinate their actions in time and space to achieve a joint outcome, as when dancing together, carrying heavy furniture together, sawing a fallen tree, synchronously rowing a boat in a team, folding a bedsheet together, or assisting a physically challenged person to move. Unlike interactive contexts involving explicit verbal signals, gaze or facial expressions, a common aspect of the above-mentioned joint actions is that agents rely on kinesthetic information regarding the task to successfully achieve the joint outcome, i.e., the most exploited channel of communication is action or movement (Pezzulo et al., 2013, [2019](#)). Joint action coordination not only requires processing one's own actions but also parallelly processing the co-actor's actions and bodily states, to integrate them to form a shared representation of the joint goal (Sebanz & Knoblich, 2009; Sacheli et al., 2013; Clarke et al., 2019, Cardellicchio et al., 2020).

For everyday joint actions, the complexity of action coordination is multifold as agents need to modulate their kinematics to spatiotemporally align with their partners' movements, while also considering the numerous environmental states and variables that might influence their movements as well (Kiverstein & Rietveld, 2021). For instance, let us take the example of two people carrying a large mattress from the ground floor, along the stairs, to the first floor of their apartment. One person is taking the lead to guide the path upstairs, while the other person is supporting the weight of the mattress from below. Ideally, each person carries half the weight of the mattress. However, their roles and the task distribution among the actors will vary along the way as the adaptation demands of the action scenario also change. Thus, to successfully transport the mattress upstairs, the carriers need to constantly adjust their movements to their partner's

movements and to the environment they are acting in. For example, if one person tilts the mattress vertically, the other automatically adjusts the angle of their joints to accommodate the tilt, or if one person loses their grip on the mattress, the other person will receive the cue from sensing an increase in the weight of the mattress they share and will tighten their grip to increase their support on the mattress. While this is about accommodating to the co-actor's kinematics, they also need to accommodate altering forces they receive from the mattress while moving it. Since the two actors' movements and bodily states are not isometric in nature, the mattress will jiggle and produce unpredictable reaction forces as they move up the stairs. The actors will then adjust their point of support, their grip, and the forces they apply to ensure stability. Along with this, the stairs also tightly constrain how the actors move their body. Thus, for a successful joint outcome in this example, the two carriers must constantly adjust their movements in space and time in relation to their own and their partner's kinematics, the object they are acting on and their action space.

1.1 Mechanisms guiding joint action coordination

How do humans achieve efficient joint action coordination? When acting alone, efficient motor control is achieved by generating predictions about unfolding of action events and its sensory consequence with the help of internal models in the motor system, a process referred to as action simulation (Wolpert & Flanagan, 2001; Wolpert, Doya & Kawato, 2003). Action simulation allows one to compute prediction error, which is the discrepancy between the predicted and the actual outcome of a motor command, which in turn aids online and automatic correction of one's movements. However, when engaged in joint action, internal models of one's own action are not sufficient to achieve joint outcomes. Action observation and corresponding reaction to the partner's actions is not a sustainable coordination strategy in dynamic and time-constrained joint action scenarios. Just like individuals cannot rely on sensory information alone to achieve a motor

outcome during individual action, as the sensory delays will significantly slow down the motor responses, individuals engaged in joint action need to implement predictive internal models of social motor interactions (Pesquita, Whitwell, & Enns, 2018, Cardellicchio et al., 2020, Cheng et al., 2022). This implies modelling of the partner's action, but this poses several problems. One problem is that agents do not have direct access to another individual's internal models. So how do people engage in joint actions despite having no access to their partner's models? Even though there have been many approaches adopted to understand the mechanisms underlying joint action (Knoblich, Butterfill & Sebanz, 2011), researchers agree that for a smooth inter-personal coordination, co-actors rely on some form of information sharing (Vesper et al., 2010).

Depending on the amount of information they have about the joint task, the joint goal, and their partner's actions, they might use different mechanisms to achieve the joint outcome. For instance, when there is ample perceptual access to each other's movements, joint action is possible through monitoring and predicting each other's observed actions or relying on an action simulation mechanism based on observing the co-actor's actions (Vesper et al., 2013, 2017). When there is limited perceptual access to each other's movements, individuals rely on mechanisms that can simplify coordination, or inform their partners about their movements, like making one's movement as consistent as possible minimizing variability, so that the partner can easily predict these movements (Vesper et al., 2011, 2013). Another possibility is to exaggerate certain kinematic parameters to inform the partners about aspects of the task that they do not know about (Sacheli et al., 2013; Vesper & Richardson, 2014; Vesper et al., 2016). Regardless of the action scenarios, these joint actions require coordinating with a different individual whose models one does not have direct access to. Thus, one must form representations and predictions of each other's actions and bodily states to make coordination possible.

Hence, just as we adopt predictive mechanisms during individual motor control, multi-joint coordination, or during tool-use, when engaging in joint actions with other individuals, we need to rely on the internal models of action control that are based on one's own and the co-actor's sensorimotor processes. Thus, joint action coordination is essentially guided by processes involving a model of the joint goal, the joint task, mutual monitoring of each other's actions and joint outcomes. Furthermore, actors modulate their movements to establish a communication channel based on the sensory-motor feedback related to their own and their partner's movements (Pezzulo et al., 2019). Action goals and kinematic cues are communicated through these channels (Hilt et al., 2019). This helps actors to form predictions about each other's movements, which in turn facilitate coordination. By adopting coordination smoothers like modulating, one's own movement parameters, agents can provide information to the co-actor or predicting co-actor's movements based on the representation of the joint action outcome and the sensorimotor feedback from the partner's movements (Vesper et al., 2017; Sebanz and Knoblich, 2021).

1.2 Joint action through haptic interaction

To understand the mechanism behind joint action coordination, it is important to realize that different processes of action coordination imply different amounts of information flow between co-actors (Chauvigné et al., 2018). In the above-mentioned examples of joint actions, the main information channel involved is the *haptic channel*, although other sensory channels could also contribute to the joint outcome. Real life joint actions, as in our mattress example or when dancing with a partner or assisting a patient during physical rehabilitation, often involve haptic coupling including interaction forces or other proprioceptive feedback coming from the partner and the object they are handling. All of these mediate the action coordination between partners (Van der Wel et al., 2011; Chackochan & Sanguinetti, 2018).

Haptic connection can be particularly efficient for joint action coordination as individuals entrain better when haptically coupled with each other, compared to other modalities of informational coupling, like visual or auditory (Sofianidis & Hatzitaki, 2015). In dyadic interactions, for example, addition of haptic feedback has been found to improve performance in visuomotor tasks, in comparison to conditions that involved visual feedback alone (Basdogan et al., 2000; Sallnäs & Zhai, 2003; Groten et al., 2012). When individuals were trained to reproduce a complex spatio-temporal trajectory with the guidance of a robotic manipulandum, haptic learning of temporal features of the trajectory was found to be better when there was no vision involved compared to a vision-alone training condition (Feygin et al., 2002). This beneficial role of haptic connections could arise because the tight physical coupling between the actors contributes to a higher coupling strength, which provides more reliable information about the co-actor's movements (Chackochan & Sanguineti, 2019). The physics of haptic interaction, like changes in force for instance, is perceived faster by our nervous system compared to perceiving spatial error through visual feedback. In other words, the sensory delay is much smaller when receiving haptic feedback compared to other sensory feedbacks (Sawers & Ting, 2014). Also, haptic information is found to be processed automatically by our nervous system even under conditions of lower attentional engagement (Hanson et al., 2009). Thus, physical coupling in a dyadic interaction promotes prediction by providing room for faster response times, in contrast to other modalities. In this way it could support coordination (Harrison & Richardson, 2009; Van der Wel et al., 2011).

1.3 Motor variability, joint action, and haptic interaction

Given that haptic connections seem to be special compared to other sensory connections present in joint action, one could assume that the coordination strategies dyads adopt in haptic interactions might differ compared to other forms of dyadic interaction. When engaged in joint

action without haptic coupling, one strategy actors adopt to facilitate coordination is reducing the variability of their movements to make oneself more predictable to their co-actor (Vesper et al., 2011, 2013; Pezzulo, et al., 2013; Sacheli et al., 2013; Hilt et al., 2019, Cardellicchio et al., 2020). Previous studies have shown that, when individuals had limited perceptual access to their co-actor's movements, their responses were overall faster and less variable in the joint condition than in the individual condition (Vesper et al., 2011). Similar results were found in a continuous target tracking task, where participants were found to strategically reduce the temporal variability of their movement to increase their predictability for the co-actor (Vesper et al., 2013).

However, when it comes to joint actions involving haptic interaction, the mechanical coupling closely ties the co-actors' motor planning and execution: a physical coupling between two actors means that one person's movement will have a direct physical impact on the other person's movement. While this coupling enriches the information channel with more knowledge about a partner's movements, haptic interaction also transmits motor execution errors back and forth between the two actors. Such errors are experienced as force perturbations by the actors. Of course, the *range of forces* the actors would experience will depend on the mechanics of the interaction, i.e., whether the interaction medium or the object they are jointly interacting with are hard or soft (Takagi et al., 2018). The higher the coupling strength, the stronger the perturbation will be. The slightest movement from one actor will certainly displace or perturb the other actor's movements. But the rigidity of the interaction medium may limit the variety of ways one could experience this perturbation. This is so because a tight coupling with another person constrains the degree of freedom of one's own movement, thus restraining the variability of the forces one may experience. For instance, when carrying a wooden table together, a dyad will experience a much stiffer interaction as they are tightly coupled, but their movements are constrained by the hard

mechanics of the table. Hence, they will experience a very small range of perturbations. In the mattress example, the interaction mechanics are softer as the mattress is flexible. Such a weaker coupling strength would displace the actors' movements less. This would allow the actors to experience a broader range of perturbations, as their movements are less constrained by the other actor. Regardless, the motor variability, actors must deal with during a haptic interaction is higher compared to an interaction mediated by any other modality of informational channeling, as they must regulate not just their own motor variability but also the partner's variability translated as the force perturbation (Melendez-Calderon et al., 2015). Nevertheless, we see that humans very skillfully engage in achieving joint outcomes through physical interactions daily and they even benefit from haptic interaction compared to when acting alone (Reed et al., 2006; Van der Wel et al., 2011; Ganesh et al., 2014). So how does variability influence the joint outcome in joint action contexts involving haptic interactions?

Motor variability (or error) was traditionally understood as a noise or a redundant feature of the motor system that needs to be reduced for achieving optimal movement. The 'error' in the movements while performing an action mostly comes from muscle contractions required to successfully run a motor program (Sánchez et al., 2017). Since there are numerous ways of coordinating the muscles required for a movement and given the abundance of 'degrees-of-freedom' involved in the process, skill learning was thought of as achieving a mastery over the redundancies of these degrees-of-freedom (Bernstein, 1967).

However, recent advances in human motor control, especially models involving reinforcement learning, replaced this traditional view with the proposal that variability may constitute a central component of motor learning, as it facilitates exploration of one's space of motor commands (Thoroughman & Shadmeh, 2000; Ziegler et al., 2010; Herzfeld & Shadmehr,

2014; Wu et al., 2014; Sawers & Ting, 2014; Sánchez et al., 2017). Through trial-and-error, this exploration can guide the motor system to learn new motor plans and control-policies that can lead to an optimal performance (Tumer & Brainard, 2007; Shadmehr et al., 2016).

Wu and colleagues (2014) showed that the variability in a person's movement can predict the rate at which they learn a motor task; the higher the variability in one's movement in the initial phase of learning, the faster the learning was. Another study showed that introducing variability to an already consolidated skill could further strengthen the motor skill (Wymbs et al., 2016). It has also been demonstrated that when variability or error in movements is reduced, our motor system recruits less muscle synergies to cut down the performance cost in a dynamic task, a mechanism referred to as "slacking" (Reinkensmeyer et al., 2004, 2009, Emken et al., 2007). This eventually leads to reduced exploration of action possibilities, thus slowing down learning and long-term retention of a skill.

Even though variability has a beneficial role in individual motor control, when individuals are involved in social motor interactions, reducing variability has been shown to be beneficial for achieving joint action coordination, as discussed earlier. However, when it comes to joint action involving haptic coupling, variability may play a different role. In fact, in dyadic interactions involving physical coupling variability or kinesthetic noise is inevitable. As individual movements can constantly be perturbed by the variability coming from the partner's movements, reducing one's own variability may not be the best way to achieve joint action coordination.

In the field of joint action, not many studies have addressed how variability is regulated in human-human haptic interactions. There is some evidence of the beneficial effects of motor variability coming from the field of human-robot interactions. In robotic assisted therapies, it has been observed that amplifying movement errors while haptically guiding patients allowed them to

explore new movement strategies (Sawers & Ting, 2014). For example, Patton and colleagues provided preliminary empirical evidence that error amplification, with the help of a robotic device during a reaching task, may help correct chronic trajectory disturbances in patients following stroke (Patton et al., 2001). Emken and colleagues showed that it is possible to aid individuals in adapting to a novel dynamic environment, i.e., alter the rate at which the internal models of motor control are built, by amplifying the dynamics of the environment (Emken et al., 2005). Their results suggest that motor learning can be accelerated by exploiting error-based learning. The key observation of their study is that motor errors are modelled by our system by the formation of internal models based on prediction error and sensorimotor feedback. Hence, augmenting movement error could induce the nervous system to compensate for the additional error by making a larger correction, and eventually leading to a faster adaptation.

Error augmentation paradigms have been widely used in the design of rehabilitation robots in recent years (Liu et al., 2018). Through a systematic review comparing error-augmentation and error-reduction strategies, Liu and colleagues show that amplifying errors in the movements in post-stroke rehabilitation of trajectory control is far more effective than training by constraining movements or reducing errors. While it is relevant to understand how variability is regulated during human-robotic interactions, it is equally relevant to have insights about the influence of a partner's motor variability during a human-human dyadic interaction as these can have tremendous application in rehabilitation programs aiding patients to regain their lost motor functions, in sports training, in surgical training etc. It will also help us to better understand the coordination mechanisms in joint actions involving haptic interactions.

1.4 Joint motor learning

One important process that has not received a lot of attention in previous research is *learning* of a motor task together with a partner through haptic coupling. Joint performance and joint learning, just like in individual action, are two distinguishable processes in joint action: while joint motor performance can be considered as the ability to perform a motor task jointly with a partner, joint motor learning involves *acquiring and retaining* the ability to perform the task as a result of training with a partner. In general, learning involves improving performance (Wolpert et al., 2001). Performance does not necessarily have to entail permanent changes in behaviour.

Whereas the mechanisms underlying *joint action performance* are well documented, the influence of shared practice or training on subsequent performances, i.e., *joint action learning*, has not been widely studied in previous research (Milanese, Iani, & Rubichi, 2010). Most of the existing literature addressing joint action learning, focuses on learning through observation, imitation, motor imagery or social interdependence in which the actions of one person are dependent on the other (Hodges & Franks, 2002; Schaal, et al., 2003; Hodges et al., 2007; Lungu & Debas, 2013; Andrieux & Proteau, 2014; Mizuguchi & Kanosue, 2017; McEllin et al., 2018; Karlinsky & Hodges, 2018). For instance, it has been demonstrated that action observation of a human model performing a task prior to the execution of that task yields better motor acquisition, relative to solo practice (Ashford, Bennett, & Davids, 2006). In another study, performance benefit was observed in piano novices when they jointly learned melodies together with a partner and later coordinated towards the shared joint goal compared to their individual action goal (Loehr and Vesper, 2016). Researchers have also investigated transfer effects from individual to joint task performance and vice versa using the social Simon task (Milanese, Iani, & Rubichi, 2010).

Given the multitude of daily life events involving haptic motor learning with another person, investigating this kind of joint learning is important because our ability to perform novel motor tasks depends on the exploitation of our knowledge acquired through learning. Very often, this knowledge acquisition is facilitated through haptic interactions. For example, imagine a parent assisting a child to walk, a therapist providing motor guidance to a patient to re-learn a lost motor skill or a rowing coach training a novice rower by physically interacting with the trainee through the paddle etc. Existing studies that investigated how humans learn novel tasks while physically interacting with others provided conflicting results.

For example, in Ganesh et al., 2014, dyads performed the same tracking movements with the help of two robotic manipulanda, by moving a cursor (representing their hand position) to a target position on their respective screens. Unknown to the actors, they were connected through a virtual elastic coupling, which produced compliant interactive forces, as though they were connected by a loose spring. Their tracking performance was tested in a solo condition, post-joint training. Their results showed that participants who learned the tracking task via the haptic coupling exhibited better performance than the control groups who carried out the task alone. They also showed that the initial individual motor learning of the interacting partners was faster. These and results from a follow up study involving a rigid coupling between the actors indicate that the learning outcome through haptic interaction depends on the coupling strength, i.e., a ‘softer’ coupling fosters better learning performance compared to a rigid coupling (Takagi, Beekers & Burdet, 2016). The earlier obtained evidence also indicates that the skill level of actors contributes to learning during haptic interaction; pairs consisting of two novices exhibit better or equal learning outcome compared to pairs consisting of an expert and novice (Ganesh et al., 2014; Mireles et al., 2017; Kager et al., 2019).

However, other studies involving more complex tasks indicate that haptic coupling may not always support learning (Batson et al., 2020). Beckers et al., 2018 investigated skill transfer to novel force dynamics of a task after intermittently training subjects with a partner through haptic coupling. They found that the haptic interaction did not lead to improved motor performance or an increase in individual learning rate. Using a balancing task, it was shown that haptic interaction with an expert may interfere with improving performance, indicating that continuous haptic guidance during interactive teaching can be detrimental to learning (Mireles et al., 2017).

At present, it is not entirely clear which factors increase the benefits of haptic interaction during joint-motor learning. It is also noteworthy that most of the previous studies involved tight constraints on the degrees-of-freedom of movements involved. Real-life scenarios like changing position in space frequently involve the modulation of several degrees-of-freedom of the action, from the rotational movements at the joints or ankles and the translational movements across different axes. Thus, the tasks used to study learning under conditions of haptic coupling do not provide a complete picture of how individuals exploit haptic interactions to learn new motor skills, when there is more freedom of movement involved. While these kinds of movements are very hard to recreate in a controlled laboratory setting, it is important to understand whether learning strategies differ according to the different kinematic requirements of a task.

An important distinction in motor learning that is important for the present purpose is between skill acquisition and skill generalization. Whereas acquisition and retention of a skill is where learning begins, the process of learning can be extrapolated to the individual's ability to generalize this learned skill to similar, yet not identical, novel scenarios. Skill acquisition and generalization are distinct processes that have been studied separately in motor control literature. Skill acquisition can be defined as the processes associated with practice-dependent reduction of

motor errors leading to relatively permanent changes in the motor behavior (Krakauer, 2006; Seidler, 2010). Acquisition of a motor skill advances through different time scales (Little & Sommer, 2013; Kim et al., 2015; Mireles et al., 2017). The initial phase of skill acquisition involves forming a rough internal model of the task dynamics through trial-and-error mechanisms, during which individuals explore their action possibilities with the help of their somatosensory inputs (Doyon & Benali, 2005; Dayan & Cohen, 2011; Bernardi et al., 2015). This is then followed by an intermediate motor consolidation stage, after which the internal models are updated and refined through practice. In this later stage, individuals exploit the action possibilities that yields the best outcome possible.

While this completes the skill acquisition process, one can generalize the learned skill to novel task contexts, by extrapolating and updating the internal models learned for one type of movement to perform another movement. Evidence shows that the brain regions involved in the early stages of learning are not re-engaged during generalization as the memory of the early-learning decays quickly (Seidler, 2010). Instead, generalization was found to be more associated with brain regions characterizing the later stage of learning. A better performance or skill acquisition during training, does not necessarily entail a better performance during *generalization* of the learned skill to a novel action context with related task characteristics. This is so because, the mechanisms involved in retention of a repeated skill are different from the ones in adapting skills to novel contexts, as the latter would involve recruiting new muscle/joint synergies or generating novel motor plans to execute the required action.

Even though skill acquisition and skill generalization are distinct processes, acquisition can influence generalization; if the acquisition of a skill involved exploring multiple movement solutions which could be utilized when generalizing to a new context, the acquisition can be said

to have a beneficial role and lead to a transfer of the learned skill (Krakauer et al., 2006). In contrast, if the learned skill limits the performance in the novel context, it can lead to a performance decrement, referred to as interference.

As in the case of joint motor learning through haptic interaction, not many studies have explored skill generalization in such joint action contexts. Previous studies have investigated how a motor skill learned through a dyadic interaction can influence generalization to bimanual solo conditions (Mireles et al., 2017). Their results indicate that training with a partner with a comparable skill level leads to better performance during generalization. And that a positive transfer of skill is possible after being trained with an expert only if the subjects had some prior knowledge about the task dynamic that was gained in the absence of any guidance from the expert partner

A further important factor to consider for the present project is the skill level of the interacting partners. There is converging evidence showing that haptically interacting with individuals of the same skill level are more beneficial for learning or transfer compared to interacting with an expert (Ganesh et al., 2014; Mireles et al., 2017; Kager et al., 2019; Batson et al., 2020). One potential explanation for why interacting with peers fosters skill acquisition or generalization is that the sensorimotor contingencies experienced by the actors in naïve-expert interactions might not truly reflect the actual interaction dynamic of the task (Mireles et al., 2017). Mireles and colleagues found that for naïve subjects, transfer to bimanual condition after haptic training with a naïve partner was better compared to an expert partner. The authors posit that this is so because an expert actor would be skilled to compensate, at least partially, for any destabilizing forces involved in the task, such as unexpected perturbations during the interactive training. One compensation strategy would be increasing the stiffness of their movements, thus making the

actions more rigid. But this would mean that a naïve subject, training with an expert, would generate an internal model by incorporating the partner's actions, which is not quite reflective of the actual task dynamics. This would detrimentally affect the performance during the transfer to a bimanual condition, where the task is performed alone without the expert partner. However, when two novices are interacting, as neither of the actors dominates the interactive dynamic, both individuals experience similar sensorimotor contingencies, which allows them to transfer the skills to the bimanual context.

It is noteworthy that this discussion points to the relevance of the role of variability, as mentioned before, in joint motor learning. The active reduction of variability by the experts is a kinematic strategy that evolves on the fly during the haptic interaction. If reducing variability interfered with the learning or generalization process, will a partner who actively induces variability promote learning? Although it should be noted that random variability, that is the variability that does not affect the successful achievement of the required movement, does not contribute to learning. Rather, it is *task-relevant variability*, which is the variability that can influence the kinematic parameters relevant to the successful task achievement (Furuki & Takiyama, 2019), that is what is found to positively influence learning in individuals. During haptic interaction, haptic coupling randomly acting as an additional source of variability, do not promote learning (Batson et al., 2020). But if the partner can induce task-relevant variability that can aid the individuals to explore their action space, to learn multiple movements strategies for the same action outcome, can it promote learning and transfer? It is also an open question whether variability plays a differential role in skill acquisition and generalization, as variability has often been found to be detrimental for immediate performances but beneficial for long term retention and generalization (Shea, Kohl & Indermill, 1990; Shea & Kohl, 1991; Krakauer, 2006).

To address the questions raised above, in my thesis, I aimed at exploring how haptic interaction mediates joint motor learning, namely skill acquisition and skill generalization. A further aim is to investigate an action scenario involving 3D movements which allows actors to move with multiple degrees of freedom while still being haptically coupled with their partners. I also investigated whether the amount of movement variability a partner produces during haptic interaction influence skill acquisition and generalization. In all studies, I analyzed individual and joint learning parameters to characterize motor learning during this interactive dynamic task. In the following I will provide a concise review of the two studies that were performed.

1.5 Research preview

The work presented in this thesis aims to understand how individuals engage in joint action to learn a novel task while physically interacting with each other and how do they stabilize their spatiotemporal performances to optimize joint learning. Specifically, I will present two empirical studies that analyses how individuals acquire new skills while being haptically coupled with a partner (Chapter 2) and how they transfer the learned skills to novel task contexts (Chapter 3). Both studies also explore how the interactive partner's motor variability influence skill acquisition and generalization. The central questions of the thesis follow below.

In Study 1 (Chapter 2), I investigated how individuals achieve skill acquisition together with a partner while physically interacting with them. Motor learning studies demonstrate that an individual's natural motor variability predicts the rate at which she learns a motor task, and higher variability fosters learning by supporting the exploration of a wider space of motor parameters. Here, I explore how individuals' variability affect learning in a joint motor task: to do so, I designed a novel sequence learning task in which participants learned to jointly perform a sequence

of movements with a confederate who was either highly variable or less variable in her movements. The actors were haptically coupled through an elastic band, which mediated the translation of partner's movement variability into a force perturbation.

I tested how the variability and predictability of force perturbations coming from a partner foster or hamper individual and joint performance. Variability was manipulated by altering the range of the magnitude of forces produced by the partner (high and low force range) and predictability was manipulated by altering the structure of the variability, meaning the order in which the low or high range of forces were delivered (completely predictable, partially predictable, or completely unpredictable). In experiment 1, the confederate produced a variable force perturbation that occurred in an unpredictable order. In experiment 2, the confederate produced a variable force perturbation in a predictable order. In experiment 3, the confederate produced a variable force perturbation in which the magnitude of force delivered was predictable whereas the direction of the force was unpredictable. I analyzed individual performance, measured as movement accuracy and joint performance, measured as interpersonal asynchrony¹.

In Study 2 (Chapter 3), I investigated how individuals generalize an acquired skill to novel joint action contexts. Addressing potential benefits of haptic interaction in joint action, I investigated how the internal model learned during joint learning is generalized to novel joint action contexts. Furthermore, I examined whether the spatial and temporal aspect of the movements are equally generalized or whether individuals use certain strategies to ensure an

¹ This study has been published. The published and submitted Supplementary Materials accompanying these studies are presented right after the main text of Chapter 2, to aid understanding of the additional analyses conducted.

efficient joint outcome during the generalization, and whether partners' motor variability exert an influence on such generalization strategies.

Specifically, I looked at how skills are generalized one from action type to another, namely discrete unit actions to sequential actions and how the various kinematic features of the movements learned during training are extrapolated to novel characteristics of the task. To address these questions, a joint task, similar to Study 1 was developed. Participants learned to perform aiming actions while being haptically coupled with a partner. The training session involved performing aiming movements in isolation, so that the training was conducted on separate action units. The haptic interaction between the actors, allowed us to train and test participants in different interaction forces. Across 4 experiments, I investigated the influence of partner's variability on the generalization. In Experiment 1, I explored how motor skills acquired through haptic interaction with a partner are generalized to novel action types (discrete to sequential movements) and novel movement characteristics (interaction forces), while the partner is producing a high variability on to the participant's movements. In Experiment 2, I addressed the same question, but the partner's movements influencing the participants movements were less variable. Experiment 3 and 4 were conducted as control studies for Experiment 1 and 2 respectively, to account for potential test-order effects observed in the results. I analyzed the spatial and temporal performance, to investigate how these kinematic measures are affected during generalization.

Finally, after having presented the empirical studies, I will provide a summary of the findings in Chapter 4 and discuss the broader theoretical implications and potential contributions of my research to the field of joint action and motor control. I will also discuss possible applications and open questions that my studies raise for future research.

Chapter 2. Skill acquisition in joint action: How does a partner's motor variability affect learning?

2. 1 Introduction

We engage in interactions with other people very often in our daily life. One type of such interactions consists of one person learning a motor skill with another person while their bodies are coupled through some means. Examples include learning to dance tango with a partner, a parent holding a child to help her walk, learning group sports like crew rowing, or a therapist moving a patient during motor rehabilitation training. Such inter-personal coupling implies that each actor's movement will have a direct impact on the partner's movements (Takagi et al., 2018).

Generally, in such joint actions, individuals adopt various coordination strategies to minimize error and improve joint performance. Enhancing predictability of one's own movement is one such coordination strategy. Vesper and colleagues demonstrated that when minimal perceptual information is available to coordinate the timing of discrete action outcomes, individuals make themselves more predictable to the co-actor by reducing the temporal variability of their actions (Vesper et al., 2011). Similar results were obtained for more complex temporally extended joint actions (Vesper et al., 2013).

Evidence for strategical variability reduction could be observed across a variety of joint action tasks (Schmidt et al., 1990; Schmidt & Richardson, 2008; Sacheli et al., 2013; Masumoto & Inui, 2012, 2015; Vesper et al., 2016). Studies involving joint grasping have shown that when a dyadic interaction involves a leader-follower dynamic between the actors, the leader tends to reduce the variability of her movements as a signaling strategy to enhance predictability of her movements for the follower (Sacheli et al., 2013). During joint force-production tasks, it was

observed that participants reduce the variability of their movement duration and force production, compared to when they act alone (Masumoto & Inui, 2012, 2015). A study by Vesper and colleagues (Vesper et al., 2016) showed that when dyads performed a movement task that required them to synchronously arrive at a target from separate starting locations, participants held their movement duration constant to facilitate coordination in cases when there was only auditory feedback available about a partner's movements. In sum, evidence from a wide range of joint action studies suggests that in coordination contexts variability in movements is detrimental for joint performances.

In contrast to the joint action literature, it was recently claimed that variability can facilitate individual motor learning. Motor variability need not necessarily be a noise in the motor system which should be minimized to achieve movement perfection, rather it could be exploited by individuals, thus, becoming a key factor enabling and facilitating motor learning and skill acquisition (Wu et al., 2014, Schmidt & Ding, 2014; Renart & Machens, 2014; Gibb et al., 2016; Barbado et al., 2017; Pacheco & Newell, 2018; Tumer & Brainard, 2007; Dhawale et al., 2017). In support of this claim Wu et al., (2014), showed that the temporal structure of motor variability naturally produced by individuals at an early phase of learning can predict the rate at which they will learn a motor task. It was shown that the rate of learning was higher in individuals who exhibited higher task-relevant variability during the early phase of learning. The study reveals an adaptive function of motor variability, as it supports a wider action exploration of motor commands: it may provide individuals with a repertoire of actions from which they can select to achieve a successful outcome in current and future movements. This adaptive role of variability has been observed in different types of learning regimes, such as reward-based learning and error-based learning (Wu et al., 2014; Barbado et al., 2017).

However, it needs to be noted that if variability of the motor outcome is random, it will not benefit learning, especially in types of learning that requires reduction of variability for achieving movement perfection. It has been proposed that even though variability can enhance action exploration in certain types of learning, a higher magnitude of variability may adversely affect learning by leading to poor retention of learned solutions (Ranganathan and Newell, 2013; Cardis et al., 2017). Also, the learning will be adversely affected if the mechanism involved is use-dependent, i.e., if the learning requires one to produce subsequent movements similar to the previous ones or if it requires coordination pattern stability, as practicing unstable movement patterns, can lead to poor learning. Similarly, Barbado and colleagues (2014) showed that the magnitude of variability in error-based learning only negatively influences the learning rate, while the structure of individuals' variability or the systematic variation in their movements enhanced their ability to detect motor error, which ultimately led to faster learning. Thus, it appears that it is the pattern of unfolding of variability, i.e., the *structure of variability*, that determines how individuals learn to refine their motor output over time, rather than the magnitude of variability itself.

The improved rate of learning in the presence of a structured high motor variability could be explained by how motor events unfold during an action exploration phase. During action exploration, individuals vary their motor parameters in search of action solutions that may yield the best outcome. This aids wider sampling of action possibilities that could be exploited in future performance of such actions. There is evidence suggesting that the nervous system actively produces variability in motor output as a means of searching for actions that ensure greater success during motor learning (Renart & Machens, 2014; Pekny et al., 2015). Exposure to variable motor parameters in a motor learning task would allow one to perfect a more flexible internal model of

the task, which in turn may allow one to generalize or adapt the learned skill to varied task demands (Krakauer, 2006). Thus, action exploration may lead to the generation of a flexible internal model that accommodate a wider range of movement solutions.

Taken together, previous research indicates that variability plays differential roles when performing joint and individual actions: when performing joint actions, reducing the variability of one's movements seems to optimize the joint performance; in individual motor learning, high variability seems to be beneficial for learning, at least under some conditions. The present study asked whether higher variability may be beneficial during *joint motor learning* where an individual learns to perform a motor task together with a partner. This would be expected especially when a joint action involves tight physical interaction between two partners where one partner's movements directly affect the other partner's movements, potentially perturbing the other's movement trajectory. Since the systematic variation or the structure of variability is a significant factor determining the functional role of variability in learning, and since predictability of partner's movements are crucial for successful joint actions, the partner's variability was delivered at different degrees of predictability or structure. It is not known whether in this type of joint action, actors will reduce the variability of their movements to maximize the efficiency of joint action or whether they will exploit the variability of their partner's movement to improve their own learning performance or both.

Present Study

In the present study, we aimed to investigate whether individuals can utilize their partner's variability for motor learning when repeatedly performing a motor task together. Specifically, we investigated whether individuals could benefit from a partner's motor variability in the context of

performing a joint task, depending on the predictability of the range of perturbations. If a partner exerts a highly variable range of perturbations on an individual's movements, one could predict that a partner's variability helps an individual engaged in a joint action to explore a larger space of movement parameters (Wu et al., 2014). This could allow her to explore a broader range of movement possibilities that can be performed to contribute to a joint goal, as well as the individual goal. If the partner exerts a small range of perturbations, the individual will only explore a narrow range of possible movement. She may therefore become less adaptive compared to someone who learned with a highly variable partner.

Because joint action requires the actor's movements to be predictable, one should expect beneficial effects of a partner's variability only in joint contexts when the individual can predict which movement the partner is going to perform and what perturbation from the partner can be expected. Thus, when a partner exerts high variability on an individual's movements in a predictable manner, this should benefit individual learning and individual contributions to the joint task. Alternatively, if the partner's high variability reduces the predictability of her upcoming movement, then the higher variability should interfere with the individual's learning and contribution to the joint task. Also, even when the partner exerts variability in a predictable manner, individuals still would need to adopt some motor strategies to account for the differential effect of variability in individual and joint action scenarios.

To test these predictions, we developed a new joint sequence learning task, in which participants learned to perform a sequence of aiming actions while being haptically coupled to one another. We manipulated the variability and predictability of a partner's perturbations exerted on participants' movements. This allowed us to investigate the differential contribution of variability (range of perturbations experienced) and predictability (order of perturbations delivered) of

perturbations to the individual's learning performance and the actors' joint performance during the joint action. Experiment 1 investigated whether individuals can benefit from high variability of their partner's movements while the partner's movement is completely unpredictable. Experiment 2 looked at whether predictability of a partner's movements enhances individuals' ability to utilize partners' high variability to improve or stabilize their own and joint performance. Experiment 3 asked whether partial predictability of a partner's movements is sufficient to obtain benefits from partner's high variability for the individual and joint performance. The study treats spatial accuracy of individuals as a measure of their individual performance and the inter-personal asynchronies between the landing times as a measure of their joint performance.

2.2 Experiment 1

In Experiment 1, we investigated whether high variability of partner's movements can aid performance in individuals, while a partner's upcoming movements are completely unpredictable. Participants performed a joint task that consisted in producing a sequence of joint force configurations with a partner (see Fig 1A). The partner was a confederate producing either highly or less variable force perturbations on the participants' movements throughout a sequence. The properties of force perturbations coming from the partner were completely unpredictable because the partner moved to a different sequence of locations in each trial. Following Wu and colleagues' (2014) account one could expect a beneficial role of high variability in individual motor learning in joint motor learning scenarios, even if a partner's movement sequence is not predictable. Individuals performing the task while experiencing a high variability in one's movements may still benefit from enhanced opportunities for action exploration. Accordingly, performing with a highly variable partner may lead to enhanced performance through better learning than performing with

a partner producing low variability (a lower range of force perturbations on the participant's movement). However, because predictability is a crucial precondition for successful joint action coordination (Vesper et al., 2011, 2013), it is also possible that being able to predict a partner's next movement while acting together in a joint context is a precondition for any potential benefit arising from an enhanced range of force perturbations experienced. Also, it has been shown that it is the structure of variability and not its magnitude that potentially facilitates learning (Barbado et al., 2017). If this is so, individuals' performance may suffer from performing joint actions with a highly variable partner whose upcoming actions cannot be predicted.

2.2.1 Methods

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Participants

Forty people participated in the study (23 Females, Mean age= 27.5 years, SD age= 1.98 years). 4 participants were excluded from the analysis as they failed to complete the task. Participants were recruited through the SONA online participation system. All participants were right-handed and reported to have normal or corrected-to-normal vision. They received monetary compensation for their participation. Two lab assistants volunteered as confederates for the experiment.

Apparatus and Stimuli

Two actors, a participant and a confederate sat on either side of the experimental table facing each other. Actors were haptically coupled using an elastic rubber band. Thirty-two circles were arranged on the table in a 4x8 array in front of each actor and defined possible target locations for participants' movements (see Fig 1A). Targets were projected using an Epson EH-TW490 Lumen projector attached to the ceiling and cued as yellow concentric circles with a red centre.

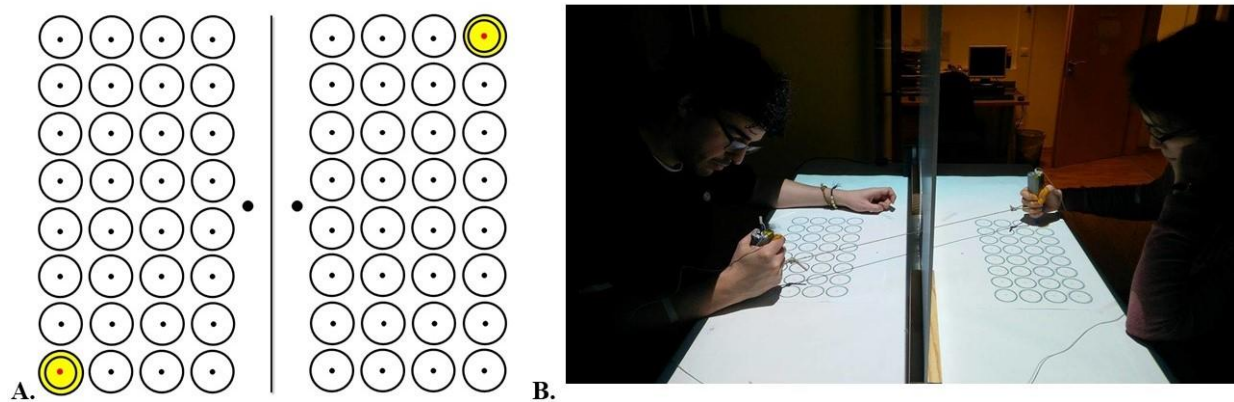


Fig 1. Experimental apparatus and stimuli. (A) 4 x 8 arrays of possible target locations for the two actors; targets were projected as yellow concentric circles with a red centre. The diameter of each of the outer circle was 4.5 cm and that of the red center was 0.5cm. A black dot above each target array marked the starting position for the movement. Two simultaneously cued target locations for the confederate and the participant constitute a *configuration*. (B) Figure shows actors haptically coupled by an elastic band, while performing in the joint action phase in which each actor had to hit the red center of their own target circles, synchronising with their partner, using the handles provided to them.

A Polhemus G4 electro-magnetic motion capture system (40 Hercules Drive, Colchester, Vermont) was used to track the movements of the two actors. Actors were given a handle with a micro-motion sensor (1.8 mm) inserted inside to perform the task (see Fig 1B). The actor's

movements were tracked at a frequency of 120 Hz. An occluder was placed between the actors to prevent them from seeing each other's movements. An opening in the bottom of the occluder allowed haptic coupling between the two actors. A stretchable rubber band was used to create the haptic coupling between the two actors. The experiment was run on a Dell Precision computer. MATLAB (R2015a) and RStudio Team (2020) was used for running the experimental script and for performing the data analyses. A force measuring gauge, Sauter FK250 Digitális Erőmérő, was used to measure the forces produced by the elastic band at each target configuration, in order to create the sequences necessary for the experiment.

Procedure

The Joint Task

A participant and a confederate performed a *joint aiming task* together. Both actors performed their actions on the target array on their side of the table (see Fig 1A). Every sequence was composed of 8 target locations for both participant and confederate (we will refer to *configuration* to indicate the ensemble of participant's and confederate's targets). For every sequence, each of the eight-target location was cued for 1000 ms simultaneously for the participant and the confederate. Participants were instructed to hit the center of the target location on their side as accurately as possible within the cueing duration and to land as synchronously as possible with their partner at the target location.

Variability Manipulation

The experiment was designed to have a between-subject manipulation with two experimental groups, **High Variability (HV)** and **Low Variability (LV)** group. The target sequences performed by participants in both groups were the same, while the confederate's sequences were manipulated

to induce high or low variability. Variability was determined by the standard deviation of the inter-personal distances of within each sequence: it was higher ($SD= 9.55\text{cm}$) for high variability sequences and lower ($SD=2.22\text{ cm}$) for low variability sequences. The haptic coupling between the two actors ensured that movements of one person impacted the other. Thus, variable or constant inter-personal distances across configurations within a sequence resulted in corresponding high variable or low variable force perturbations on the participant's movements (see Fig 2A and 2B). However, the average inter-personal distances, within every sequence, in both groups were comparable (Mean Inter-personal Distance for HV= 50.22 cm and LV= 49.77 cm).

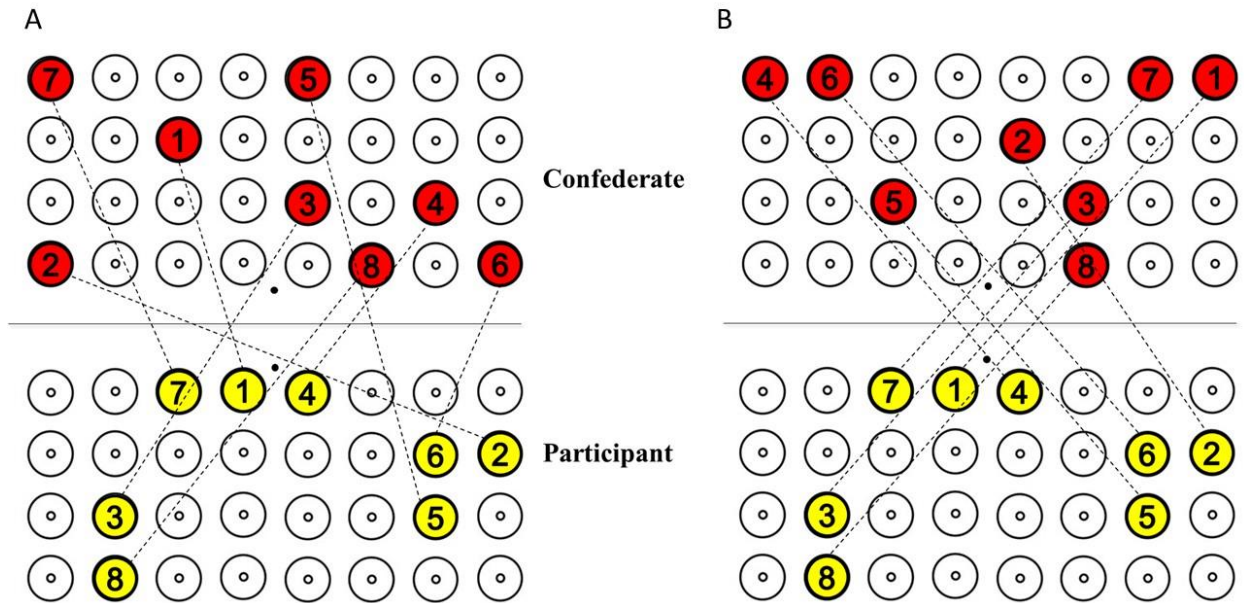


Fig 2. Example of a HV and LV sequence. Red circles denote confederate's targets and yellow circles denote participant's targets. Black dashed lines represent various target configurations within the sequence. (A) High variability sequence with varying inter-personal distances across all eight configurations in a sequence. (B) Low variability sequence with similar inter-personal distance across all eight configurations. Average inter-personal distances of the configurations for the two groups are the same. Participants in the HV and LV group received the same targets. Confederate's target locations were manipulated to produce sequences with different degrees of variability and predictability.

Predictability of a partner's movements was disrupted by breaking any regularity of the vector properties of force perturbations is coming from the partner (direction and magnitude of the forces). At each repetition of participant's sequence, the confederate was given a different sequence to perform both in the HV and LV group. In each block, participants repeated a single sequence 10 times, but the confederate performed 10 different movement sequences (see Fig 3). Thus, the force perturbations exerted by the confederate across every repetition of a sequence were unpredictable. The order of the blocks was counter-balanced across participants. Short breaks were taken in between blocks.

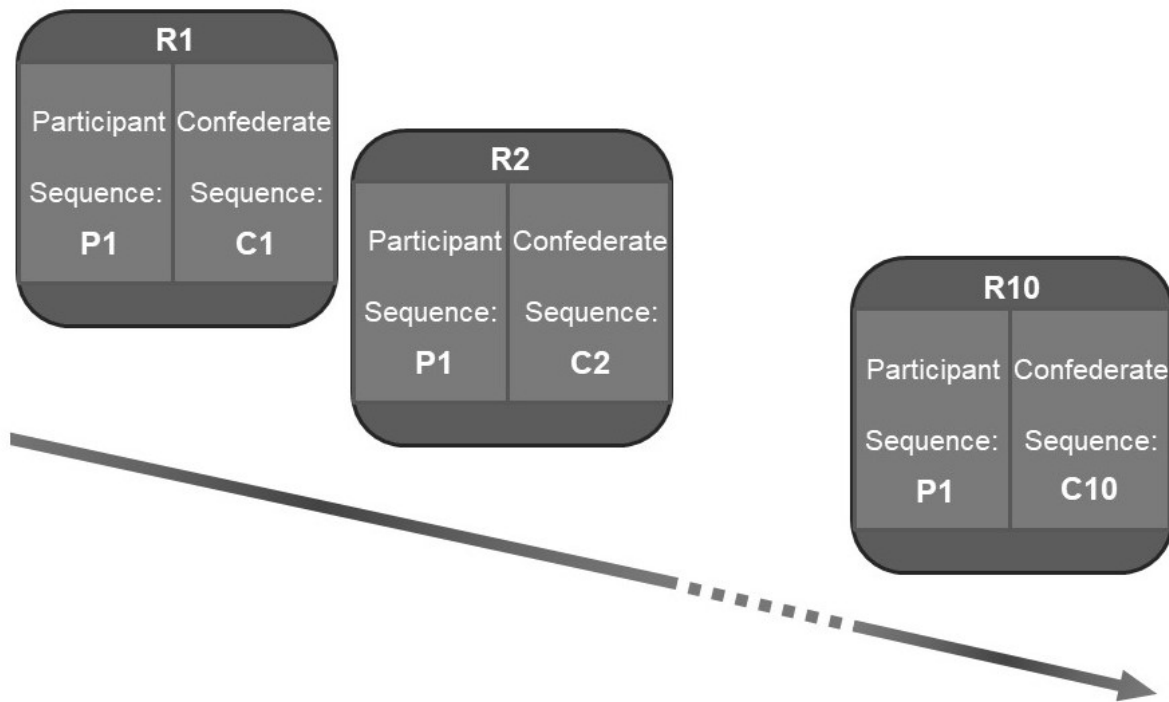


Fig 3. Manipulation of variability and predictability in Experiment 1. Only a single block is shown in the figure. *Variability* in both groups is manipulated by varying the inter-personal target distances. Predictability was manipulated by making the participant repeat the same movement sequence (P1) across repetitions R1-R10, while the confederate performs 10 different sequences (C1-C10) across R1-R10, to produce *completely unpredictable* movements.

Experiment Timeline

The experiment consisted of 8 blocks in which each block corresponded to a specific sequence of target configurations. Each block consisted of three phases as following: *Demonstration phase*: participants observed the upcoming sequence of their individual targets in the sequence. Each target was highlighted for a duration of 1000 ms followed by the next target. *Individual action phase*: participants individually performed the sequence they needed to perform during the joint action, without experiencing any force perturbation. This phase was introduced only to familiarize the participants with the aiming task they need to perform. Participants started a trial from the starting position, and then went on hitting the eight target circles as they lit up one after the other. Participants were instructed to hit each target within its 1000 ms cueing duration. After the presentation of the eighth target, the whole array of target circles turned black. During this interval, the actors had to get back to their start position (See Fig 4). Participants repeated the sequence 5 times.

Joint phase: Participant and confederate performed the task together. In this phase, the actors were haptically coupled. They were instructed to hit the centre of the cued targets as accurately as possible, and to be temporally synchronized with their partner, i.e., hit their respective targets at the same time. Within a single block, participants repeated the corresponding sequence 10 times, while confederate performed the sequences according to the variability condition, as detailed in the previous section. The 32 potential target positions for each actor were calibrated as reference coordinates for every duo before the start of the experiment. The overall duration of the experiment was about 35 minutes.

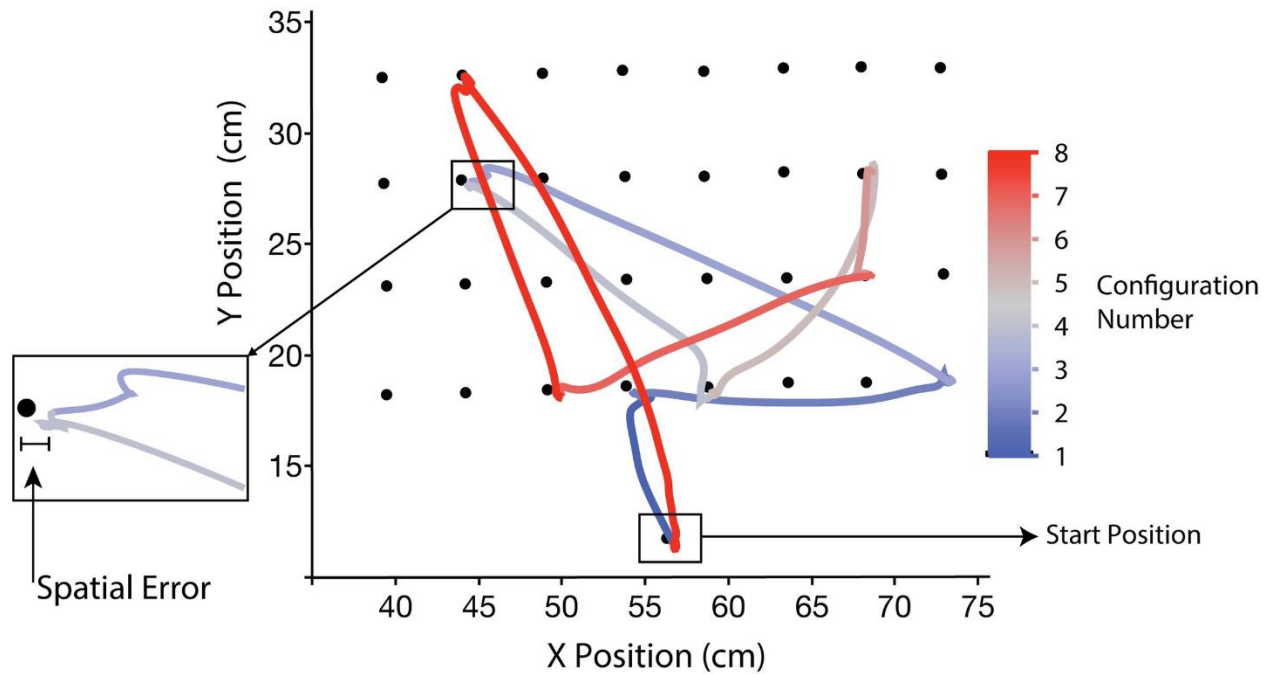


Fig 4. Example trajectories of participant's movements in a joint-action phase. The figure shows the kinematic data of a participant across all eight targets of a movement sequence. Spatial error marks the distance between the target position that participants were supposed to hit and where they hit at the end of each trajectory which is referred to as landing position.

Data Processing and Analysis

We segmented the participant's and confederates' kinematic data by retrieving the landing positions, which are the final position of the handle after an actor hit the target (target-to-target movement). The landing positions were identified as the 2D coordinates of the actor's movements when their movement velocity (m/s) was minimal (~ 0 cm/sec) for each configuration, using an automatized algorithm in MATLAB. The landing positions were used to measure the spatial error produced by the actors and also the variability of participant's movements on the horizontal and vertical dimension.

Participants' *movement variability on horizontal and vertical dimension (cm)*, normalized over the distance covered in each trajectory, were computed as a measure of the variations that occurred in their motor performance. The variability was calculated as the average deviations of the spatial coordinates on the two spatial components of their movements separately, namely the horizontal and the vertical dimension, divided by the distance covered in each trajectory. The measure was subjected to a mixed 2x2x10 ANOVA with Group (High Variability (HV) and Low Variability (LV) group) as between-subject factor and the Axis-dimension (horizontal and vertical) and Repetition (R1-R10) as the within-subject factors. Greenhouse-Geisser corrected values were used for factors that violated Mauchly's sphericity test for every analysis.

As a measure of individual performance, the *spatial error (cm)* of the actor's hits were obtained by calculating the Euclidean distance between the landing position and the actual target position. Trials in which actors moved to positions 5 cm or more away outside the target array were considered as outliers and removed from the analysis. 0.13% trials were removed from HV group and 0.27% trials were removed from LV group through outlier removal. The reduction of spatial error over repetitions were analysed to see how the actors learned to predict the force configurations. The mean spatial error across sequences in all 8 blocks was calculated for each of the 10 repetitions of the sequences and was subjected to a mixed 2x10 ANOVA with Group (HV and LV) as the between-subject factor and Repetitions (R1-R10) as the within-subject factor. The spatial error of participants was also correlated with the magnitude of force perturbations experienced by the participants from the partner, to understand how the participant's motor performance changes with different forces. A repeated measures correlation (rmcorr) was computed to assess the correlation between the spatial error across different magnitude of force perturbation, in the first (R1) and last repetition (R10) separately. Outliers were removed from the

correlation analysis using (mean \pm 2.5 SD) rule. 3.03 % trials and 3.5 % trials from the repetitions R1 and R10 respectively of HV group and 0.61% trials from R1 of LV group was removed through outlier removal.

To assess the joint performance, *Absolute Asynchronies (sec)* between the actors were computed as a measure of inter-personal temporal coordination. The absolute asynchronies were derived from the raw asynchronies that were calculated as the difference between the time point of the participant's landing time and the confederate's landing time. The asynchronies were subjected to a mixed 2x10 ANOVA with Group (HV and LV) as the between-subject factor and Repetitions (R1-R10) as the within-subject factor. Greenhouse-Geisser corrected values were used for factors that violated Mauchly's sphericity test.

All significant main effects and interactions were further analysed by applying Bonferroni correction for multiple comparisons.

2.2.2 Results

Movement Variability on Horizontal and Vertical Dimension

The mixed ANOVA revealed a main effect of Repetition with Greenhouse-Geisser correction ($\epsilon = 0.721$), indicating that participants in both groups reduced their variability over time ($F(9, 306) = 7.926$, $p < 0.0001$, $\eta^2 = 0.189$, see Fig 5A). Post-hoc analyses revealed that variability at first repetition, R1 (mean=0.120, SE= 0.007) was significantly higher compared to other repetitions (all $p < 0.005$). The main effect of axis-dimension was also significant ($F(1, 34) = 22.885$, $p < 0.0001$, $\eta^2 = 0.402$) with the variability on the horizontal dimension being larger (mean=0.091, SE= 0.004) than the variability on the vertical dimension (mean= 0.074, SE= 0.004). The analysis also showed a significant main effect of group ($F(1, 34) = 11.667$, $p = 0.002$, $\eta^2 = 0.255$), indicating

that the HV group participants had a higher movement variability (mean= 0.095, SE=0.005) compared to the LV group (mean= 0.069, SE=0.005). The interaction between repetition and group ($F(9, 306) = 2.443$, $p = 0.011$, $\eta^2 = 0.067$) was significant with Greenhouse-Geisser correction ($\epsilon = 0.509$), with the largest mean difference driven by the higher variability of HV group participants at R1 (mean=0.148, SE=0.011) compared to LV group (mean= 0.093, SE= 0.011). This was confirmed by post-hoc analysis ($p=0.001$). This indicates a faster reduction of variability by HV group compared to LV group. All other interactions were non-significant ($ps > 0.06$; see Supporting Information, Section 2.6.1).

Spatial Error

The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.583$) revealed a main effect of the repetitions, indicating that participants in both groups learned to reduce spatial error over time ($F(9,306) = 27.173$, $p < 0.0001$, $\eta^2 = 0.444$). Post-hoc analysis revealed that the spatial error at R1 (mean= 1.240, SE= 0.055) was higher compared to all other repetitions, R2-R10 (all $ps < 0.001$). The analysis also showed a significant main effect of group, with the HV group (Mean= 1.03, SE = 0.05) having significantly larger errors than the LV group (Mean = 0.857, SE = 0.05), ($F(1, 34) = 6.089$, $p = 0.019$, $\eta^2 = 0.152$; See Fig 5B). The interaction between the two factors was also significant ($F(9, 306) = 3.503$, $p = 0.0004$, $\eta^2 = 0.093$). Initial reduction in error from the first to the second repetition was larger in the HV group (mean= 1.405, SE= 0.078) than in the LV group (mean= 1.075, SE= 0.078), which was confirmed by the post-hoc analyses ($p=0.005$). The analysis on confederate's spatial accuracy could be found in the supporting information (Section 2.6.2).

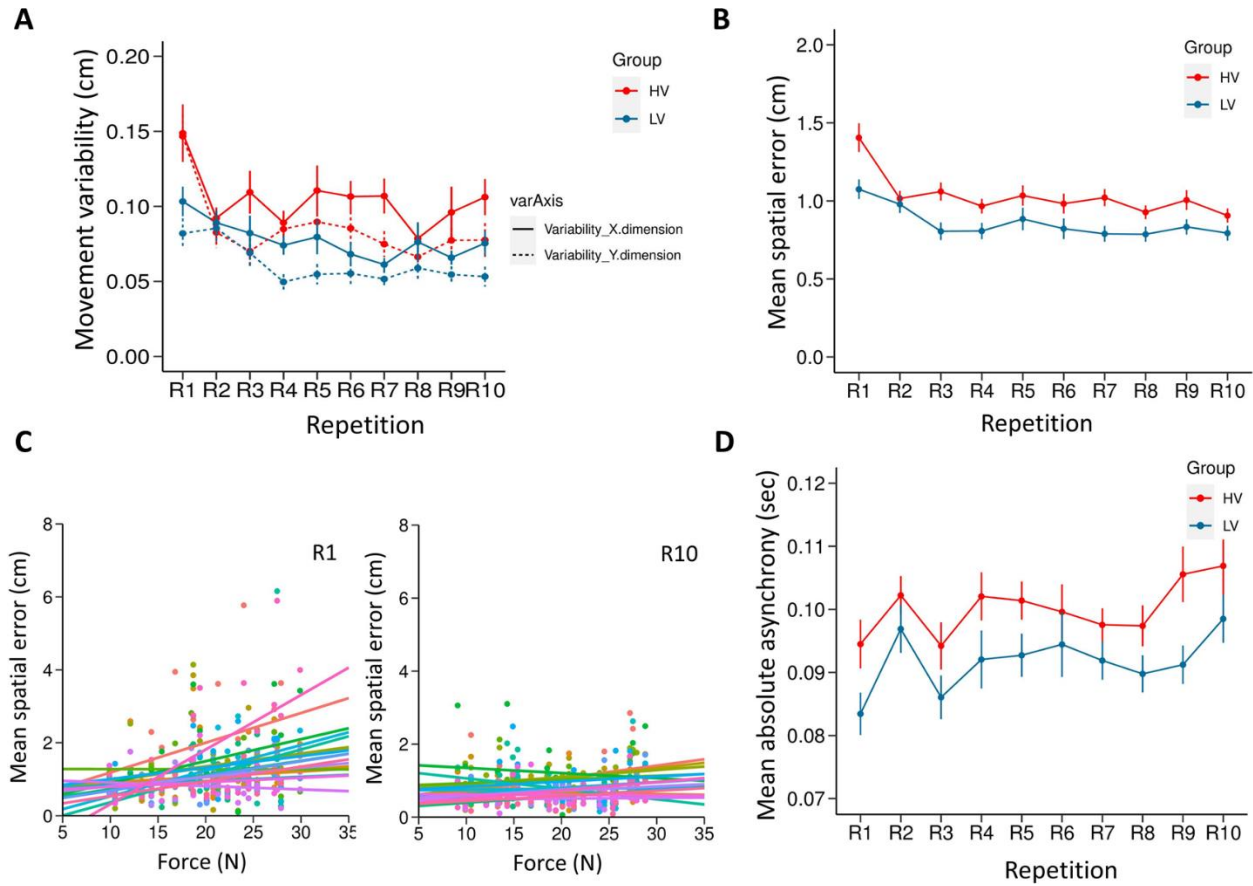


Fig 5. Results of Experiment 1. (A) Normalized variability of participant's movement in the horizontal and vertical dimension. (B) Spatial error as a measure of individual performance. The spatial error at each repetition is an average of all 8 configurations from each of the 8 blocks. (C) Repeated measures correlation analysis between the force perturbation experienced and the spatial error of the participants in the HV group, for R1 and R10 separately. Each participant's data and corresponding rmcorr fit lines are shown in different colors. (D) Absolute Asynchronies as a measure of joint performance. All error bars display standard error of mean.

A repeated measures correlation (rmcorr) was computed to determine the relationship between force perturbation and the spatial error in the HV group participants. The correlation was done on the first (R1) and last repetitions (R10) separately. The analysis revealed a significant correlation between the force perturbation experienced and the spatial error at R1 ($r_{\text{rm}}(364) = 0.290$, $p < 0.001$, 95% CI= 0.1935913 0.3819815) and as well as at R10 ($r_{\text{rm}}(414) = 0.126$, $p = 0.009$, 95% CI= 0.03092686 0.2206055). A scatter plot (see Fig 5C) summarizes the results. The results show that

participants made more errors when they experience larger force perturbations. As the LV group experienced a significantly lower range of varying forces leading to comparatively smaller number of force magnitudes, the correlation on the LV group is not of direct interest in the main discussion. Hence, the analysis on LV group in the current and following experiments are included in the supporting information (see Section 2.6.3).

Absolute Asynchronies

The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.729$) on the absolute asynchronies between the two actors revealed a main effect of Repetition ($F(9, 306) = 5.959, p < 0.0001, \eta^2 = 0.149$, see Fig 5D). The post-hoc revealed that the effect was mediated mainly by R1 (mean = 0.089, SE = 0.003) being significantly lower to R2 (mean = 0.100, SE = 0.002), R9 (mean = 0.098, SE = 0.003) and R10 (mean = 0.103, SE = 0.003) (all p s < 0.01). The main effect of mean asynchronies between HV group (mean = 0.100, SE = 0.003) and LV group (mean = 0.092, SE = 0.003) showed a trend towards significance ($F(1, 34) = 4.117, p = 0.0503, \eta^2 = 0.108$). The interaction between the two factors was not significant ($F(9, 306) = 0.701, p = 0.708, \eta^2 = 0.020$).

2.2.3 Discussion

In the current study we investigated whether high variability of a partner's movements can aid performance in individuals while learning a motor task together. In our task successful individual performance or learning implies improvement in the ability to compensate force perturbations from a partner over time, by modulating one's own movements. Our results indicate that having a partner producing highly variable movement in an unpredictable order negatively affects individual performance compared to having a partner producing movements that are less variable. The correlation analysis revealed that participants in the high variability group had difficulty in

adapting to larger force perturbations. There were no indications of a beneficial effect of variability in joint action contexts where a partner performs movements in an unpredictable order. One possible explanation for this result is that in the high variability condition, there was hardly any opportunity to improve predictions of a partner's behavior as a different force perturbation occurred at every trial. The HV group also suffered detrimental effects of partner's variability in their joint performance, compared to LV group, which can be observed from their difference in asynchrony measures. However, it is important to note that even though participants in the high variability group were consistently less accurate in their performance, they reduced their spatial error over time at a rate comparable to participants in the low variability group. The learning could have been achieved by successful reduction of individual's own movement variability over time, which is observed from the variability analysis. It should also be noted that participants were generally more variable on their horizontal dimension compared to the vertical dimension, owing to the possibility of participants exploring their motor parameters on the dimension that was less constrained by the haptic coupling. This indicates that a highly variable but unpredictable partner does not preclude learning during joint action, however, does not contribute to learning either. Taken together, results of Experiment 1 shows that having a partner who exerts high variability on one's movements in an unpredictable manner does not benefit individual or joint performance.

2.3 Experiment 2

In this experiment, we investigated whether predictability of a partner's movement sequence may be a necessary precondition to observe beneficial effects of variability in a joint action scenario. Variability was manipulated as in the previous experiment with the partner producing small or large range of force perturbations. However, in Experiment 2, the partner produced predictable

force perturbations in both the low and high variability conditions because he repeated the same movement sequence. If predictability of a partner's movements is a necessary precondition for individuals to exploit a partner's high variability, one should expect that participants in the high variability group should exhibit better individual performance in Experiment 2, as higher variability allows individuals to explore their action space and learn multiple action possibilities while the predictability of a partner's moves will aid the joint action. Alternatively, if predictability does not serve any benefits to utilizing partner's variability, one should expect that partner's high variability cannot be beneficial in a joint context and hence we should see the same pattern of results as in Experiment 1.

2.3.1 Method

Participants

Forty people participated in the study (25 Females, Mean Age= 25.42 years, SD age= 3.1 years). All participants were right-handed and reported to have normal or corrected-to-normal vision. A confederate was hired to participate throughout the study for all 40 participants. They received monetary compensation for their participation.

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Procedure

The Joint Task

The joint task was the same as in Experiment 1, in which both the participant and the confederate performed the joint aiming task together while being haptically coupled.

Variability Manipulation

Variability of the confederate's movements were manipulated as in Experiment 1. The standard deviation of the inter-personal distances within every sequence was manipulated to induce the difference in confederate's variability across groups. The standard deviations for high variability sequences were 11.85 cm and for low variability sequences 0.46 cm. However, the average inter-personal distances, within every sequence, in both groups, were maintained the same as in Experiment 1 (Mean Inter-personal Distance for HV= 52.13 cm and LV= 51.88 cm). Differently from Experiment 1, in the current study, the movement sequence confederates performed was predictable (see Fig 6). This also made upcoming force perturbations more predictable. The confederate repeated the same movement sequence within a block of trials. Thus, in a single block, both the participant and the confederate received a single sequence (8 target configurations) at every repetition.

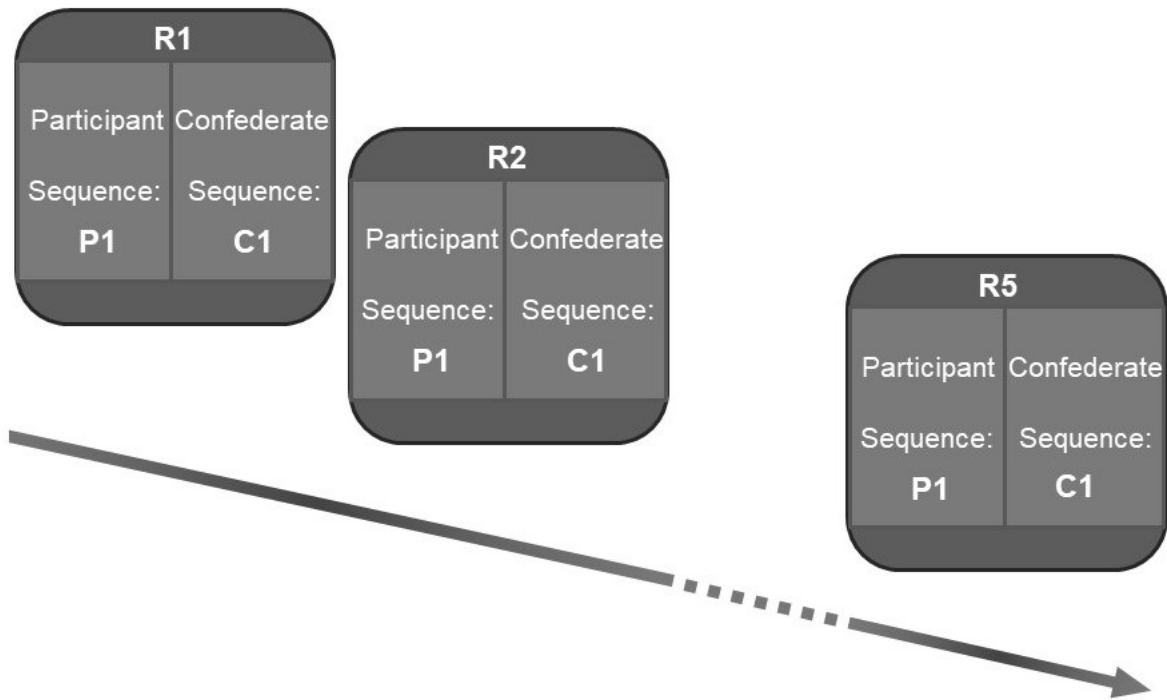


Fig 6. Manipulation of variability and predictability in Experiment 2: Only a single t block is shown in the figure. Variability in both groups are manipulated by varying the inter-personal target distances. Predictability was manipulated by making the participant repeat the same movement sequence (P1) across repetitions R1-R5, while the confederate also repeats her sequence (C1) across R1-R5, to produce predictable movements.

Experiment Timeline

As in Experiment 1, current experiment consisted of 8 blocks with each block corresponding to a specific sequence of target configurations. Each block involved three phases as following: *Demonstration phase*- participants observe the sequence of targets corresponding to the current block. Each target was highlighted for a duration of 1000 ms followed by the next target. *Individual action phase* - participants practiced the sequence they needed to perform during the joint action repeatedly for 5 times, without experiencing any force perturbation. *Joint phase*-Participant and confederate performed the task together. Actors were haptically coupled and were instructed to hit

the centre of the cued targets as accurately as possible and to be temporally synchronized with their partner, i.e., hit their respective targets at the same time. Actors were supposed to hit the targets within the 1000 ms cueing duration provided to them. Within a single block, participants repeated the corresponding sequence 5 times, differently from the 10 repetitions in Experiment 1. The number of repetitions were reduced in the current experiment to ensure that there were no performance decrements across repetitions due to fatigue. The confederate performed the sequences according to the variability condition, as detailed in the previous section. The 32 potential target positions for each actor were calibrated as reference coordinates for every duo before the start of the experiment. The overall duration of the experiment was about 25 minutes.

Data Processing and Analysis

Participant's and confederates' kinematic data was segmented using their landing positions, as in Experiment 1. The landing positions were used to measure the spatial error produced by the actors and the variability of participant's movements on the horizontal and vertical dimension. 0.17% trials from HV group and 0.02% trials from LV group was removed as outliers.

Participants' *movement variability on horizontal and vertical dimension (cm)* were computed as a measure of the variations that occurred in their motor performance. The variability was calculated as the average deviations of the spatial coordinates on the two spatial components of their movements separately, namely the horizontal and the vertical components, and normalized to the distance travelled in each trajectory. The measure was subjected to a mixed 2x2x5 ANOVA with Group (HV and LV) as between-subject factor and the Axis-dimension (horizontal and vertical) and Repetition (R1-R5) as the within-subject factors. Greenhouse-Geisser corrected values were used for factors that violated Mauchly's sphericity test for all analyses.

Spatial Error (cm) of the actor's performance was subjected to a mixed 2x5 ANOVA with Group (High Variability (HV) and Low Variability (LV) group) as the between-subject factor and Repetitions (R1-R5) as the within-subject factor. The spatial error of participants was subjected to a repeated measures correlation (rmcorr) along with the magnitude of force perturbations experienced by the participants from the partner, to understand how the participant's motor performance changes with different forces. The rmcorr was performed on first (R1) and last repetition (R5) separately, as in Experiment 1 (outliers were removed using (mean \pm 2.5 SD) rule). 4.38 % trials and 2.50 % trials from repetitions R1 and R5 respectively of the HV group was removed through outlier removal.

Absolute Asynchronies (sec) between the actors were retrieved as a measure of inter-personal temporal coordination by computing the difference of participant's and confederate's landing times and was subjected to a 2x5 ANOVA as for the spatial error measure.

All significant main effects and interactions were further analyzed by applying Bonferroni correction for multiple comparisons.

2.3.2 Results

Movement Variability on Horizontal and Vertical Dimension

The mixed ANOVA revealed a main effect of Repetition with Greenhouse-Geisser correction ($\epsilon = 0.705$), indicating that participants in both groups reduced their variability over time ($F(4,152) = 13.384$, $p < 0.0001$, $\eta^2 = 0.260$, see Fig 7A). Post-hoc analysis revealed that the variability at first repetition, R1 (mean = 0.092, SE = 0.008) was significantly higher compared to other repetitions (all p s < 0.01) and R5 was also significantly different from all other repetitions (mean = 0.045, SE =

0.004, all $ps < 0.025$). The main effect of axis-dimension was also significant ($F(1,38) = 55.940$, $p < 0.0001$, $\eta^2 = 0.595$) with the variability on the horizontal dimension being larger (mean=0.075, SE=0.005) than the variability on the vertical dimension (mean=0.054, SE=0.04). The main effect of group did not reach a significance ($F(1,38) = 1.289$, $p = 0.263$, $\eta^2 = 0.033$) (HV group: mean=0.060, SE= 0.006; LV Group: mean=0.069, SE= 0.006). The interaction between repetition and axis-dimension ($F(4,152) = 6.640$, $p < 0.0001$, $\eta^2 = 0.149$) was found to be significant with a Greenhouse-Geisser correction ($\epsilon = 0.668$). Post-hoc revealed that the variability on the horizontal dimension was significantly higher than the vertical dimension in all 5 repetitions (all $ps < 0.005$). There was also a significant interaction between the group and axis-dimension ($F(1, 38) = 10.544$, $p < 0.001$, $\eta^2 = 0.595$). However, post-hoc analyses did not reveal any significant difference (all $ps > 0.07$). All other interactions were non-significant ($ps > 0.86$; see Supporting Information, Section 2.6.1).

Spatial Error

The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.590$) revealed a main effect of Repetition, indicating that participants in both groups learned to reduce spatial error over time ($F(4, 152) = 46.580$, $p < 0.0001$, $\eta^2 = 0.551$, see Fig 7B). The post-hoc analysis revealed that spatial error at R1 (mean= 1.149, SE= 0.069) was significantly higher compared to R2-R5 (all $ps < 0.0001$) and R5 (mean= 0.705, SE= 0.042) was significantly lower compared to R1-R4 (all $ps < 0.001$). However, the main effect of group was not significant ($F(1, 38) = 0.072$, $p = 0.789$, $\eta^2 = 0.002$; HV group: Mean= 0.854, SE= 0.06; LV group: Mean= 0.879, SE= 0.06). The interaction between the factors was also not significant ($F(4,152) = 0.328$, $p = 0.756$, $\eta^2 = 0.009$). The analysis on confederate's spatial accuracy can be found in the supporting information (Section 2.6.2).

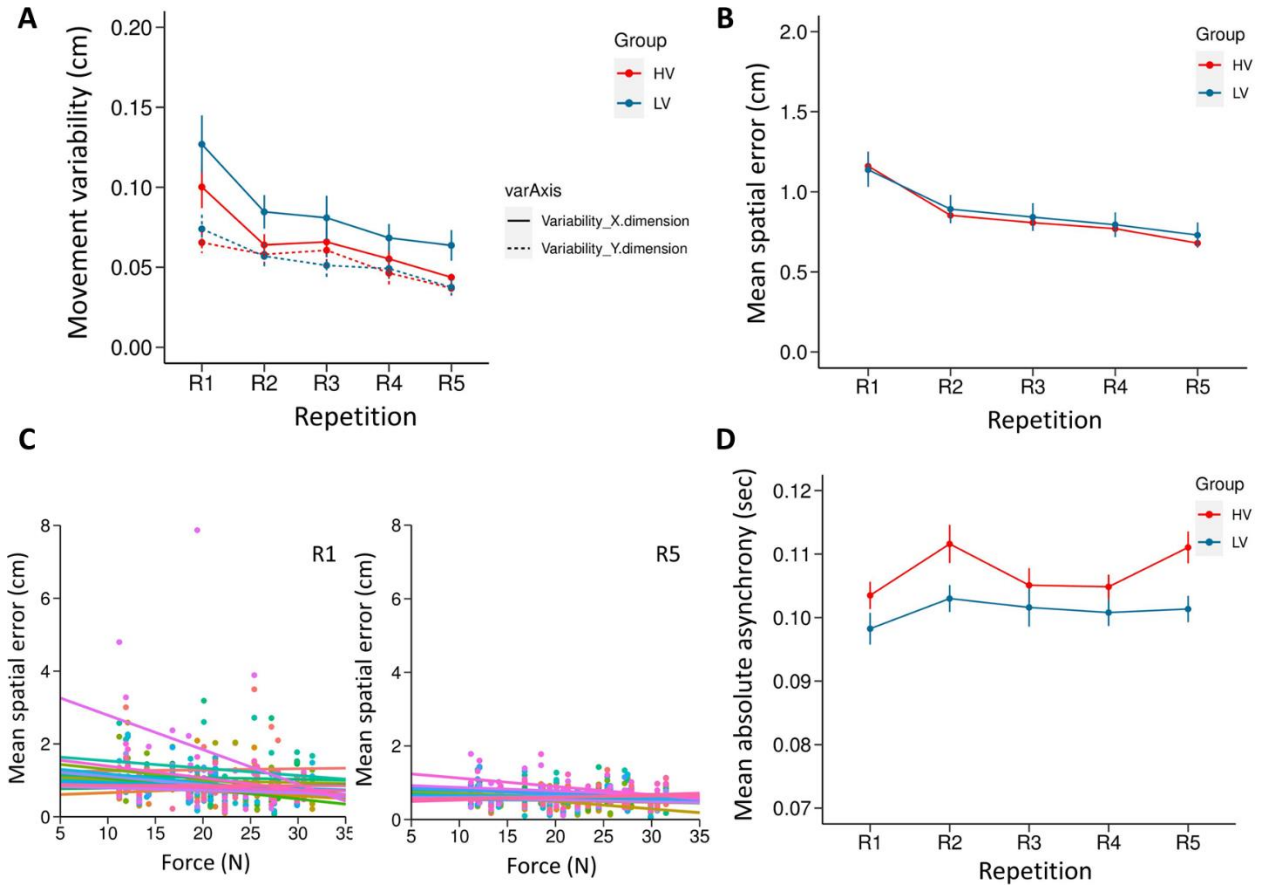


Fig 7. Results of Experiment 2. (A) Normalized variability of participant's movement in the horizontal and vertical dimension. (B) Spatial error as a measure of individual performance. The spatial error at each repetition is an average of all 8 configurations from each of the 8 blocks. (C) Repeated measures correlation analysis between the force perturbation experienced and the spatial error of the participants in the HV group, for R1 and R5 separately. Each participant's data and corresponding rmcorr fit lines are shown in different colors. (D) Absolute Asynchronies as a measure of joint performance. All error bars display standard error of mean.

A Bayesian Independent Samples T-Test was performed to assess the likelihood of the spatial accuracy performance between HV and LV groups being similar. The average spatial error across repetitions and learning blocks was computed for both groups and subjected to comparison across the two groups. We tested the null hypothesis, H_0 : mean spatial error of HV = mean spatial error of LV, and the alternate hypothesis, H_1 : mean spatial error of HV \neq mean spatial error of LV. The prior is described by a Cauchy distribution centred around zero and a default width parameter

of 0.707. The analysis resulted in a Bayes Factor, $BF_{01} = 3.146$ (see Table1 for descriptive). This Bayes Factor implies moderate evidence for H_0 , which means that the data are 3.146 times more likely to occur under H_0 than under H_1 . The Bayes Factor provides moderate evidence in favour of the null hypothesis that the HV and LV groups are not different.

95% Credible Interval						
Group	N	Mean Spatial Error	SD	SE	Lower	Upper
HV	20	0.854	0.192	0.043	0.764	0.944
LV	20	0.879	0.370	0.083	0.706	1.053

Table 1. Descriptive statistics: Descriptives of the comparison of mean spatial error in HV and LV group of Experiment 2, by means of a Bayesian independent t-test.

A repeated measures correlation (rmcorr) was computed to determine the relationship between force perturbation and spatial error in the HV group for R1 and R5 separately. The analysis revealed a significant negative correlation between the force perturbation experienced and the spatial error at R1 ($r_{rm}(437) = -0.154$, $p = 0.001$; 95% CI= 0.007834378, 0.1892928) and at R5 ($r_{rm}(447) = -0.135$, $DF = 447$, $p = 0.004$; 95% CI= -0.2254212 -0.04330164). A scatter plot summarizes the results (see Fig 7C). The results indicate that in the HV group, participants achieved higher accuracy when encountering larger perturbations under conditions of predictability, suggesting that they learned to adapt to larger forces by becoming more resilient.

Absolute Asynchronies

The ANOVA conducted on the absolute asynchronies between the two actors revealed a main effect of Repetition ($F(4, 152) = 2.439$, $p=0.049$, $\eta^2 = 0.06$, see Fig 7D). The post-hoc revealed that R1 (mean= 0.101, SE= 0.002) was significantly lower than R2 (mean= 0.107, SE=0.002) and R5 (mean= 0.106, SE= 0.002) (all $ps<0.03$), indicating that asynchrony increased over repetitions. The mean asynchrony between the two groups were also found to be significantly different ($F(1,38)= 12.541$, $p= 0.001$, $\eta^2=0.248$) with HV group having a higher asynchrony (mean= 0.107, SE= 0.001) compared to the LV group (mean= 0.101, SE= 0.001). The interaction between the factors was not significant ($F(4,152) = 0.714$, $p= 0.583$, $\eta^2 = 0.018$).

2.3.3 Discussion

Analysis of participants movement variability indicate that participants were successfully regulating their own variability by reducing it over repetitions. Participants were generally more variable in their horizontal dimension as in the previous experiment, but differently from Experiment 1, HV group participants were not more variable compared to LV group participants. Also, participants who performed joint actions with a highly variable partner were as accurate as participants who performed joint actions with a less variable partner. Thus, varying force perturbations from a partner was not detrimental to the individual performance. This result indicated that participants in the HV group were able to predict upcoming variable force perturbations and to offset these perturbations. Further support for this interpretation comes from the correlation analysis indicating a negative correlation between the force experienced and the spatial error of participants in the high variability group. The results suggest that participants in the HV group adapted more to larger force perturbations, possibly becoming more resilient under

conditions of predictability. Taken together, these results suggest that predictability of partner's movement sequence seems to be a pre-condition for potential benefits of individual performance. However, it should be noted that the joint performance in HV group was worse than LV group in the current experiment, as was the case with a non-predictable partner in Experiment 1. Thus, it seems that when the partner is predictable, participants can improve the efficiency of their individual performance but not the joint performance.

2.4 Experiment 3

In this experiment we aimed to better understand what needs to be predictable about a partner's movement sequence so that individuals can start to benefit from performing joint actions with a more variable partner. There are two potential properties of force that are relevant in the present task, the magnitude and the direction of the force perturbation exerted by the partner. To tease apart the contributions of these two factors in Experiment 3, we investigated whether partial predictability of a partner's movements is sufficient to achieve high accuracy of performance with a highly variable partner. Here, the partner produced force perturbations that followed a predictable structure in terms of the magnitude of force across the movement sequences, while the direction of force kept changing. Thus, participants could only predict the magnitude of upcoming perturbations but not the direction of the perturbations. If predictability of a partner's movements is necessary to offset negative effects of high variability on performance, the pattern of results should be similar to Experiment 1 where neither force nor direction of force perturbations were predictable. If partial predictability is sufficient to reduce the negative impact of highly variable force perturbations, the pattern of results should resemble Experiment 2.

2.4.1 Method

Participants

Forty people participated in the study (26 Females, Mean Age= 26.35 years, SD age= 3.62 years). One participant was later excluded from the analysis due to technical error in the data encoding. All participants were righthanded and reported to have normal or corrected-to-normal vision. Two confederates were hired to participate throughout the study for all 40 participants.

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Procedure

The procedure was the same as in Experiment 2, except for the predictability manipulation in which confederate's movements were made partially predictable. For the participant, magnitude of the force perturbation exerted by the confederate was predictable across repetitions while the direction of the force perturbation changed from repetition to repetition. This was made possible by making the confederate move to a new target location at each repetition of participant's sequence, which changed the direction of the force applied but kept the distance between the target position for the participant and the confederate constant. Hence, in a single block, participants received a single sequence (8 target configurations) that was repeated 5 times, whereas the confederate performed 5 different sequences in which the magnitude of force produced across eight consecutive configurations remained (relatively) constant while the direction of the force

changed from repetition to repetition. The standard deviation of the inter-personal distances within every sequence was used to manipulate the variability of confederate's movement across the two groups: it was 11.11 cm for high variability sequences and 1.26 cm for low variability sequences. However, the average inter-personal distances within every sequence in both groups were maintained the same as in the previous experiments (Mean Inter-personal Distance for HV= 52.24 cm and LV= 52.47 cm).

Data Processing and Analysis

Participant's and confederates' kinematic data was segmented and analysed following the same protocol as in Experiment 2. A total of 0.02% trials from HV group and 0.14% trials from LV group were removed as outliers. For the repeated measures correlation analysis, a total of 2.247 % trials and 2.40% trials were removed as outliers from repetitions R1 and R5 of HV group respectively.

2.4.2 Results

Movement Variability on Horizontal and Vertical Dimension

The mixed ANOVA revealed a main effect of Repetition, indicating that participants in both groups reduced their variability over time ($F(4,148)=5.992$, $p<0.0001$, $\eta^2 = 0.139$, see Fig 8A). Post-hoc analysis revealed that the variability at first repetition, R1 (mean=0.076, SE= 0.005) was significantly higher compared to other repetitions (all $ps<0.01$). The main effect of axis-dimension was also significant ($F(1,37)=26.637$, $p<0.0001$, $\eta^2 = 0.419$) with the variability on the horizontal dimension being larger (mean= 0.066, SE= 0.004) than the variability on the vertical dimension (mean= 0.055, SE= 0.004). The main effect of group did not reach a significance ($F(1,37) = 1.975$,

$p = 0.168$, $\eta^2 = 0.051$; HV group: mean=0.066, SE= 0.005; LV group: mean=0.056, SE= 0.005). None of the interactions were significant (all p s >0.14; see Supporting Information, Section 2.6.1).

Spatial Error

The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.667$) revealed a main effect of Repetition, confirming that participants in both groups learned to reduce spatial error over time ($F(4, 148) = 12.164$, $p < 0.0001$, $\eta^2 = 0.247$, see Fig 8B). Post-hoc analysis showed that spatial error at R1 (mean= 1.034, SE= 0.056) was significantly higher compared to R2-R5 (all p s <0.01). The main effect of Group (HV group: Mean= 0.879, SE= 0.06 and LV group: Mean= 0.842, SE= 0.060) failed to reach a significance ($F(1, 37) = 1.179$, $p = 0.675$, $\eta^2 = 0.005$). The interaction between the factors was also not significant ($F(4, 148) = 0.707$, $p = 0.534$, $\eta^2 = 0.019$). The analysis on confederate's spatial accuracy could be found in the supporting information (Section 2.6.2).

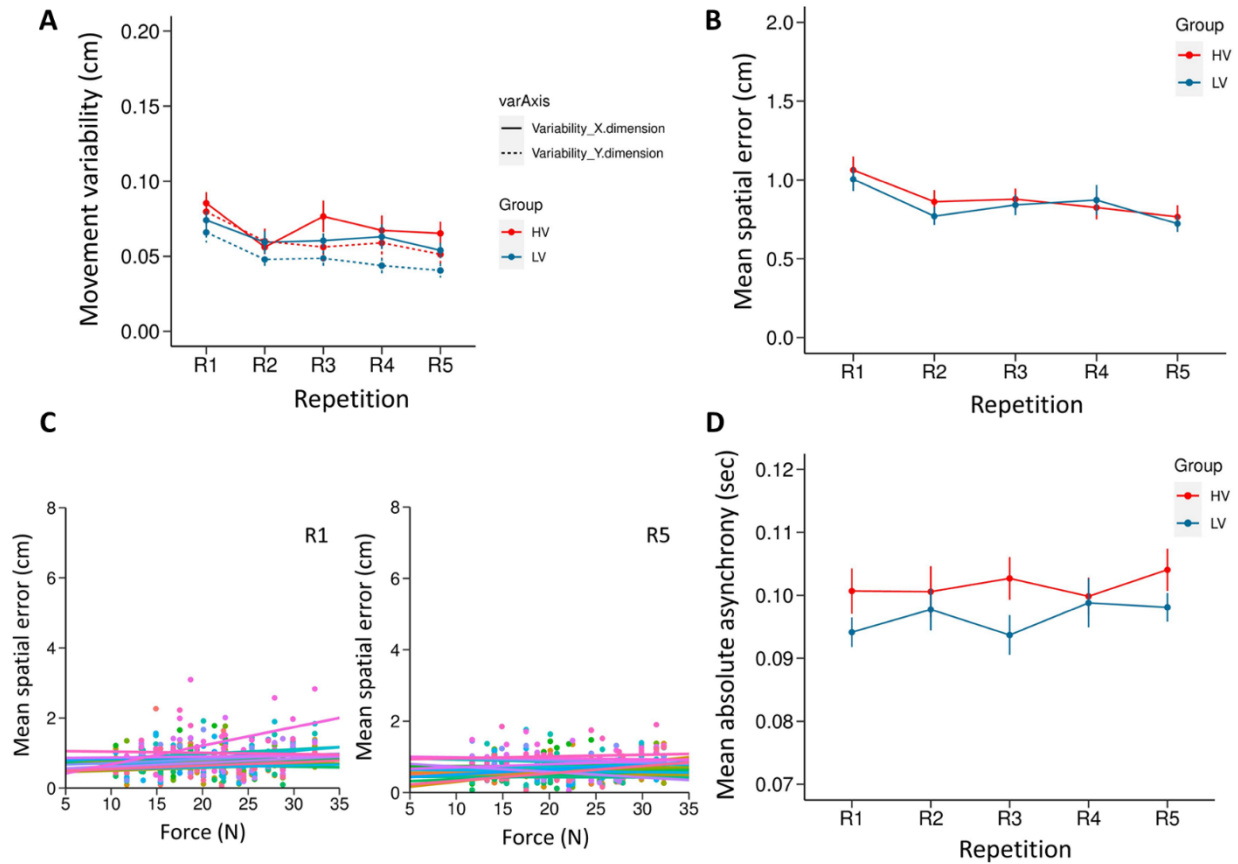


Fig 8. Results of Experiment 3. (A) Normalized variability of participant's movement in the horizontal and vertical dimension. (B) Spatial error as a measure of individual performance. The spatial error at each repetition is an average of all 8 configurations from each of the 8 blocks. (C) Repeated measures correlation analysis between the force perturbation experienced and the spatial error of the participants in the HV group, for R1 and R5 separately. Each participant's data and corresponding rmcrr fit lines are shown in different colors. (D) Absolute Asynchronies as a measure of joint performance. All error bars display standard error of mean.

A Bayesian Independent Samples T-Test was performed to assess the likelihood of performance in the HV and LV group being equal. The average spatial error across each repetition and learning block was computed for both groups and means were subjected to comparison. The null hypothesis, H_0 : mean spatial error of HV = mean spatial error of LV, was tested against the alternate hypothesis, H_1 : mean spatial error of HV \neq mean spatial error of LV. The prior is described by a Cauchy distribution centered around zero and a default width parameter of 0.707.

The analysis resulted in a Bayes Factor, $BF_{01} = 2.986$ (see Table 2 for descriptive). This value of the Bayes Factor indicates anecdotal evidence for H_0 , which means that the data are 2.986 times more likely to occur under H_0 compared to H_1 . The Bayes Factor provides anecdotal evidence in favor of the null hypothesis than the alternative hypothesis.

Group	N	Mean Spatial Error	SD	SE	95% Credible Interval	
					Lower	Upper
HV	19	0.879	0.278	0.064	0.745	1.013
LV	20	0.842	0.260	0.058	0.720	0.964

Table 2. Descriptive statistics: Descriptives of the comparison of mean spatial error in HV and LV group of Experiment 3, by means of a Bayesian independent t-test.

In addition, a Bayesian Independent Samples T-Test was performed to assess the likelihood of the performance of HV group participants in Experiment 2 and 3 being similar. The average spatial error across each repetition and learning block was computed for HV groups from both experiments and the means were subjected to comparison. The null hypothesis, H_0 : mean spatial error of HV group in Experiment 2 = mean spatial error of HV group in Experiment 3, was tested against the alternate hypothesis, H_1 : mean spatial error of HV group in Experiment 2 \neq mean spatial error of HV group in Experiment 3. The prior is described by a Cauchy distribution centered around zero and a default width parameter of 0.707. The analysis resulted in a Bayes Factor, $BF_{01} = 3.074$ (see Table 3 for descriptive). This value of the Bayes Factor indicates moderate evidence for H_0 , meaning that the data are 3.074 times more likely to occur under H_0 compared to H_1 . In

other words, the Bayes Factor provides more evidence in favour of the null hypothesis that there is no difference in spatial error between the HV groups in Experiment 1 and 2.

Group	N	Mean	SD	SE	95% Credible Interval	
					Lower	Upper
Experiment 2	20	0.854	0.192	0.043	0.764	0.944
Experiment 3	19	0.879	0.278	0.064	0.745	1.013

Table 3. Descriptive statistics: Descriptives of the comparison of mean spatial error in HV groups of Experiment 2 and 3, by means of a Bayesian independent t-test.

A repeated measures correlation (rmcorr) was computed for R1 and R5 separately, to determine the relationship between the force perturbation experienced and the spatial error in the HV group. The analysis revealed a significant correlation between the force perturbation and the spatial error at R1 ($r_{\text{rm}}(415) = 0.131$, $p = 0.007$, 95% CI= 0.0355664 0.2247967). However, there was no correlation observed at R5 ($r_{\text{rm}}(385) = 0.067$, $p = 0.181$, 95% CI= -0.03217353 0.166803) suggesting that participants learned to adapt to larger forces as in Experiment 2, over the course of training. A scatter plot (see Fig 8C) summarizes the results.

Absolute Asynchronies

The ANOVA conducted on the absolute asynchronies of the two actors did not show a significant main effect of repetition ($F(4,148) = 0.563$, $p = 0.690$, $\eta^2 = 0.015$) indicating that asynchrony between the actors remained the same across repetitions (see Fig 8D). The mean asynchrony between the two groups (HV group: Mean= 0.102, SE= 0.002; LV group: mean= 0.097, SE=0.002)

also did not reach significance ($F(1,37)= 2.406$, $p=0.129$, $\eta^2 =0.0.061$). The interaction between the factors was also not significant ($F(4,148) = 0.725$, $p= 0.576$, $\eta^2 = 0.019$).

A Bayesian Independent Samples T-Test was performed to assess the likelihood of the absolute asynchrony in the HV and LV group being equal. The average asynchrony across each repetition and learning block was computed for both groups and the means were subjected to comparison. The null hypothesis, H_0 : mean absolute asynchrony of HV= mean absolute asynchrony of LV, was tested against the alternate hypothesis, H_1 : mean absolute asynchrony of HV \neq mean absolute asynchrony of LV. The prior is described by a Cauchy distribution centred around zero and a default width parameter of 0.707. The analysis resulted in a Bayes Factor, $BF_{01} = 1.253$ (see Table 4 for descriptive). This value of the Bayes Factor indicates anecdotal evidence for H_0 , meaning that the data are 1.253 times likely to occur under H_0 compared to H_1 . The Bayes Factor provides anecdotal evidence in favour of the null hypothesis that absolute asynchrony in HV and LV groups are not different.

	Group	N	Mean	SD	SE	95% Credible Interval	
						Lower	Upper
Absolute Asynchrony	HV	19	0.102	0.011	0.002	0.096	0.107
	LV	20	0.097	0.009	0.002	0.092	0.101

Table 4. Descriptive statistics: Descriptives of the comparison of mean absolute asynchrony in HV and LV groups by means of a Bayesian independent t-test.

2.4.3 Discussion

As in Experiment 2, participants successfully regulated the variability of their own movements over time. It was also observed that participants were more variable on the horizontal axis, which was less constrained by haptic coupling, owing to wider action exploration on this dimension. There was also no indication of a difference in the participant's individual performance or learning between the high and the low variability group. The correlation analysis suggests that while the force perturbations predicted the spatial error in the first repetition, participants became equally accurate for large force perturbations as for smaller force perturbations in the last repetition, despite the direction of the force perturbations being unpredictable. Thus, partial predictability of the force perturbations of the partner's movement sequence was sufficient to offset the negative effects of high magnitude of partner's variability. Also, contrary to Experiment 2, there was no main effect of group for the joint performance, measured by the temporal asynchronies, when partners' movements were only partially predictable. Our results indicate that, when interacting with a partner who is only partially predictable but highly variable, participants seem to improve both their individual and joint performances over time.

2.5 General Discussion

During joint action coordination that involves physical coupling, motor variability produced by an actor can have a direct impact on the partner's movements. In the current study, we investigated whether individuals could regulate their own and their partner's variability when learning a motor task together. Specifically, we looked at how variability at different degrees of predictability of force perturbations coming from a partner, during a joint action, foster or hamper individual and joint performance. Furthermore, we aimed at identifying what strategies individuals can adopt to

benefit both individual and joint performance. Motor learning generally involves reduction of variability or error in one's movement over practice. Action exploration and subsequent exploitation of the best explored actions are found to be aiding this learning process in specific types of learning. In our study, participants could either utilize their own variability, their partner's variability, or both, to explore possible motor refinements that allow successful learning.

The finding on participants' movement variability showed that in all three experiments, participants were generally more variable on the dimension that was less constrained by haptic coupling, that is the horizontal dimension. Also, participants learned to reduce their movement variability and consequentially, their spatial error over time in all three experiments. We suggest that regardless of the experimental condition, individuals utilised their internal variability to explore their motor parameters relevant for the task which benefitted their individual performance. However, individuals might adopt different strategies when it comes to utilizing external variability coming from their partner during a joint action.

In Experiment 1, where partner's variability was unpredictable, individuals learned to reduce their spatial error over time, but HV group participants were worse than LV group in their performance. Also, the correlation analysis showed that when the partner's movements were not predictable, individuals were unable to compensate for large perturbations. These results suggest that the high variability of the partner was not providing any task-relevant information as participants' movements were perturbed in random directions. In other words, the partner's variable and unpredictable movements had a detrimental effect on individual performance. However, the fact that participants learned to reduce their spatial error over time points to the possibility that they could resort to another strategy, i.e. the modulation of their own variability to ensure exploration and improvement in performance. In Experiment 2 and 3, where the partner's

movements were completely or at least partially predictable, spatial accuracy was not impacted. Importantly, it was observed that individuals learned to compensate for a wide range of force perturbations when the partner's movements were partially predictable and even more when they were completely predictable, suggesting that they developed resilience to larger perturbations. These results indicate that predictability becomes a necessary pre-condition for partner's variability to positively influence individual's performance. In Experiment 2 and 3, the improvements in individual performance were possibly aided by both regulation of their own movement variability as shown by the variability analysis as well as their partner's variability. Taken together the results on individual performances of the three experiments, it seems that it is not the magnitude of variability, rather the structure of task-relevant variability coming from the partner that might support individual learning and action exploration. (However, one can confirm the beneficial role of partner's variability in these experiments, only if the participants' performance in the current experiments could be compared to the performance in a SOLO condition. This has been discussed later under limitations of the study).

We propose that under conditions of predictability, a varied range of force perturbations experienced from a partner allows individuals to generate a flexible internal model accommodating various movement solutions for a wider range of task parameters (in our case, various force perturbations) (Krakauer, 2006). Thus, in the high-variability condition, instead of forming a single motor plan required to perform the task under a constant force, individuals generated multiple motor plans for performing the task under a varying task environment. Depending on the perturbation experienced, the most optimal plan could be exploited for improving the efficiency of outcome achievement. This allowed them to exhibit similar performance as in the low-variability condition (Experiment 2 and 3). Had a wider action exploration not been fostered by

partner's variability in these cases, participants in the high-variability group should have performed worse than the low variability group due to the more varied force perturbations.

It is important to note that the individual performance does not necessarily reflect the success of joint performance. The results of the analyses on joint performance show that participants in the HV group in Experiment 1 and 2 were worse than participants in the LV group at synchronising with their partners. As the asynchrony increased while the individual spatial accuracy decreased over repetitions, our results indicate that individuals traded off the spatial accuracy and the temporal coordination in Experiment 1 and 2. This suggests that individuals failed to accommodate high variability coming from a partner to benefit the joint performance. On the other hand, the results of individual movement performance show a different pattern, as mentioned before. While the partner's high variability seemed to hamper performance in Experiment 1, the partners high variability produced in a predictable manner in Experiment 2 allowed individuals to explore their action space and gather motor information relevant for the task. This was reflected in a benefit of individual performance. The differential effects seen in the individual and joint performances in Experiment 2 is rather interesting. If anything, one would have expected the joint performances of both groups to benefit from the predictability of the partner's movements as conditions for an optimal joint performance are hard-wired in this experiment (due to *predictability* of partner's movements). This should have allowed individuals to adopt predictability as a coordination strategy for improving their joint performance. However, it seems that under such optimal conditions for joint action, a higher variability of the partner's movements (as in the HV group) only interferes in successful reliance on predictability as a coordination strategy. In other words, it is reasonable to assume that individuals will benefit from such predictability within the joint action context only when partner's kinematics are the least variable.

In Experiment 3, even though results of the Bayesian analysis only provide anecdotal evidence for no difference in the temporal asynchronies between the two groups, one could speculate that when the partner's variability was high and the perturbations were *partially* predictable, participants may have exploited action exploration strategies to improve their joint performance. It is important to note that, unlike in Experiment 2, optimal conditions for joint action were not hard-wired in Experiment 3, i.e., the partner's movements are only *partially predictable*. It is possible that the variability coming from the partner's movement provided some room for parameters exploration that could be exploited by participants to support the performance of not only their individual action, but also the joint action.

Our findings indicate that individuals might modulate their action exploration strategy by selectively relying on either their own or on the partner's variability to improve their individual performance, joint performance, or both- depending upon the structure of variability provided to them by their partner.

One potential limitation of the current paradigm is the lack of a test phase following the training phase which would have allowed us to measure how the training contributes to long term retention of the learned skill or the transfer of the learned skill to a different movement context. However, the extensive training sessions over multiple movement sequences, in all three experiments, provides actors with sufficient time to reach an asymptote or saturation of individual performance, as can be observed from all the spatial error analyses. Additionally, it was observed that participants offset potential speed-accuracy trade off in performance (see supporting information, Section 2.6.4, for movement time analysis), which is a characteristic of skill learning. Thus, even though we do not capture long-term retention with the current experimental design, our data indicate that individual and joint action learning took place within the experimental sessions

(Smith et al., 2006; Krakauer, 2009). Also, the lack of a SOLO condition poses a limitation to the attribution of beneficial effect of partner's variability on the individual's performance. This is the case because unless one captures how individuals perform when the variability is *not* externally introduced, it is unclear how one can disintegrate partner's contribution to the learning and the individuals' own learning performance. However, in the current study, the variability is introduced by the partner through means of haptic interaction; meaning, the variability is experienced through interaction forces. Hence a SOLO condition in our task should include interaction forces that does not come from an interacting partner. One way to achieve a SOLO condition on this regard, would be to have the elastic band fixed to one position on the confederate's side and let the participant to perform the task. But this would not allow us to capture variability that is introduced externally, because the only way one can experience variability in this setup would be if the participant's targets are manipulated to create varying forces. But this is different from variability coming from an external source. Thus, while a SOLO condition would have allowed us to clearly establish the role of partner's variability on individuals learning, it was not possible to design a SOLO task that could serve as a clean baseline that compliments our joint condition.

A potential future research direction could be to investigate how the individual and joint performances will differ if both actors hold symmetrical knowledge about the task and test the contribution of high variability training on long term retention of the learned skill.

2.6 Supplementary Material

2.6.1 Interactions effects from participants' movement variability analysis

The following texts include the interaction effects that were not significant in the 2x2x10 ANOVA performed on participants normalized movement variability on the horizontal and vertical dimension. All the significant interactions have been reported in the main manuscript.

2.6.1.1 Experiment 1

The interactions between axis-dimension and group did not reach a significance ($F(1,34)=0.144$, $p=0.706$, $\eta^2=0.004$) and neither did the interaction between repetition and axis-dimension ($F(9,306)=0.750$, $p=0.663$, $\eta^2=0.022$). The three-way interaction between the factors also failed to achieve significance ($F(9,306)=1.120$, $p=0.0348$, $\eta^2=0.032$).

2.6.1.2 Experiment 2

The interaction between repetition and group ($F(4,152)=0.317$, $p=0.866$, $\eta^2=0.008$) was not significant. The three-way interaction between the factors also failed to achieve significance ($F(4,152)=0.308$, $p=0.872$, $\eta^2=0.008$).

2.6.1.3 Experiment 3

The interaction between repetition and group ($F(4,148)=0.189$, $p=0.944$, $\eta^2=0.005$) was not significant and neither was the interaction between axis-dimension and group ($F(1,37)=0.876$, $p=0.355$, $\eta^2=0.023$). The interaction between axis-dimension and repetition ($F(4,148)=1.761$, $p=0.140$, $\eta^2=0.045$) was also not significant, as well as the three-way interaction between the factors also failed to achieve significance ($F(4,148)=0.437$, $p=0.225$, $\eta^2=0.037$).

2.6.2 Analysis of confederate's spatial accuracy performance

We analyzed the confederate's data to understand how the confederate modulated their movements over time, in all the three experiments.

2.6.2.1 Experiment 1

The *spatial error (cm)* of the confederate's performance was subjected to a mixed 2x10 ANOVA with Group (High Variability (HV) and Low Variability (LV) group) as the between-subject factor and Repetitions (R1-R10) as the within-subject factor. Greenhouse-Geisser corrected values were used for factors that violated Mauchly's sphericity test. The spatial error for all 10 repetitions of the sequences was calculated and averaged across all 8 blocks. The results are as follows:

The ANOVA on the confederate's data with a Greenhouse-Geisser correction ($\epsilon = 605$) revealed a main effect of the repetitions, indicating that confederates in both groups showed reduction of spatial error over time ($F(9, 306) = 12.169, p < 0.0001, \eta^2 = 0.264$). The analysis also showed a significant main effect of group, with the HV group (Mean = 1.377, SE = 0.092) having significantly larger errors than the LV group (Mean = 1.032, SE = 0.092), ($F(1, 34) = 7.075, p = 0.012, \eta^2 = 0.172$). The interaction between the two factors was also significant ($F(9, 306) = 7.646, p < 0.0001, \eta^2 = 0.184$), where R4, R5, R6 and R7 of HV group was significantly different from all other levels (all $ps < 0.05$).

2.6.2.2 Experiment 2

The *spatial error (cm)* of the confederate's performance was subjected to a mixed 2x5 ANOVA with Group (High Variability (HV) and Low Variability (LV) group) as the between-subject factor and Repetitions (R1-R5) as the within-subject factor. Greenhouse-Geisser corrected values were used for factors that violated Mauchly's sphericity test. The spatial error for all 5 repetitions of the sequences was calculated and averaged across all 8 blocks. The results are as follows:

The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.364$) revealed a main effect of Repetition, indicating that confederates in both groups reduced their spatial error over time ($F(4, 152) = 41.260, p < 0.0001, \eta^2 = 0.521$). However, spatial error of the HV group (Mean = 0.625, SE = 0.028) did not differ from that of the LV (Mean = 0.550, SE = 0.028) group ($F(1, 38) = 3.578, p = 0.066, \eta^2 = 0.086$). The interaction between the factors was significant ($F(4, 152) = 4.686, p = 0.022, \eta^2 = 0.110$). Post-hoc analysis revealed that the interaction was driven by R1 and R2 of HV group which was significantly different from that of the LV group.

2.6.2.3 Experiment 3

The confederate's data was processed and analysed as in Experiment 2. The results are as follows:

The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.673$) revealed a main effect of Repetition, confirming that confederates in both groups learned to reduce their spatial error over time ($F(4, 148) = 6.010, p < 0.0001, \eta^2 = 0.140$). There was no main effect of Group ($F(1, 37) = 2.90, p = 0.097, \eta^2 = 0.073$), indicating that spatial error did not differ significantly between HV group (Mean = 1.152, SE = 0.121) and LV group (Mean = 0.864, SE = 0.118). The interaction between the factors was significant ($F(4, 148) = 7.235, p < 0.001, \eta^2 = 0.164$). The post-hoc revealed that R3 of HV group was significantly different from the other levels ($p = 0.005$).

2.6.2.4 Discussion

Taken together, the results show an overall learning effect, as confederate also improves her performance between first and last repetitions across experiments. On one hand, this is a desired pattern as it adds to the ecological validity of the motor interaction between co-actors. On the other hand, this could be a confound with respect to the source of participants' learning. In fact, participants could be simply mimicking the confederate's movements without learning. But this

cannot be the case in the current study, as participants and confederate never perform the same movements, neither do they perform similar trial by trial movements, nor do they cover the same distance (therefore experience the same pull). Hence, participants would not improve their performance if they were only mimicking the confederate's movements (see supporting information, Section 2.6.5 for further analyses and discussion).

2.6.3 Repeated measures correlations (rmcorr) on LV group data

2.6.3.1 Experiment 1

A repeated measures correlation (rmcorr) was computed for R1 and R10 separately, to determine the relationship between the force perturbation experienced and the spatial error in the LV group. The correlation analysis did not reveal any significant correlations neither at R1 ($r_{rm}(142)=-0.082$, $p=0.328$, 95% CI= -0.2434504 0.083848) nor at R10 ($r_{rm}(179)=0.019$, $p=0.794$, 95% CI= -0.127582 0.1656539). A scatter plot (see Fig S1) summarizes the results.

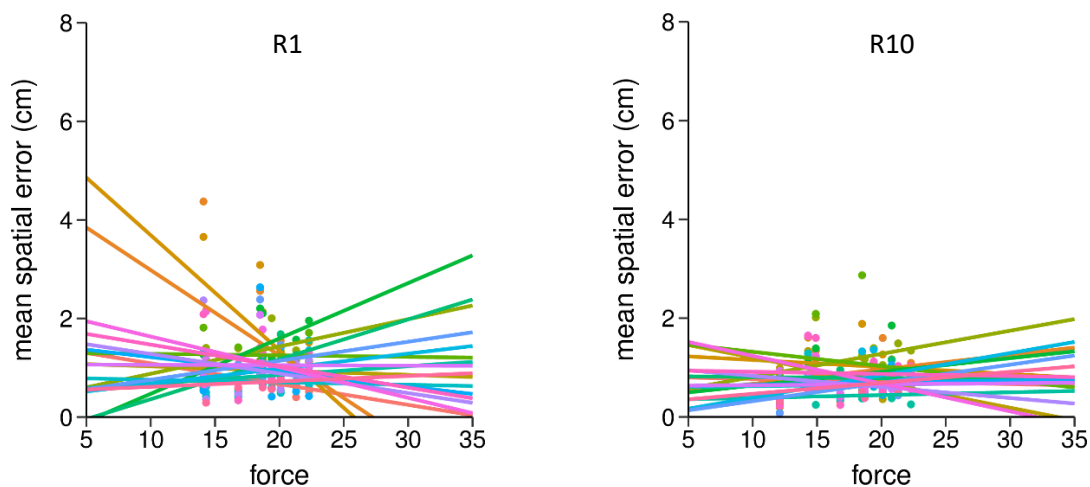


Fig S1. Results of Experiment 1. Repeated measures correlational analysis between the force perturbation experienced and the spatial error of the participants in the LV group, for R1 and R10 separately. Each participant's data and corresponding rmcorr fit lines are shown in different colors.

2.6.3.2 Experiment 2

A repeated measures correlation (rmcorr) was computed for R1 and R5 separately, to determine the relationship between the force perturbation experienced and the spatial error in the LV group. The correlation analysis did not reveal any significant correlations neither at R1 ($r_{\text{rm}}(59)=0.085$, $p=0.510$, 95% CI= -0.1740236, 0.3346091) nor at R10 ($r_{\text{rm}}(59)=0.039$, $p=0.761$, 95% CI= -0.2186034, 0.2928067). A scatter plot (see Fig S2) summarizes the results.

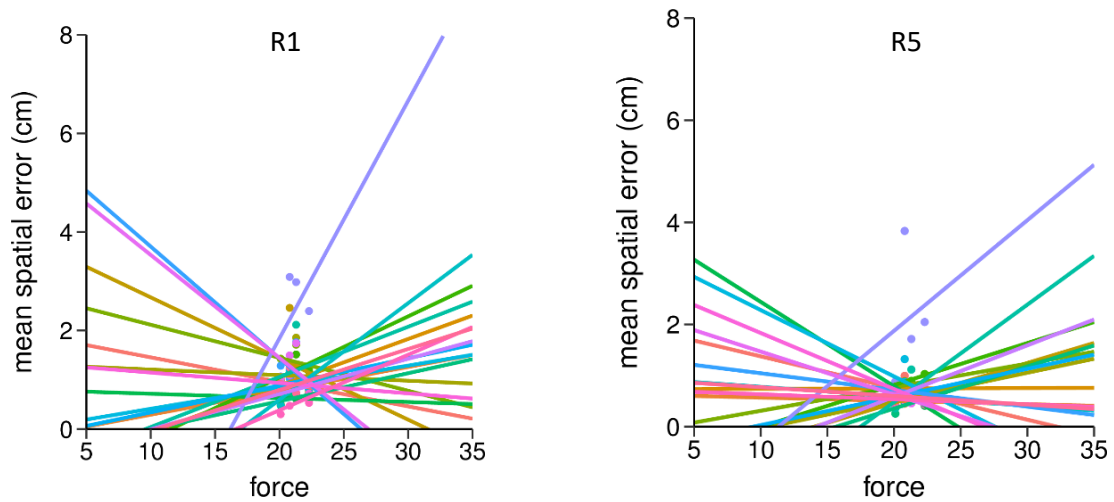


Fig S2. Results of Experiment 2. Repeated measures correlational analysis between the force perturbation experienced and the spatial error of the participants in the LV group, for R1 and R 5 separately. Each participant's data and corresponding rmcorr fit lines are shown in different colors.

2.6.3.3 Experiment 3

A repeated measures correlation (rmcorr) was computed for R1 and R5 separately, to determine the relationship between the force perturbation experienced and the spatial error in the LV group. The correlation analysis revealed a significant positive correlation at R1 ($r_{\text{rm}}(99)=0.217$, $p=0.029$;

95% CI= 0.02048916, 0.3974088) and no correlation at R5 (0.029, $p = 0.770$; 95% CI= -0.1690251, 0.2254713). A scatter plot (see Fig S3) summarizes the results.

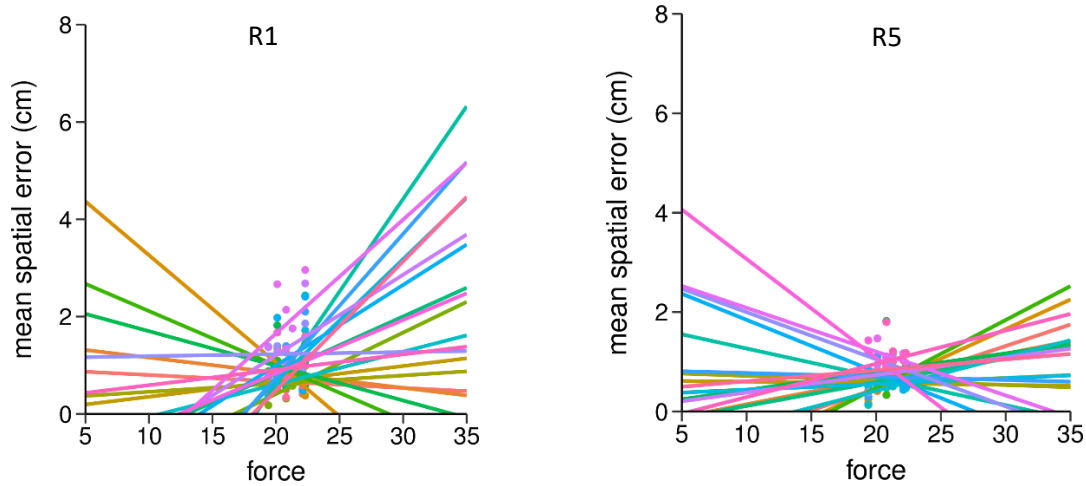


Fig S3. Results of Experiment 3. Repeated measures correlational analysis between the force perturbation experienced and the spatial error of the participants in the LV group, for R1 and R5 separately. Each participant's data and corresponding rmcorr fit lines are shown in different colors.

2.6.4 Participants' movement time analysis

Actors in our experiments were instructed to synchronize with an isochronous sequence of tones that dictated moving within the 1000 ms cue period of the targets (this has been clarified under the Experimental Timeline of each experiment in the manuscript). Thus, a speed-accuracy trade-off seems unlikely in the present task. Nevertheless, we performed additional analyses on the movement times of the participants. We here report the analysis of participant's movement times (defined as the time from target to target). Movement time was subjected to a repeated measures ANOVA with Group (2) as between-subject factor and Repetitions (10 or 5) as within-subject factor. The analysis reveals that in all the three experiments, participants show a main effect of

repetition, with the movement time at R1 always higher than the final repetition. Taking these results, together with the reduction of spatial error observed in the main analysis of spatial error (submitted in the manuscript) it is evident that, while participants learn to get more accurate in their movements, they also get faster in all three experiments. If there was a speed-accuracy trade-off, the change in movement time and spatial error over repetitions should have followed opposite trends, which is not what we observe in our data. The analysis on the movement times are as follows:

2.6.4.1 Experiment 1

The 2 x 10 ANOVA on the participant's movement time revealed a main effect of the repetitions, indicating that participants in both groups reduced their movement time over repetitions ($F(9,306) = 6.612$, $p < 0.0001$, $\eta^2 = 0.163$, see Fig S4). Post hoc revealed that the first repetition R1 was significantly different from all other repetitions (mean= 0.842, SE= 0.004, all $ps < 0.005$). The main effect of group (HV group: mean=0.832, SE=0.006 and LV group: mean=0.829, SE= 0.006) failed to reach a significance ($F(1,34) = 0.103$, $p = 0.7495$, $\eta^2 = 0.003$). Even though the interaction between the two factors was significant ($F(9, 306) = 2.601$, $p = 0.007$, $\eta^2 = 0.071$), post-hoc analysis did not reveal any significant differences (all $ps > 0.1$).

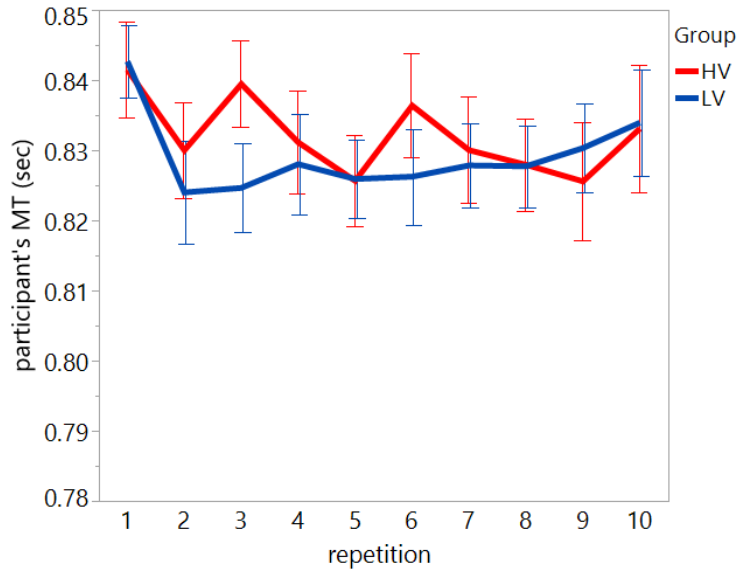


Fig S4. Analysis of participants' movement time in Experiment 1.

2.6.4.2 Experiment 2

The 2 x 5 ANOVA on the participant's movement time revealed a main effect of Repetition, indicating that participants in both groups showed reduction of movement time across repetitions ($F(4,152) = 31.447, p < 0.0001, \eta^2 = 0.453$, see Fig S5). Post-hoc analyses revealed that R1 (mean = 0.827, SE = 0.005) was significantly higher than all other repetitions (all $ps < 0.0001$). The main effect of group (HV group: mean = 0.812, SE = 0.006 and LV group: mean = 0.806, SE = 0.006) was not significant ($F(1,38) = 0.437, p = 0.513, \eta^2 = 0.011$). The interaction between the two factors was significant ($F(4,152) = 5.838, p < 0.001, \eta^2 = 0.133$). Post-hoc revealed that the HV group had a higher movement time at R1 (mean = 0.837, SE = 0.007) compared to the LV group (mean = 0.816, SE = 0.007).

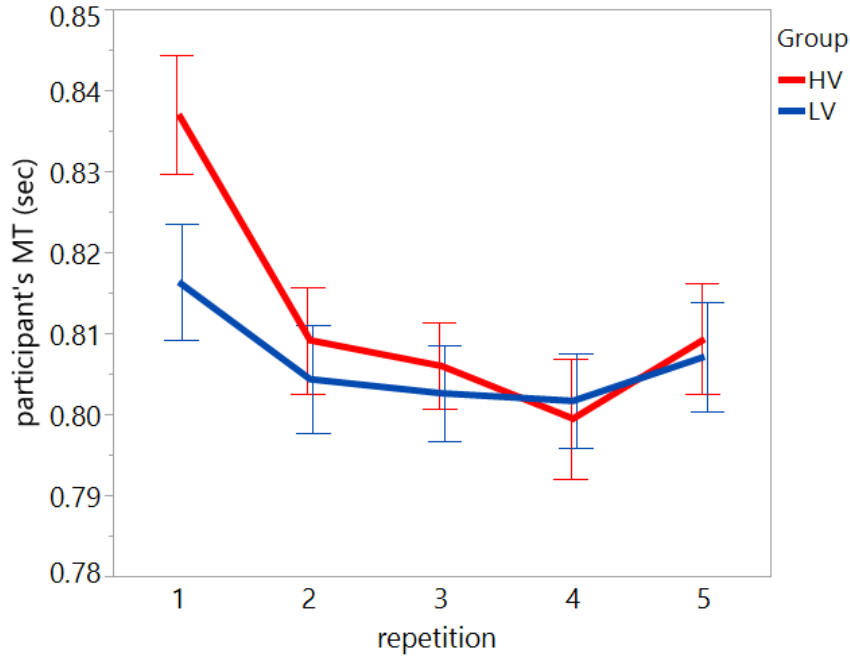


Fig S5. Analysis of participants' movement time in Experiment 2.

2.6.4.3. Experiment 3

The 2 x 5 ANOVA on the participant's movement time revealed a main effect of Repetition, indicating that participants in both groups showed reduction of movement time over repetition ($F(4,148) = 7.630$, $p < 0.0001$, $\eta^2 = 0.171$, see Fig S6). Post-hoc revealed that movement time at R1 (mean= 0.826, SE= 0.004) was significantly higher compared to R2-R4 (all $ps < 0.006$). The main effect of group (HV group: mean= 0.818, SE=0.008 and LV group: mean= 0.820, SE= 0.008) did not reach a significance ($F(1,37) = 0.099$, $p = 0.755$, $\eta^2 = 0.003$). The interaction between the two factors was significant ($F(4,148) = 2.665$, $p = 0.034$, $\eta^2 = 0.067$). However, post-hoc tests did not reach a significance (all $ps > 0.16$).

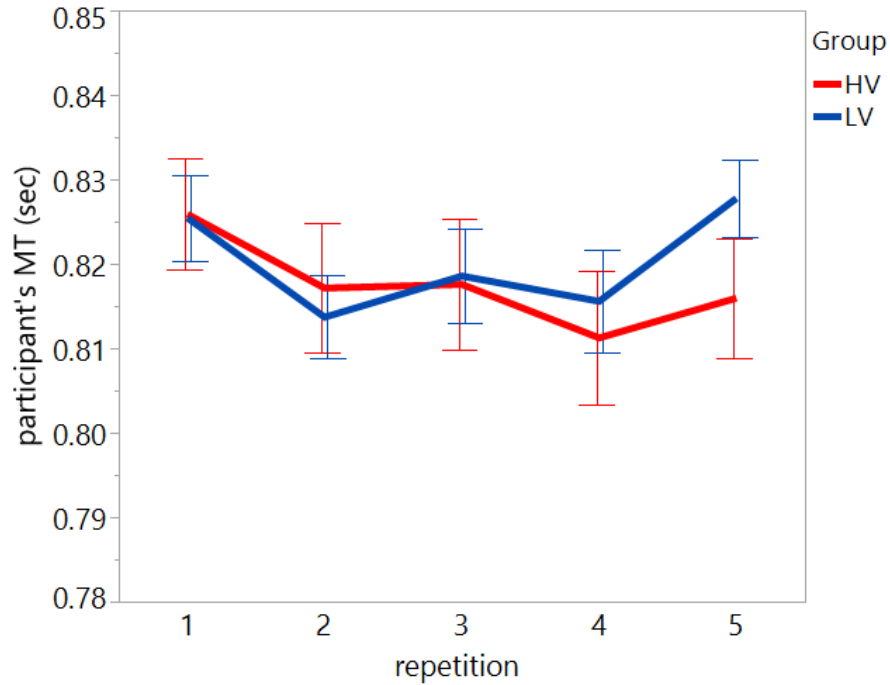


Fig S6. Analysis of participants' movement time in Experiment 3.

2.6.5 Analysis of Repetition 1 of Block 1 on consecutive targets

In the spatial error analyses submitted in the manuscript, the HV and LV group performances are already different at R1 in Experiment 1, while they are not different in Experiment 2 and 3. Since, predictability of confederate's movements can only be experienced after the first repetition (as predictability is the order in which the forces are delivered), one could assume that there is a potential confound driving the difference between groups at R1 in Experiment 1. To address this concern, we analyzed the average spatial error performance of the first repetition (R1) of the **first block** - which includes 8 different target locations. This represents the first instance of participants' performance of a sequence (8 targets) in the presence of force perturbations. Since the first repetition of the first block is unpredictable regardless of the experimental condition, one would

expect no difference in performance for all participants in both groups and across the three experiments. We subjected the participants' spatial error to a 2 x 8 mixed ANOVA with Group (2) as the between-subjects factor and Target Number (8) as the within-subjects factor.

2.6.5.1 Experiment 1

The ANOVA, with Greenhouse-Geisser correction ($\epsilon = 0.435$), on the participant's spatial error at R1 of Block 1 revealed a main effect of the Targets, indicating that participants reduced their spatial error across consecutive targets ($F(7, 238) = 10.047, p < 0.0001, \eta^2 = 0.228$, see Fig S7). The main effect of Group (HV group: mean = 2.601, SE = 0.233 and LV group: mean = 2.114, SE = 0.233) failed to reach a significance ($F(1,34) = 2.183, p = 0.149, \eta^2 = 0.060$). The interaction between the two factors was also not significant ($F(7,238) = 1.901, p = 0.070, \eta^2 = 0.053$).

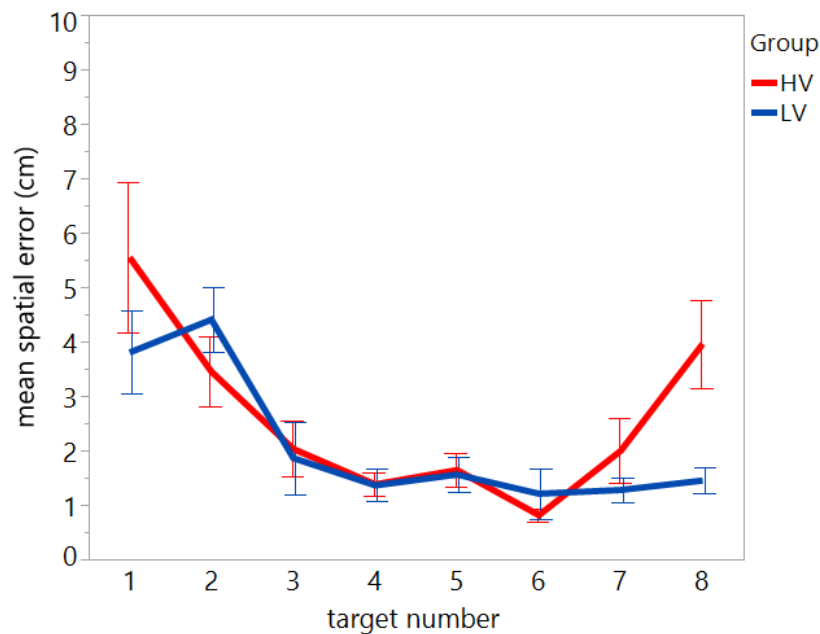


Fig S7. Experiment 1. Analysis of spatial error across consecutive targets at R1 of Block1

We then performed a Bayesian Independent Samples T-Test on the average spatial error in HV and LV groups (the spatial error was averaged across the eight targets at R1 of Block 1 separately for both groups). We tested the hypotheses that H_1 : spatial error of HV at R1 of Block 1 \neq spatial error of LV at R1 of Block 1; and H_0 : spatial error of HV at R1 of Block 1 = spatial error of LV at R1 of Block 1. The prior is described by a Cauchy distribution centred around zero and a default width parameter of 0.707. The analysis resulted in a Bayes Factor, $BF_{01} = 1.340$ (see Table S1 for descriptive). This value of the Bayes Factor indicates that the data are 1.340 times more likely to occur under H_0 compared to H_1 . The Bayes Factor of 1.340 provides anecdotal evidence in favour of the null hypothesis (that HV and LV groups are not different).

	Group	N	Mean	SD	SE	95% Credible Interval	
						Lower	Upper
Spatial Error	HV	18	2.601	1.180	0.278	2.014	3.188
	LV	18	2.114	0.752	0.177	1.740	2.488

Table S1. Descriptive statistics. Descriptives of the comparison of spatial error in HV and LV groups, at R1 of Block 1, by means of a Bayesian independent t-test.

2.6.5.2 Experiment 2

The ANOVA with Greenhouse-Geisser correction ($\epsilon = 0.354$) on the participant's spatial error at R1 of Block 1 revealed a main effect of the Targets, indicating that participants reduced their

spatial over the first eight targets ($F(7, 259) = 6.139$, $p < 0.0001$, $\eta^2 = 0.142$, see Fig S7). The analysis did not show a main effect of Group, ($F(1, 38) = 0.435$, $p = 0.514$, $\eta^2 = 0.12$; HV group: mean = 2.315, SE = 0.335; LV group: mean = 2.007, SE = 0.326). The interaction between the two factors was significant ($F(7, 266) = 4.107$, $p < 0.001$, $\eta^2 = 0.100$). Post-hoc analyses revealed that R2 of HV group (mean = 7.280, SE = 1.581) was significantly different from that of LV Group (mean = 2.278, SE = 1.541). The higher mean at R2 was due to particularly higher error produced by three participants at Target 2.

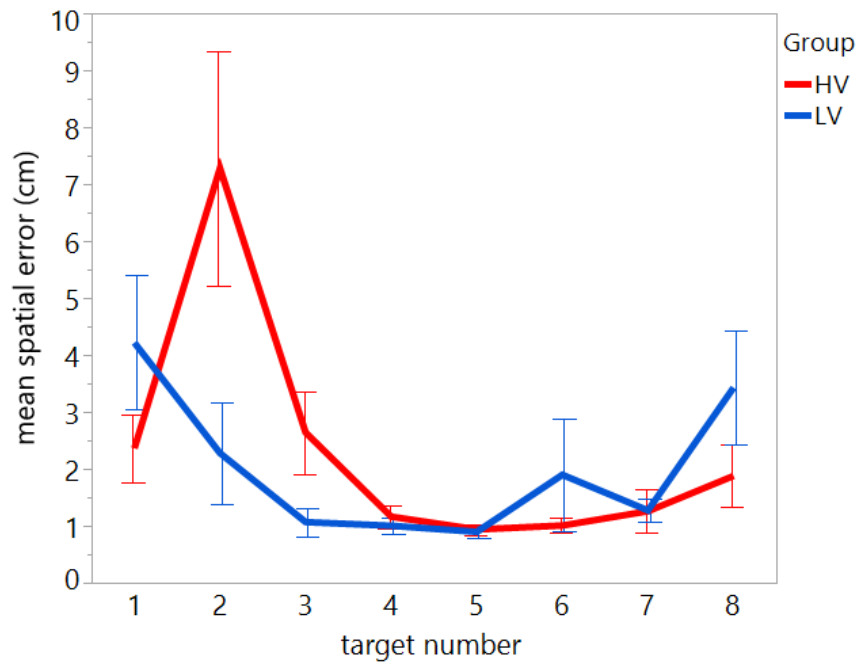


Fig S8. Experiment 2. Analysis of spatial error across consecutive targets at R1 of Block1

A Bayesian Independent Samples T-Test was performed to assess the likelihood of the spatial error in the HV and LV group being equal. The spatial error at all eight targets at R1 of Block 1 was averaged and subjected to comparison. We tested the null hypothesis, H_0 : spatial error of HV at R1 of Block 1 = spatial error of LV at R1 of Block 1 and the alternate hypothesis, H_1 :

spatial error of HV at R1 of Block 1 \neq spatial error of LV at R1 of Block 1. The prior is described by a Cauchy distribution centred around zero and a default width parameter of 0.707. The analysis resulted in a Bayes Factor, $BF_{01} = 2.698$ (see Table S2 for descriptives). This value of the Bayes Factor indicates anecdotal evidence for H_0 , which means that the data are 2.698 times more likely to occur under H_0 compared to H_1 . The Bayes Factor provides anecdotal evidence in favour of the null hypothesis (that HV and LV groups are not different).

						95% Credible Interval	
	Group	N	Mean	SD	SE	Lower	Upper
Spatial Error	HV	19	2.315	1.554	0.357	1.566	3.065
	LV	20	2.007	1.363	0.305	1.369	2.645

Table S2. Descriptive statistics. Descriptives of the comparison of spatial error in HV and LV groups, at R1 of Block 1, by means of a Bayesian independent t-test.

2.6.5.3 Experiment 3

The ANOVA with Greenhouse-Geisser correction ($\epsilon = 0.465$) on the participant's spatial error at R1 of Block 1 revealed a main effect of Target as in previous two experiments, indicating that participants reduced their spatial error over the 8 targets ($F(7, 259) = 7.976$, $p < 0.0001$, $\eta^2 = 0.177$, see Fig S9). The main effect of group (HV group: mean = 1.539, SE = 0.172 and LV group: mean = 1.557, SE = 0.168) was not significant ($F(1,37) = 0.005$, $p = 0.941$, $\eta^2 = 0.000$). The interaction between the two factors was also not significant ($F(7, 259) = 0.849$, $p = 0.548$).

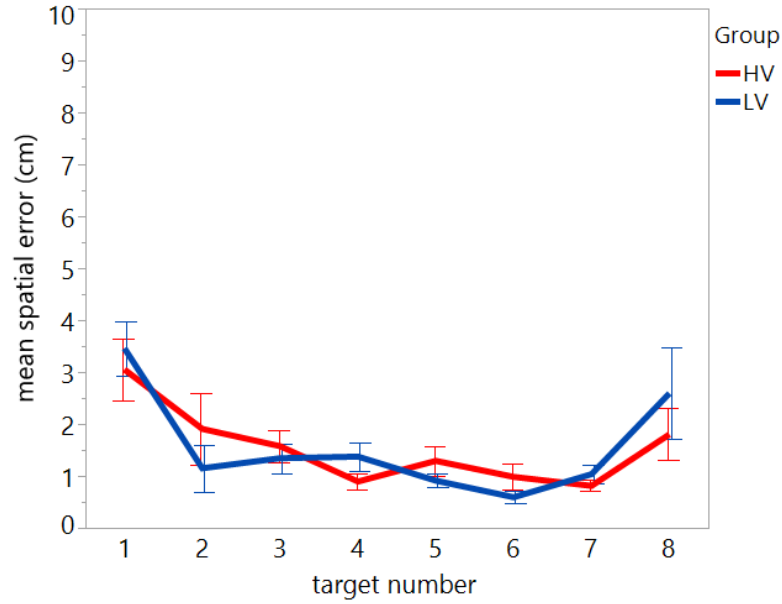


Fig S9. Experiment 3. Analysis of spatial error across consecutive targets at R1 of Block1

A Bayesian Independent Samples T-Test was performed to assess the likelihood of the spatial error in the HV and LV group being equal. The spatial error at all eight targets at R1 of Block 1 was averaged and subjected to comparison. We tested the null hypothesis, H_0 : spatial error of HV at R1 of Block 1 = spatial error of LV at R1 of Block 1 and the alternate hypothesis, H_1 : spatial error of HV at R1 of Block 1 \neq spatial error of HV at R1 of Block 1. The prior is described by a Cauchy distribution centred around zero and a default width parameter of 0.707. The analysis resulted in a Bayes Factor, $BF_{01} = 3.199$ (see Table S3 for descriptive). This value of the Bayes Factor indicates moderate evidence for H_0 , which means that the data are 3.199 times more likely to occur under H_0 than H_1 . The Bayes Factor provides moderate evidence in favour of the null hypothesis, i.e., that HV and LV groups are not different.

						95% Credible Interval	
	Group	N	Mean	SD	SE	Lower	Upper
Spatial Error	HV	19	1.539	0.727	0.167	1.189	1.890
	LV	20	1.557	0.770	0.172	1.197	1.917

Table S3. Descriptive statistics. Descriptives of the comparison of spatial error in HV and LV groups, at R1 of Block 1, by means of a Bayesian independent t-test.

The Bayesian analyses in Experiment 1 and 2 provide anecdotal evidence for no difference in spatial error between the two groups and the analysis on Experiment 3 provides moderate evidence for the same. These results along with the repeated measures ANOVA, provide converging evidence that the performance level of the two groups in R1 are not different. As our predictability manipulation only works from the second repetition on as one can only discover whether their partner is predictable or not through practice, similar performance at R1 in Block 1 suggests that both groups start at the same performance level in all three experiments. In Experiment 1, upon exposure to partner's variability produced in an unpredictable manner, HV group suffers a disadvantage, but only later in the course of training (which was shown in the main analysis with the grand averaged spatial error).

2.6.6 Influence of confederates' 'improvement in performance' on participants' performance

To investigate whether participants' performance was influenced by the confederates' improvements in performance (observed from main effect of Repetition in the confederates' data in all three experiments; see supporting information, Section 2.6.2), we analysed whether the

correlation between the two actor's spatial errors predicts how much the participant learns. We computed correlations between the participant's and confederate's spatial errors, on a trial-by-trial basis, for each pair separately. We then performed a group correlation analysis where we correlate r values with the participants' averaged spatial error (Analysis 1) and with the participants' difference in performance between Block 1 and Block 8, indicating the magnitude of participants' learning (Analysis 2).

A significant correlation in Analysis 1, between the r values and the averaged spatial error would indicate that participants' spatial error can be predicted by the degree of correlation between the actors. On the contrary, if the correlations are not significant, this would indicate that there is no significant relationship between the degree of correlation between the actors and the participant's spatial error performance implying that there is no indication that the learners' individual learning profile was dependent on the confederate's performance. Similarly, Analysis 2 would reveal how the degree of correlation between the actors predicts the participants' overall learning performance.

2.6.6.1 Experiment 1

A Pearson product-moment correlation was computed to determine the relationship between r values (correlations for participant and confederate's spatial error) produced for each pair and the overall spatial error of the corresponding participant in the pair (Analysis 1, see Fig S10). There was no relationship between the variables neither in the HV group ($r=0.178$, $n= 18$, $p= 0.478$) nor the LV group ($r= -0.187$, $n= 18$, $p= 0.456$). A Pearson product-moment correlation was computed to determine the relationship between r values (correlations for participant and confederate's spatial error) produced for each pair and the difference in performance between Block 1 and Block

8 of that participant (Analysis 2). The analysis also did not show any significant relationship between the two variables in HV group ($r = 0.192$, $n = 18$, $p = 0.435$) nor LV group ($r = -0.209$, $n = 18$, $p = 0.403$).

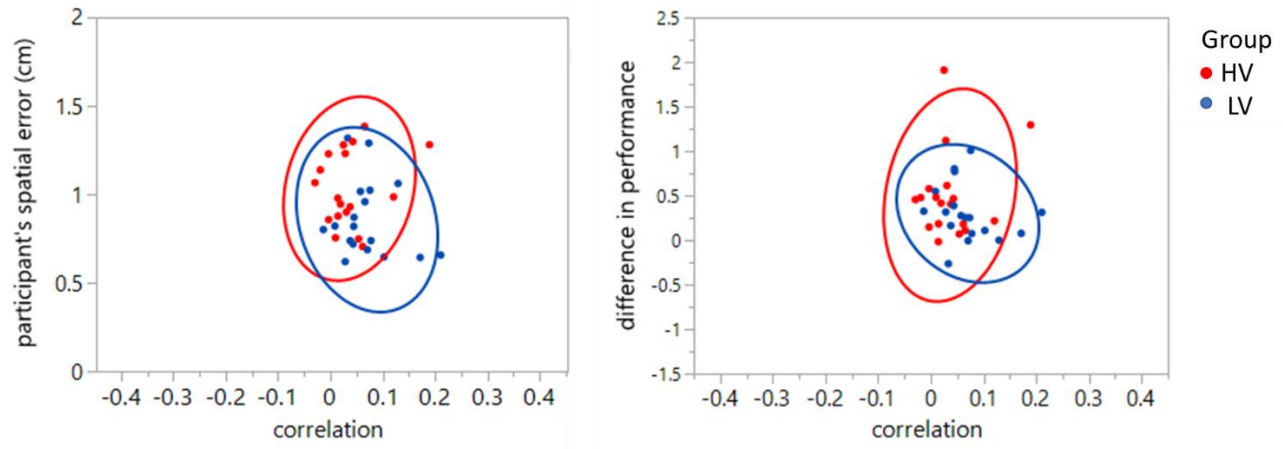


Fig S10. Correlation between inter-personal correlation values and participants' performance in Experiment 1. (A) Analysis 1 (B) Analysis 2

2.6.6.2 Experiment 2

The Pearson product-moment correlation computed to determine the relationship between r values and the overall spatial error of the participants (Analysis 1, see Fig S11) did not reveal any correlation between the variables neither in the HV group ($r = -0.064$, $n = 20$, $p = 0.785$) nor the LV group ($r = -0.340$, $n = 19$, $p = 0.153$). The Pearson product-moment correlation performed on the r values and the difference in performance between Block 1 and Block 8 of the participant (Analysis 2) also did not show any relationship between the two variables neither in HV group ($r = -0.019$, $n = 20$, $p = 0.934$) nor in LV group ($r = 0.250$, $n = 20$, $p = 0.287$).

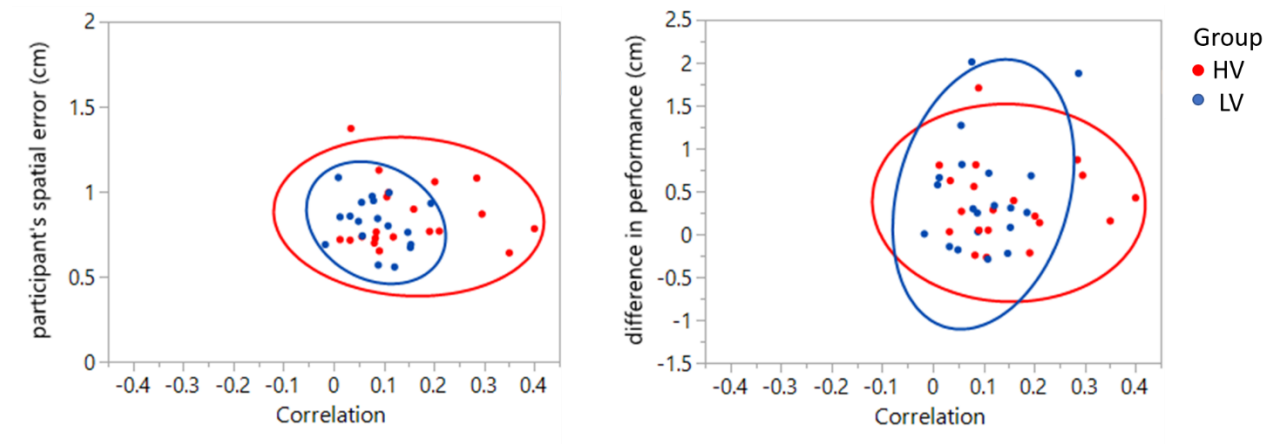


Fig S11. Correlation between inter-personal correlation values and participants' performance in Experiment 2. (A) Analysis 1 (B) Analysis 2

2.6.6.3 Experiment 3

The Pearson product-moment correlation computed to determine the relationship between r values and the overall spatial error of the participants (see Fig S12) did not reveal any significant relationship between the variables neither in the HV group ($r = -0.156$, $n = 19$, $p = 0.521$) nor in the LV group ($r = -0.430$, $n = 19$, $p = 0.065$). The correlation on the r values and the overall change in performance between Block 1 and Block 8 of the participant was also not significant neither in HV group ($r = 0.275$, $n = 19$, $p = 0.253$) nor in the LV group ($r = 0.256$, $n = 19$, $p = 0.289$).

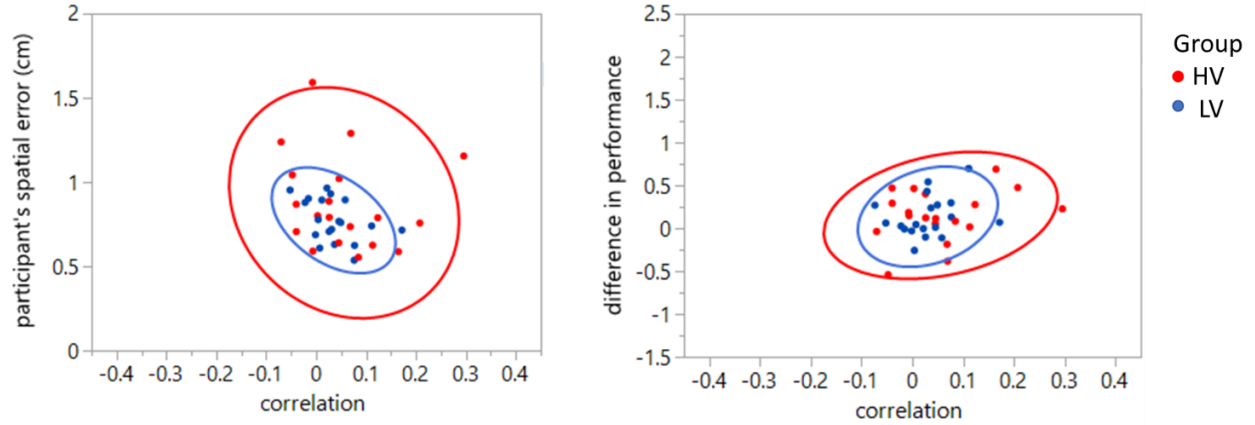


Fig S12. Correlation between inter-personal correlation values and participants' performance in Experiment 3. (A) Analysis 1 (B) Analysis 2

We collapsed the data from all three experiments to test whether the interactors' correlations predicted the participants' performance and learning regardless of the experimental manipulation (see Fig S13). Analysis 1 did not reveal any significant correlation between the inter-actor correlations and the spatial error performance of the participants in HV ($r = -0.132$, $p = 0.329$, $n = 56$) or LV group ($r = -0.223$, $p = 0.098$, $n = 56$). Analysis 2 also did not reveal any significant correlation between the inter-actor correlations and the participants' learning in either group (HV: $r = 0.098$, $p = 0.477$, $n = 54$; LV: $r = 0.076$, $p = 0.583$, $n = 54$).

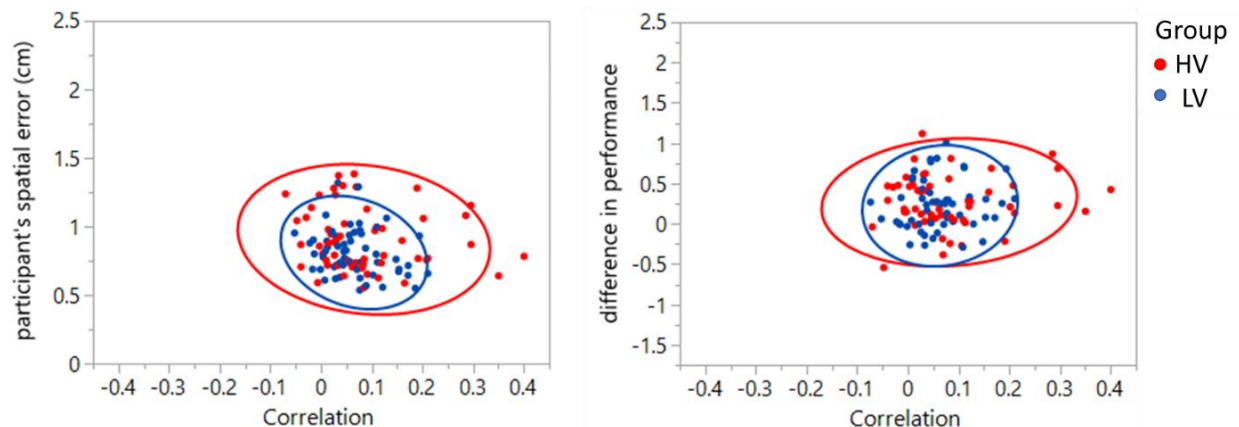


Fig S13. Correlation between inter-personal correlation values and participants' performance from Experiment 1, 2 and 3. (A) Analysis 1 (B) Analysis 2

The results of the correlation analyses did not provide evidence that the degree of correlation between partners' movements (which can be expected given the haptic coupling in our experimental setup) predicts the degree of participants' improvement over time. There is only an indication of the same in Analysis 1 of Experiment 3 conducted on the LV group data ($r = -0.430$, $n = 19$, $p = 0.065$), however, the results were not significant. This seems to indicate that we can separate the influence of the confederate's movements on the learners' movement (which is inevitable provided our experimental set up) from the learners' individual learning profile, which seem to be independent from the confederate's performance.

Chapter 3. Skill generalization in joint action: Does variability matter?

3. 1 Introduction

We often engage in joint actions with another person or a group of people while being physically coupled with each other, like when learning to dance together with a partner, when a parent helps a child learning how to walk, when sporting in a team like rowing, or when a therapist assists a patient in re-learning lost motor skills. These type of social motor behaviors require *joint-motor learning*, where actors actively engage in learning together with a partner while physically interacting with each other. It has been observed that motor coordination through physical interaction benefits individual performance as the physical coupling allows individuals to obtain additional task-related information from their partner (Van der Wel., 2011; Groten et al., 2012; Ganesh et al., 2014; Takagi et al., 2017; Batson et al., 2020). Specifically, individuals exploited the haptic interaction with a partner to generate haptic information channels that allowed them to improve their performance.

Even though prior studies have investigated the benefit of haptic coupling during dyadic interactions, little is known about the motor control mechanisms behind joint-learning in these scenarios. Joint action research has often explored motor coordination, task representation and similar mechanisms underlying joint actions. However, how individuals acquire internal models required for learning a novel task while acting with a partner and how they transfer these dynamic models to a different task scenario, remains an open question. Are the principles underlying joint motor learning the same as the ones underlying individual motor learning?

Individual motor learning fundamentally involves the ability to acquire, adapt and flexibly modify motor skills. *Skill acquisition* and *skill generalization* have thus been extensively investigated to understand motor learning principles. While skill acquisition refers to the voluntary control over movements of joints and body segments as part of solving a motor problem and achieving a task goal (Magill and Anderson, 2010), skill generalization refers to our ability to apply what has been learned in one context to other untrained action contexts (Krakauer et al., 2006).

Recent studies have investigated skill acquisition in joint action (Ganesh et al., 2014; Takagi, Beckers & Burdet, 2016; Mireles et al., 2017; Kager et al., 2019; Sabu et al., 2020), but little is known about skill generalization in joint action learning. Generalization of a learned skill can happen when the newly acquired skill could be reproduced by employing a new set of motor parameters (Seidler et al., 2001; Shadmehr & Mussa-Ivaldi, 1994), as when transferring under varying task contexts. Generalization can also be observed when generalizing from one action type to another, for example, from discrete to continuous movements (Abeele & Bock, 2003).

Skill generalization in individual learning generally involves retrieval and modification of the newly acquired or learned internal models of motor control. In terms of mechanisms, joint action involves additional variables and processes compared to individual action performance, as coordination of individual behaviors are required to perform joint tasks, and actors must aim to improve not only their individual but also the joint performance. Assuming some overlap between joint and individual motor learning mechanisms, such as retrieval and adaptation to novel action contexts, there are some important differences: especially if joint learning involves physical interaction, as the storage of task information within the action models and the strategies adopted to update these models could differ, as the sensorimotor feedback involved in these tasks are

different compared to when acting alone. In other words, the spatiotemporal parameters and the kinematics learned will be different if the learning involved coordinating with another individual, compared to navigating through the action space alone, thus, different mechanisms might be at play in these two action scenarios. Hence, the current set of studies aims to explore how motor skills are generalized during joint-motor learning that involves constant physical interaction with the partner.

Present Study

In individual learning, it has been observed that when individuals transfer their skill to a task involving novel mechanical characteristics, like an external force perturbation, generalization of the dynamic model learned during training is limited, as the model is sensitive to the limb dynamics (Krakauer et al., 1999; Malfait et al., 2002, 2005). However, the nature of transfer might be different in action contexts involving dyadic interaction, especially if physically coupled. This is because dynamic joint action models for tasks involving physical interaction are likely to include additional task information compared to when acting solo. This could impact skill transfer to novel action contexts. Specifically, the sensorimotor information attained through the dyadic interaction could accommodate a wider range of action possibilities compared to solo performance.

Generalizing a motor skill to a novel task can either prove to be beneficial for performance in a new task, resulting in *transfer*, or it can be detrimental, resulting in *interference* (Krakauer et al., 2006). Previous studies have explored skill generalization from joint action to individual action scenarios, often showing that joint learning promotes transfer to individual action contexts (Mireles et al., 2017; Beekers et al., 2018). However, little is known on whether generalization in joint learning from one joint action context to other leads to transfer or interference. In the current study, we investigate how the internal model learned during joint learning involving physical

coupling, is generalized to novel or untrained joint action contexts. In motor rehabilitation, to regain a lost motor skill, therapists train patients to relearn single action units, so that they can combine these isolated movements to implement a sequence of these movements (Dahms et al., 2020). In the current study we investigate a similar scenario where individuals are engaged in joint learning while they are haptically coupled: they first learn to produce single action units, and later are tested on the performance of sequential movements. We also test how they generalize their intrinsic dynamics, i.e., the motor primitives employed for the training task, to varying mechanical characteristics of the novel task such as external perturbations experienced through the physical interaction. In this task, during training, the aiming movements were isolated from each other; thus, individuals learned to perform separate action units. The actors were haptically coupled using an elastic band, which exposed them to a wide range of force perturbations during the training. We then measured participants' movement kinematics, including individual and joint measures of spatial and temporal performance, during generalization.

Previous research indicates that when performing different types of joint action (discrete vs. continuous) individuals modulate different movement parameters and mechanisms (van der Wel et al., 2015). Also, neurobiological evidence suggests that action sequences are processed as action units that are hierarchically organized and are then combined to produce sequential movements (Jin & Costa, 2015). In the present task, we designed different test phases to investigate how participants generalize their learned skill to a novel action type, namely sequential movements.

As a further test of generalization, we asked whether individuals can extrapolate from a learned range of forces experienced with a co-actor to novel forces that go beyond the learned range. The force perturbation coming from the haptic coupling between the actors in our task can

lead to spatial distortions and temporal delays in their individual movements. Thus learning, in this joint action context, consists in fine tuning spatiotemporal parameters of individual movements to minimize spatial distortions and temporal delays.

While we are mainly interested in knowing how the individual performance, i.e., the spatial accuracy, is affected during generalization, understanding how the joint performance, i.e., the temporal asynchronies between the actors, unfolds in the task, will provide us a clearer picture on how the dyadic interaction influences generalization. Hence, we assessed how the spatial and temporal accuracies of a skill learned during training are generalized to sequential movements and varying force perturbations.

To summarize, in the current study, participants were tested for skill generalization to action sequences and to new forces resulting from perturbation from a joint action partner. This allowed us to investigate whether and how the dynamic model learned during joint training with haptic coupling is generalized to new action contexts and different levels of force perturbations.

3.2 Experiment 1 A

In Experiment 1A, we investigated how motor skills learned during a joint learning, involving physical interaction, could be generalized to novel action contexts. We specifically looked at how the skills are generalized one from action type to another, namely discrete unit actions to sequential actions and how the motor parameters learned during training are extrapolated or generalized to novel mechanical characteristics of the task.

During training participants performed a joint aiming task that consisted of producing isolated targeted aiming movements with a partner. The actors were haptically coupled using an elastic band. Thus, partners' movements implied force perturbations on each other's movements. The

confederate's target positions were purposely selected in a way that implied a certain range of force perturbations. The spatial and temporal accuracy of the participants' movements were calculated as measures of performance.

Participants were then tested in various test conditions that required generalizing the learned skill to novel joint action scenarios. The tests required participants to generalize from action units to sequential movements and to generalize from the learned range of force perturbation to various ranges of force perturbation. If learning a motor task through a physical interaction with a partner benefits skill generalization to novel joint action scenarios, one should expect that spatial and temporal accuracy of the participants in the test will be similar or better than the spatio-temporal accuracy they reached at the end of the training session. Alternatively, if generalization of skill from one joint action context to another during a dyadic interaction leads to interference, one should observe a significant worsening of spatial and temporal accuracy, compared to the floor performance in the training.

3.2.1 Method

Participants

Twenty people participated in the study (12 Females, Mean_{age} = 28.36 years, SD_{age} = 2.881 years). The data coming from one participant was not recorded due to technical issues and therefore the participant was removed from all analyses. Participants were recruited through the SONA online participation system. All participants were right-handed and reported to have normal or corrected-to-normal vision. They received monetary compensation for their participation. One lab assistant volunteered as the confederate for the experiment.

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Apparatus and Stimuli

The experimental setup consisted of a table, on which, two 4x8 arrays of circles were marked on either side and defined as possible target locations (see Fig 9). The targets were projected using an Epson EH-TW490 Lumen projector attached to the ceiling, above the table and were cued as yellow concentric circles. Two actors, a participant and a confederate were seated on each long side of the table facing each other. An occluder was placed in the middle of the table to prevent the actors from seeing each other's movements. An opening in the bottom of the occluder allowed haptic coupling between the two actors. Actors were haptically coupled using a stretchable rubber band. A force measuring gauge, Sauter FK250 Digitális Erőmérő, was used to measure the forces produced by the rubber band at each target configuration, to create the sequences necessary for the experiment.

The actors' movements were tracked online and recorded using a Polhemus G4 electro-magnetic motion capture system (40 Hercules Drive, Colchester, Vermont). Both actors were given a handle with a micro-motion sensor (1.8 mm) inserted inside to perform the task. The Polhemus motion sensor tracked the actors' movements at a frequency of 120 Hz. Each of the 32 potential target positions for both actors were calibrated as reference coordinates before the start of the experiment. The experiment was run on a Dell Precision computer. MATLAB (R2015a) was used for running experimental script and data preparation and Rstudio Team (2020) and IBM SPSS 20 was used for performing the data analyses.

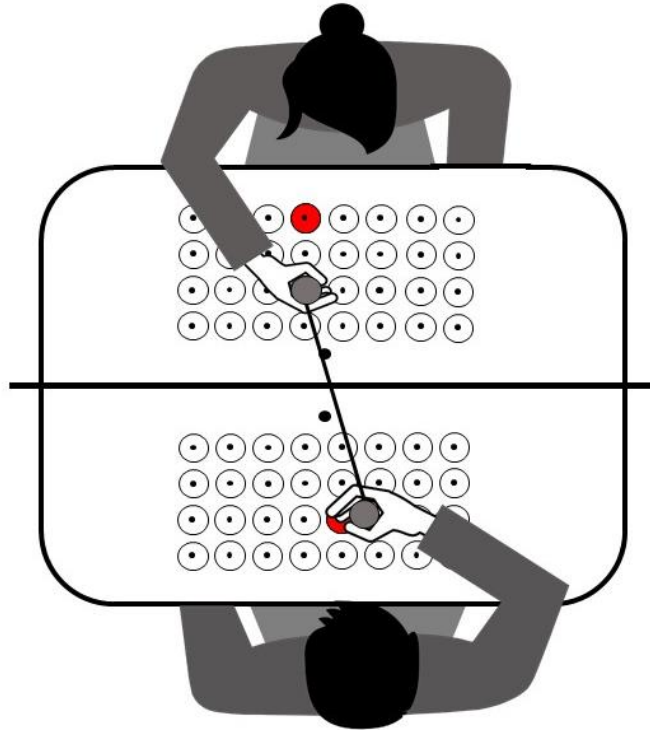


Fig 9. Experimental apparatus and stimuli. Figure shows the setup with target arrays marked on the experimental table for both participant and the confederate. Each array consists of 32 circles arranged in a 4x8 matrix and a black dot above each array marking the start position. Each circle has a diameter of 4.5 cm, with a center marked as a small black circle with a diameter of 0.5 cm. Target circles are cued in red using a projector and actors are instructed to aim at the center of the cued target, upon its onset. One target from each array is cued simultaneously for the participant and the confederate. Together, the two targets constitute a *target configuration*. The figure also illustrates the haptic coupling between the actors using an elastic band.

Procedure

A participant and a confederate performed a *joint aiming task* together. Both actors were instructed to perform their actions on the target array presented in front of them, on their side of the

experimental table. The experiment consisted of a familiarization phase, a training phase, and a test phase.

In the *familiarization phase*, actors received 15 targets that were to be aimed at discretely. These trials were introduced to familiarize the actors with the aiming task to be performed in the joint phase. The trials were performed individually, without experiencing any force perturbation. Actors started from the starting position, which was then followed by the target cue for a 1000 ms duration, during which, they had to hit center of the cued red circle, with the handles provided to them. Then, all circles turned black, at which point, actors were instructed to return to the start position.

The familiarization was followed by the *joint training phase* in which the participant and the confederate performed the task together. In this phase, the actors were haptically coupled with each other through an elastic band. Each of the targets were cued for 1000 ms simultaneously for the participant and the confederate. Participants were instructed to hit the center of the cued targets as accurately as possible within the cue duration and to temporally synchronize their movements with their partner so as to land on their respective targets at the same time (see Fig 10A). The joint-training phase included 8 blocks, each block consisting of 30 targets each for both actors. Each of the target movements were performed in isolation from each other, i.e, both actors returned to their starting position after completion of each aiming movement.

The inter-target distances between the actors were manipulated to produce various force perturbations across each movement. The forces were selected from a uniform distribution of forces ranging from [9-27] N (see Table 5). These forces are separated into six bins, each of which had a width of 3N. Five different target configurations were selected from each of the six bins to construct blocks of 30 targets. Short breaks were taken in between each block.

Bin Number	Force Range (N)
1	9.0 - 12.0
2	12.0 - 15.0
3	15.0 - 18.0
4	18.0 - 21.0
5	21.0 - 24.0
6	24.0 - 27.0

Table 5. Force Range for Training: Uniformly distributed forces selected for the joint-training session, separated into six bins, each having a width of 3N. The upper and lower limit of each of the bins were excluded from the force selection, i.e., only the forces within the range, excluding the category borders, were selected to form each block (e.g., 10N and 11N in Bin 1).

The training phase was followed by a 10-min resting period. The resting duration was chosen based on prior research on practice-dependent learning showing within session improvements in motor performance when tested after 10 minutes of training (Walker et al., 2003; Boutin et al., 2013).

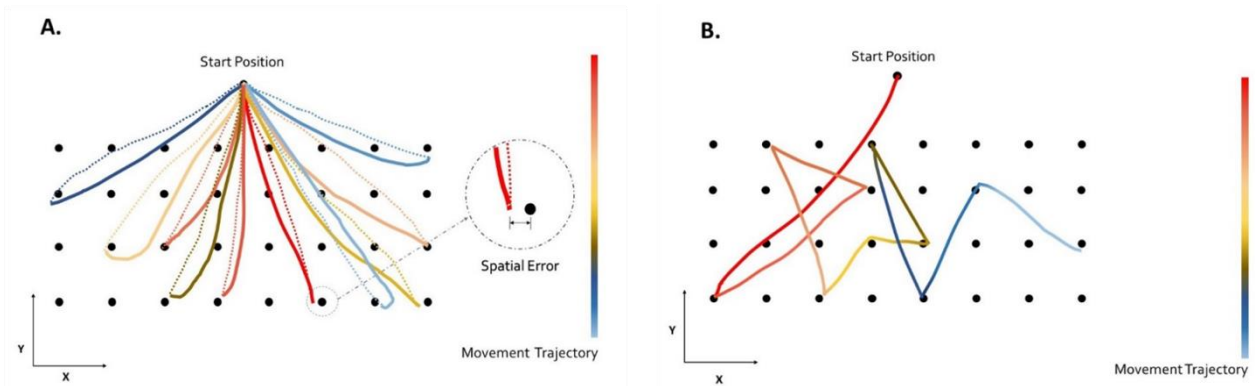


Fig 10. Example participant's movement trajectories in the training and test phase: Figure shows a schematic representation of a participant's movement trajectory across different target positions. For ease of demonstration, only ten trajectories are shown in the figure (each block of movement in training and tests consisted of 30 movements each). Spatial error marks the distance between the target position and their actual landing position. (A) Single movement units in *training phase*, where participants start from the start position, hit the target within the cue duration (bold

lines) and return to the start position (dotted lines). (B) Sequence of movements in the *test phase*, where participants start from start position and move from one target to the other.

The rest period was followed by the test phase that included three different test conditions, each consisting of 2 blocks with 30 targets per block. Each of the 30 movements were to be performed as a sequence. Hence the targets were cued one after another, unlike in the training phase. The actors did not return to the start position after each movement (see Fig 10B). All the test conditions assessed whether participants generalized their skill to a novel action type, i.e., sequential movements with various ranges of forces induced by a partner.

Test 1 consisted of sequentially arranged movements that produced novel force configurations. Forces were selected from three different force bins, each having a width of 3N, and consisted of novel and larger forces compared to the training phase, ranging from [27-36] N (see Table 6). Ten different force configurations were selected from each of the three bins to create the sequence of 30 target positions. There was one such sequence for each of the two blocks.

Test 2 included sequentially arranged movements that included forces from the training range, [9-27] N. However, forces were selected in a way that 50% of the targets were picked from the smaller force bins, i.e., [9-24] N and 50% of the targets were picked from the largest force bin, [24-27] N. *Test 3* included sequential movements, in which the forces produced at each target were familiar or pre-exposed forces, ranging from [9-27] N.

Test Condition	Force Range (N)
Test 1	27.0 - 30.0 30.0 - 33.0 33.0 - 36.0
Test 2	09.0 - 24.0 24.0 - 27.0
Test 3	09.0 - 12.0 12.0 - 15.0 15.0 - 18.0 18.0 - 21.0 21.0 - 24.0 24.0 - 27.0

Table 6. Force Range for Test Phases: Test1 included novel and larger forces selected from three different bins ranging from [27-36] N, Test 2 included equal distribution of smaller and larger forces separated into two bins, selected from the training range [09- 24] and [24- 27] N, and Test3 included pre-exposed forces from training, distributed across 6 different bins ranging from [09- 27] N.

A short *Stroop task* was introduced between each test, as a wash-out task, to avoid any transient effect of learning between consecutive tests. The Stroop task involved 120 trials in which participants were primed with words like ‘RED’, ‘GREEN’, ‘BLUE’ printed in different target colors. They were instructed to respond to the print color and ignore the meaning of the word. The prime was congruent or incongruent to the target color for 50% of the trials. Participants had no knowledge about the congruency of the trials. Each Stroop task lasted about 5 minutes. The overall duration of the experiment was about 50 minutes.

Data Processing and Analysis

The kinematic data obtained through motion tracking, from both the participant and the confederate, was segmented to retrieve the landing positions at each target. Landing positions are defined as the final position of the handle, after the actor hit the cued target circle. At the end of each target movement within the cue duration (1000 ms), when the movement velocity (cm/s) was minimal (~ 0 cm/sec), the 2D coordinate of the sensor was identified as the landing position. An automatized MATLAB algorithm was used to segment the data. The landing positions were used to further calculate the dependent variables.

The *spatial accuracy* of the actors' movements was calculated using the landing positions, as a measure of their individual performance. The *spatial error (cm)* of each target movement was obtained by calculating the Euclidean distance between the landing position and the target coordinates. For the joint-training data, spatial errors at each of the 30 targets within a single block were then averaged. The averages were subjected to a Repeated measures ANOVA with Blocks (B_1 - B_8) as the within-subject factor. The averaged spatial error of both blocks in each of the tests were compared against the spatial performance at the first and last block of the training phase. This analysis was performed to assess the change in performance in the test phases in comparison with the pre (B_1 of training) and post (B_8 of training) learning performance. Repeated measures ANOVA with Block (from training and test) as the within-subject factor were performed to assess statistical significance. In Test 2, a separate 2 (Block) x 2 (Force) ANOVA was also conducted to see the difference in performance in the small and large force conditions within the test.

The time stamps recorded at the landing positions were used to calculate the *accuracy of temporal coordination* between the actors (participant and confederate), as a measure of their joint performance. For the joint-training data, the average temporal asynchronies at each block were

subjected to a Repeated measures ANOVA with Block (B₁- B₈) as within-subject factor. For each of the three tests, the average asynchronies at the first and the second block of the test were compared against the pre (B₁ of training) and post (B₈ of training) learning performance using a repeated measures ANOVA. As in the spatial data of Test 2, the temporal asynchronies were subjected to a separate 2 (Block) x 2 (Force) ANOVA to see the difference in performance in the small and large force conditions within the test.

Trials in which landing positions were recorded to be 5 cm or more outside the target matrix were considered as outliers and removed from analysis. A total of 0.68% trials of the training, 0.33% trials from Test 1, none from Test 2 and 0.5% trials from Test 3 were removed from Experiment 1A as part of the outlier removal. Greenhouse-Geisser corrected values were used for factors that violated Mauchly's sphericity test. All significant main effects were further analyzed by applying Bonferroni correction for multiple comparisons.

3.2.1 Results

Spatial Accuracy

Training Phase: The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.497$) revealed a main effect of Block, indicating that participants learned to reduce their spatial error over time ($F(7,126) = 5.079$, $p = 0.002$, $\eta^2 = 0.220$, see Fig 11). The post-hoc analysis revealed that spatial error at B₁ (mean= 1.757, SE= 0.141) was significantly higher compared to B₂- B₈ (all $ps < 0.05$).

Test 1 (Novel-force test): The average spatial error measured from the two blocks was compared against the first and last blocks of the training phase through four separate repeated measures ANOVA. The ANOVA performed on the spatial accuracies at B₁ of training (mean= 1.757, SE= 0.141) and B_{1-T1} (mean= 1.508, SE= 0.140) revealed no significant main effect of Block, indicating

that participants exhibited a similar spatial performance as in their pre-training trials, when they were introduced to novel and larger forces and performed sequential movements ($F(1,18) = 2.337$, $p = 0.144$, $\eta^2 = 0.115$, see Fig 11). Analysis on B_1 and B_{2_T1} (mean = 1.144, SE = 0.081) revealed a significant reduction of spatial error at the second block of the test compared to their initial performance in the task ($F(1,18) = 24.317$, $p < 0.0001$, $\eta^2 = 0.575$, see Fig 11). The ANOVA performed on spatial accuracies at B_8 (mean = 1.316, SE = 0.082) and B_{1_T1} revealed no significant difference in performance ($F(1,18) = 2.301$, $p = 0.147$, $\eta^2 = 0.113$, see Fig 11) and so was the case at B_{2_T1} , indicating that participants maintained their post-training performance (at B_8) even under conditions of novel task characteristics ($F(1,18) = 2.720$, $p = 0.116$, $\eta^2 = 0.131$, see Fig 11).

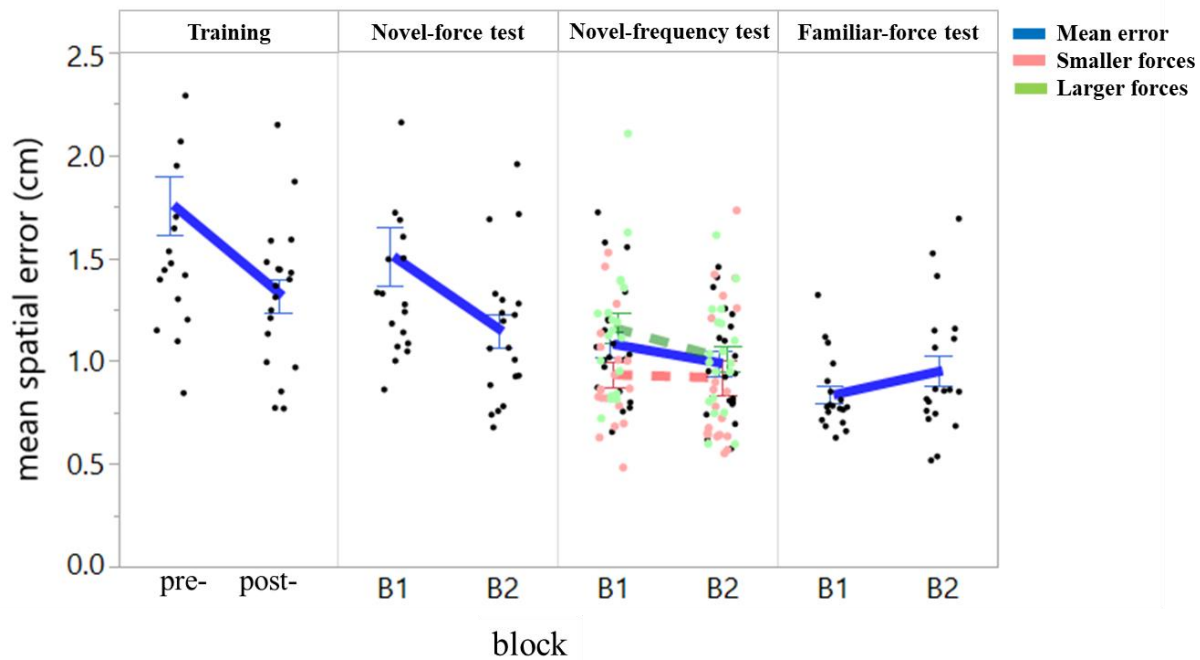


Fig 11. Mean spatial error during training and test phases in Experiment 1A: The figure shows the mean spatial error of participants' movements in the training and test conditions, in separate panels. The first panel shows mean spatial error at the pre- and post-training blocks. From the test phases, each panel shows mean spatial error at Block 1 (B_1) and Block 2 (B_2) for *novel-force test*, *novel-frequency test*, and *familiar-force test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 2 (Novel-frequency test): The average spatial error at each of the two blocks in the test was compared to the pre (B_1) and post-training (B_8) performances, through separate analyses of variances. The ANOVA performed on the spatial accuracies at B_1 of training and B_{1_T2} , revealed a significant main effect of Block, $F(1,18) = 34.827$, $p < 0.0001$, $\eta^2 = 0.659$, see Fig 11), with the improved spatial accuracy at B_{1_T2} (mean = 1.048, SE = 0.058) compared to B_1 (mean = 1.757, SE = 0.141). The ANOVA comparing B_1 of training and B_{2_T2} (mean = 0.966, SE = 0.058) also revealed a significant reduction of spatial error, indicating that participants maintained their initial performance throughout the test phase when smaller forces were exerted ($F(1,18) = 34.158$, $p < 0.0001$, $\eta^2 = 0.655$, see Fig 11). A significant improvement of spatial accuracies was also observed during comparison of the post-training performance, B_8 (mean = 1.316, SE = 0.082) and B_{1_T2} ($F(1,18) = 9.071$, $p = 0.007$, $\eta^2 = 0.335$, see Fig 11). Similar results were obtained from the ANOVA comparing B_8 and B_{2_T2} indicating that participants improved their spatial accuracy throughout the test (16.076, $p = 0.001$, $\eta^2 = 0.472$, see Fig 11). A separate 2 (Block) x 2 (Force) ANOVA conducted on the within-test data comparing B_{1_T2} and B_{2_T2} , revealed no significant main effect of the block, $F(1,18) = 0.1982$, $p = 0.176$, $\eta^2 = 0.099$, suggesting participants did not improve their performance across blocks within the test. However, a significant main effect of force revealed $F(1,18) = 11.183$, $p = 0.004$, $\eta^2 = 0.383$, a worse spatial performance in the larger force condition (mean = 1.088, SE = 0.060) compared to the smaller force condition (mean = 0.926, SE = 0.050). The interaction effect was not significant ($F(1,18) = 1.022$, $p = 0.325$, $\eta^2 = 0.054$).

Test 3 (Familiar-force test): The average spatial error in the two blocks of *Test3* was compared against the first and last blocks of the training phase through four separate repeated measures ANOVA. The ANOVA performed on the spatial accuracies at B_1 of training (mean = 1.757, SE = 0.141) and B_{1_T3} (mean = 0.835, SE = 0.041) revealed a significant main effect of Block, with the

spatial error being less at B_{1-T3} ($F(1,18) = 48.954, p < 0.0001, \eta^2 = 0.731$, see Fig 11). The accuracies were less at B_{2-T3} (mean = 0.953, SE = 0.074) as well compared to B₁ of training ($F(1,18) = 35.794, p < 0.0001, \eta^2 = 0.665$, see Fig 11). The spatial accuracies at B₈ (mean = 1.316, SE = 0.082) and B_{1-T3} was also significantly different, indicating that participants improved their spatial accuracies from their post-training performance ($F(1,18) = 32.468, p < 0.0001, \eta^2 = 0.643$, see Fig 11). Participants improved their spatial accuracies at B_{2-T3} compared to B₈, ($F(1,18) = 15.440, p = 0.001, \eta^2 = 0.462$, see Fig 11), indicating an improved performance from the post-training accuracy throughout the test.

Temporal Accuracy

Training Phase: The ANOVA performed on the absolute asynchronies measured from the training data revealed no significant main effect of Blocks, indicating that actors did not improve their temporal synchrony over time ($F(7,126) = 1.019, p = 0.421, \eta^2 = 0.054$, see Fig 12).

Test 1 (Novel-force test): The average absolute asynchronies of the actors at first and second block of *Test1* were compared against their temporal performance at the first (B₁) and last blocks (B₈) of the training phase through four separate repeated measures ANOVAs. The temporal asynchronies at B₁ of training (mean = 0.094, SE = 0.004) and B_{1-T1} (mean = 0.104, SE = 0.004) was significantly different, with the asynchronies being higher at B_{1-T1} ($F(1,18) = 6.059, p = 0.024, \eta^2 = 0.252$, see Fig 12). Similar results were obtained at B_{2-T1} (mean = 0.113, SE = 0.005) compared to B₁, indicating that actors could not improve their temporal synchrony from their initial performance in the task, even with time ($F(1,18) = 15.909, p = 0.001, \eta^2 = 0.469$, see Fig 12). The ANOVA performed on the temporal asynchronies at B₈ (mean = 0.091, SE = 0.005) and B_{1-T1} also showed a significant worsening of synchrony at B_{1-T1}, ($F(1,18) = 7.513, p = 0.013, \eta^2 = 0.294$, see

Fig 12). They continued to get worse at B_{2_T1}, indicating that the actors were more asynchronous throughout the test phase compared to their post-training performance ($F(1,18) = 10.329$, $p = 0.005$, $\eta^2 = 0.365$, see Fig 12).

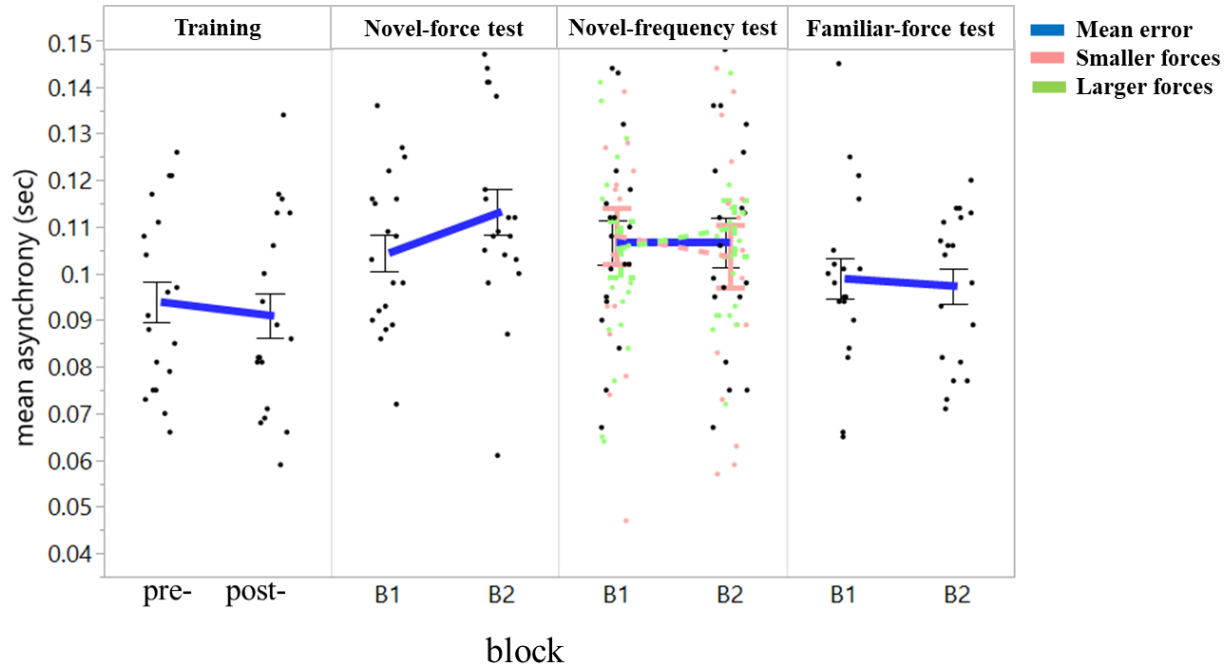


Fig 12. Mean temporal asynchrony during training and test phases in Experiment 1A: The figure shows the mean temporal asynchrony of the actors' landing times from the training and test phases in separate panels. The first panel shows mean asynchrony at the pre- and post-training blocks. From the test phases, figure shows mean asynchrony at Block 1 and Block 2 for *novel-force test*, *novel-frequency test*, and *familiar-force test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 2 (Novel-frequency test): The average asynchronies at each of the two blocks in the test were compared to the actors' pre (B₁) and post-training (B₈) joint performances separately. The ANOVA conducted on the temporal asynchronies at B₁ of training (mean = 0.094, SE = 0.004) and B_{1_T2} (mean = 0.107, SE = 0.005), revealed a significant worsening of synchrony at the test block ($F(1,18) = 7.725$, $p = 0.012$, $\eta^2 = 0.300$, see Fig 12). The ANOVA comparing the temporal asynchronies at B₁ and B_{2_T2} (mean = 0.107, SE = 0.005) also revealed a significant worsening of

the asynchronies in the test main effect indicating that participants managed to return to their initial temporal performance at the second block of the test ($F(1,18) = 10.061$, $p = 0.005$, $\eta^2 = 0.359$, see Fig 12). Further, comparison of the temporal accuracies at B_8 (mean = 0.091, SE = 0.005) and B_{1_T2} , revealed a significant worsening in performances in the test block, indicating that participants could not maintain their post-training performance, in the first block of test ($F(1,18) = 8.122$, $p = 0.011$, $\eta^2 = 0.311$, see Fig 12). Similar results were obtained at B_{2_T2} , suggesting that the temporal performance was worse throughout the test, compared to their floor performance achieved during training ($F(1,18) = 6.905$, $p = 0.017$, $\eta^2 = 0.277$, see Fig 12).

The within-test analysis conducted with the block and force as the within-subject factors, revealed no main effect of block ($F(1,18) < 0.000$, $p = 0.998$, $\eta^2 < 0.0001$) or force ($F(1,18) = 0.117$, $p = 0.736$, $\eta^2 = 0.006$), suggesting no difference in performance, neither across blocks nor across the smaller or larger force conditions. The interaction effect was also not significant ($F(1,18) = 0.598$, $p = 0.449$, $\eta^2 = 0.032$).

Test 3 (Familiar-force test): The average absolute asynchronies of the actors at the two blocks of *Test3* was compared against their temporal performance at the first (B_1) and last blocks (B_8) of the training phase through four separate repeated measures ANOVA. The analysis performed on the temporal asynchronies at B_1 of training (mean = 0.094, SE = 0.004) and B_{1_T3} (mean = 0.099, SE = 0.004) did not reveal any difference between the two performances ($F(1,18) = 2.059$, $p = 0.168$, $\eta^2 = 0.103$, see Fig 12) and so was the case at B_{2_T3} (mean = 0.097, SE = 0.044, $F(1,18) = 0.510$, $p = 0.484$, $\eta^2 = 0.028$). There was no difference in the asynchronies at B_8 (mean = 0.091, SE = 0.005) and B_{1_T3} either ($F(1,18) = 2.260$, $p = 0.150$, $\eta^2 = 0.112$, see Fig 12). Similar results were obtained from the comparison of absolute asynchronies at B_8 and B_{2_T3} , suggesting that actors exhibited

similar synchrony as that of their floor synchrony reached in training ($F(1,18) = 2.604$, $p = 0.124$, $\eta^2 = 0.126$, see Fig 12).

3.2.3 Discussion

In the current study, we investigated how the dynamic internal model learned during joint learning, under the influence of haptic interaction with a partner, is generalized to conditions of varying task contexts, i.e., novel action type and novel movement parameters. We trained participants in an aiming task in which they performed joint aiming movements, as separate action units, while they were haptically coupled with a partner. Following the joint-learning, participants were tested for their ability to generalize the aiming skill learned as separate action units to sequential movements and their ability to generalize their movement kinematics to varying force perturbations. They were tested in three consecutive phases, under three different force perturbations. A successful *transfer* of skill, in the current experiment, would mean that individuals improved their spatiotemporal accuracies in their test performance compared to their training performance and an *interference* would mean that they exhibited a worse performance in the test in either of the two movement parameters under study, compared to their training.

In Test 1, when tested under the context of novel and larger forces, individuals' initial spatial performance at the test, i.e., at B_{1_T1} , show no generalization as their spatial accuracy is same as in the first block of training (B_1). This suggests that their spatial performance was same as in their first encounter to the task. However, in their second block of test (B_{2_T1}), they improved their spatial accuracy compared to the initial performance. Also, they exhibited a similar performance as in the last block of training (B_8), indicating that participants require more training in the novel movement context to re-calibrate their motor parameters and show any generalization. This slower transfer could be attributed to the higher task difficulty involved in the task. Even

though the improvement at B_{2_T1} suggests that the training provided some room for generalization, it is possible that the training did not have an influence on the test performance, rather, learning happened over the first block of the test. An effect of training on the test performance can only be proven with a control condition in which participants perform the test blocks without undergoing training. It needs to be noted that, even though they exhibited a slower transfer of learning in the spatial dimension, they suffered a decrement in performance in the temporal dimension. This could be attributed to a spatiotemporal tradeoff in generalization, i.e., an interference on the temporal dimension while generalizing in the spatial dimension.

In Test 2, participants produced sequential movements under the influence of perturbation selected from their training range, although the frequency of the various forces experienced were different from the training. They received an equal distribution of smaller and larger forces in the test. The results suggest that individuals exhibited transfer in the spatial dimension, for their overall performance, with an additional performance increment compared to their post-training performance (B₈). But, overall, they exhibited a worse synchrony compared to the training, indicating a spatiotemporal tradeoff. However, the within-test analysis, with forces and block as the repeated factors, revealed that participants' spatial performance was worse when they received larger forces, compared to when they received smaller forces, presumably because they needed longer training to adjust to the task demands of performing under a larger force perturbation. However, the temporal synchrony between the actors did not differ in the two force conditions.

In Test 3, under conditions of least task difficulty, individuals showed a benefit in regard to the spatial accuracy. Also, they did not suffer any trade-off cost, as their temporal performance was not different from training.

Taken together, the results of Experiment 1A suggest that individuals can successfully generalize the skill learned during joint learning involving physical interaction with the partner, to novel movement scenarios. Importantly, a transfer (positive generalization) was mostly observed in individual performance, i.e., the spatial accuracy, but not in the joint performance, i.e., the temporal accuracy of interpersonal coordination. Also, when the task difficulty of the novel action context is lower, individuals do not only generalize the spatial performance but also exhibit further learning benefits by further improving their performance compared to training. When the task difficulty in the novel action context is higher, individuals tradeoff the improvement in performance on the spatial dimension by suffering an interference on the temporal dimension.

3.3 Experiment 1 B

As mentioned earlier, skill generalization can either lead to a *transfer* of the learned skill, or it can be detrimental and lead to an *interference* of the skill (Krakauer et al., 2006). Many intrinsic and extrinsic factors can determine whether the generalization leads to transfer or interference. Motor variability has been understood as a key intrinsic factor that determines successful motor learning in individuals. In joint action, the variability involved in the task is twofold as individuals must deal with not just their own internal variability, but also with their partner's variability. Especially if the task involves tight physical coupling between the actors, each actor's movements will have a direct physical impact on the other's movement. Whether variability of a partner's movements leads to transfer of learned skill or whether it causes interference while generalizing the learned skill to a novel movement context remains an open question.

An interesting finding from the individual learning literature on skill generalization is that for maximizing the rate of learning and degree of generalization to novel action contexts, the

learning phase should encompass a varied motor learning experience (Seidler, 2007; Bock & Schneider, 2002). It is known that one way in which our brain achieves this is by actively modulating the variability of our movements during the early stage of motor learning, so that a wider exploration of one's action space is ensured. This, in turn, allows one to gather more information regarding the task and the environment (Wu et al., 2014; Barbado et al., 2017). Learning a task with such enhanced action exploration would allow one to acquire internal models that accommodate a wide range of dynamic contingencies or movement solutions, which could further be beneficial during skill generalization. As mentioned earlier, since variability involved in a joint-motor learning scenario is twofold compared to individual learning, it becomes particularly interesting to see how variability influences skill generalization in joint action. Although variability seems to have some functional role during skill acquisition in specific joint-action contexts (when partner's movements are predictable, as seen in Sabu et al., 2020), variability is also known to be actively discounted during joint actions to achieve successful coordination among actors (Vesper et al., 2011, 2013). Thus, it is possible that a partner's variability can have differential effects on skill acquisition and skill generalization during joint learning.

To explore how variability of partner's movements can influence skill generalization in individuals, we designed Experiment 1B, where we manipulated the confederate's movement variability. In Experiment 1A, the force perturbations exerted by the confederate on the participants' movements were selected from a wide range, the variability of the confederate's movements were consequentially higher. There is no evidence from the results of Experiment 1A suggesting a negative impact of high variability, coming from the partner, on the motor performance during generalization. However, to fully understand how skill generalization will be

impacted by variability of partner's movements, one must also look at how the performance alters when partner exerts less variability during the training involving haptic interaction. Hence, we designed Experiment 1B, where we investigated how the motor parameters were regulated when participants generalize their skill to novel action contexts after being trained with a partner whose movements caused force perturbations that had low variability.

As in Experiment 1A, the current experiment specifically focused on how the spatial and temporal accuracy was affected during the test, where individuals produced sequential movements. If a partner's variability helps with generalization, learning with a less variable partner should lead to a lower spatial and temporal precision of the participants' performance during the test phases. Not being able to explore one's action parameters due to the rigidity in partner's movements, might even lead to a *skill interference* during generalization. In contrast, variability might have a detrimental effect on generalization in joint-learning scenarios, as variability is generally not a beneficial movement property during joint actions. In this case, having a less variable partner while learning a motor task might lead to better *skill transfer*. Another interesting prediction is that variability does not matter as much in skill generalization in joint action because individuals might be relying on motor learning strategies other than action exploration to generalize the learned skill. In this case, the results should resemble those of Experiment 1A.

3.3.1 Method

Participants

Twenty people participated in the study (10 Females, Mean_{age} = 26.58 years, SD_{age} = 3.019 years). Participants were recruited through the SONA online participation system. All participants were right-handed and reported to have normal or corrected-to-normal vision. They received monetary

compensation for their participation. One lab assistant volunteered as the confederate for the experiment.

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Procedure

The experimental procedure was the same as in Experiment 1A. Actors performed a familiarization trial, followed by the joint-training, and the test phases. Differently from Experiment 1A, confederates in the current task produced much less variability in their movements during the joint-training phase. Variability of the partner's movements was reduced by assigning target positions to the partner in a way that the joint force configurations produced would include a narrow range of forces. Forces were selected from a single bin that ranged from [24-27] N (see Table 7). The test phases were similar to Experiment 1A, in which *Test1* included 2 blocks that required sequential movements across 30 different targets each and forces at each target were larger and novel forces, selected from force bins ranging from [27-36] N. *Test2* included the full range of forces used in Experiment 1A, i.e., [9-27] N. Similar to Experiment 1A, 50% of the force configurations were selected from the smaller force range, [9-24]N and remaining 50% of the force configurations were selected from the larger force range [24-27]N. In contrast to Experiment 1A, participants in the current experiment did not get pre-exposed to the smaller force range during the training phase, as they got trained only with a narrow set of forces in the larger force range. This will be later addressed in the discussion. In *Test3*, actors received two sequences of 30 target movements each, with force configurations selected from the trained force range, [24-27] N.

Experimental Condition	Force Range (N)
Training	24.0 - 27.0
Test 1	27.0 - 30.0 30.0 - 33.0 33.0 - 36.0
Test 2	09.0 - 24.0 24.0 - 27.0
Test 3	24.0 - 27.0

Table 7. Force Range for different experimental conditions in Experiment 1B: Training included only a narrow range of forces, ranging from [24-27] N. Test 1 included novel and larger forces selected from three different bins ranging from [27-36] N, Test 2 included equal distribution of smaller and larger forces separated into two bins, [09-24] and [24-27] N, and Test 3 included pre-exposed forces from the training, [24-27] N.

Data Processing and Analysis

The landing positions at each target for both participants and confederate were retrieved by segmenting the kinematic data, as in Experiment 1A. The landing positions were then used to measure the *spatial accuracy* of the actors and time stamps at these landing positions were used to measure the *accuracy of temporal coordination* between the actors. In total, 0.395% trials from the training, 0.166% from Test 1, 0.083% trials from Test 2 and none from Test 3 were removed from the dataset as part of outlier removal.

The average *spatial error (cm)* of the actor's performance, from the joint-training phase, was subjected to a repeated measures ANOVA with Blocks (B_1 – B_8). The average spatial error obtained from both blocks in each of test phases were also subjected to repeated measures

ANOVAs, in which each of the block was compared to the pre (B₁) and post (B₈) joint-training performance to understand how the spatial accuracies have changed in the test phases compared to the training. An additional ANOVA comparing the performance within the Test 2 alone was also conducted to assess the difference in performance in the different force conditions (smaller and larger forces) across the two blocks.

The average *absolute asynchronies (sec)* of the actors were computed, as in Experiment 1A, as a measure of their inter-personal temporal coordination. The absolute asynchronies from the training data were subjected to a repeated measures ANOVA with Block (B₁ - B₈) as the within-subject factor. The average asynchronies from all three tests were also subjected to repeated measures ANOVAs, to compare each of its Block to the first (B₁) and last block (B₈) of the training phase. And a similar within-test analysis, as with the spatial data, was also done to compare the performances in the different force conditions.

All significant main effects were further analyzed by applying Bonferroni correction for multiple comparisons.

3.3.2 Results

Spatial Accuracy

Training Phase: For the training phase, the ANOVA revealed a main effect of Block, indicating that participants learned to reduce their spatial error over time ($F(7,133) = 6.379, p < 0.0001, \eta^2 = 0.251$, see Fig 13). The post-hoc analysis revealed that spatial error at B₁ (mean = 1.663, SE = 0.094) was significantly higher compared to all other blocks (all $ps < 0.05$), except B₄.

Test 1 (Novel-force test): The average spatial error at B₁ and B₂ of *Test1* was compared against the first and last blocks of the training phase through four separate repeated measures ANOVA.

The analysis on the spatial accuracies at B₁ (mean = 1.633, SE = 0.094) of training and B_{1_T1} (mean = 1.574, SE = 0.122) revealed no significant difference in accuracies ($F(1,19) = 0.534$, $p = 0.474$, $\eta^2 = 0.027$, see Fig 13). The ANOVA ran on the average spatial accuracies at B₁ of training and B_{2_T1} (mean = 1.323, SE = 0.128) revealed a significant reduction of spatial error, indicating that participants generalized the learned skill to novel forces and sequential movements at the second block of the test compared to their initial performance in the task ($F(1,19) = 9.011$, $p = 0.007$, $\eta^2 = 0.322$, see Fig 13). The ANOVA comparing the spatial accuracies at the post-training performance, B₈ (mean = 1.299, SE = 0.107) and B_{1_T1} revealed a significant main effect of blocks, with the spatial accuracy at B_{1_T1} being worse compared to B₈ ($F(1,19) = 6.044$, $p = 0.024$, $\eta^2 = 0.241$, see Fig 13). This effect indicates that participants could not maintain their post-training performance when tested under conditions of novel task context. However, their performance improved at B_{2_T1}, indicating that participants learned to improve their performance through the second block of the test and returned to the post-training performance ($F(1, 19) = 0.057$, $p = 0.814$, $\eta^2 = 0.003$, see Fig 13).

Test 2 (Novel-frequency test): As in Experiment 1A, the average spatial errors at each of the two blocks in the test were compared to the pre (B₁) and post-training (B₈) performances. The ANOVA performed on the spatial accuracies at B₁ of training (mean = 1.663, SE = 0.422) and B_{1_T2} (mean = 1.198, SE = 0.079) revealed a significant reduction of errors at B_{1_T2} ($F(1,19) = 20.059$, $p < 0.0001$, $\eta^2 = 0.514$, see Fig 13). Similar comparison of B₁ with B_{2_T2} (mean = 1.157, SE = 0.099) also revealed a significant reduction of spatial error at the test block, indicating that participants improved from their initial performance in the task, throughout the test ($F(1,19) = 28.518$, $p < 0.0001$, $\eta^2 = 0.600$, see Fig 13). Comparison of spatial accuracies at B₈ (mean = 1.298, SE = 0.477) and B_{1_T2} did not reveal any significant difference in performances ($F(1,19) = 1.016$, $p =$

0.326, $\eta^2 = 0.051$, see fig 13). Similar results were obtained from the ANOVA comparing B₈ and B_{2_T2} suggesting that participants maintained their floor performance achieved in training, throughout the test, while experiencing smaller forces ($F(1,19) = 1.716$, $p = 0.206$, $\eta^2 = 0.083$, see Fig 13).

The within-test 2x2 ANOVA conducted on the test data alone, did not reveal a main effect of block, suggesting that participants did not improve their performance across B_{1_T2} and B_{2_T2} in the test phase ($F(1,19) = 0.179$, $p = 0.677$, $\eta^2 = 0.009$). The main effect of forces also failed to reach significance, suggesting that the spatial accuracies were the same for the smaller (mean = 1.118, SE = 0.079) and the larger (mean = 1.236, SE = 0.091) forces ($F(1,19) = 1.996$, $p = 0.174$, $\eta^2 = 0.095$). The interaction between the factors was also not significant ($F(1,19) = 1.740$, $p = 0.203$, $\eta^2 = 0.084$).

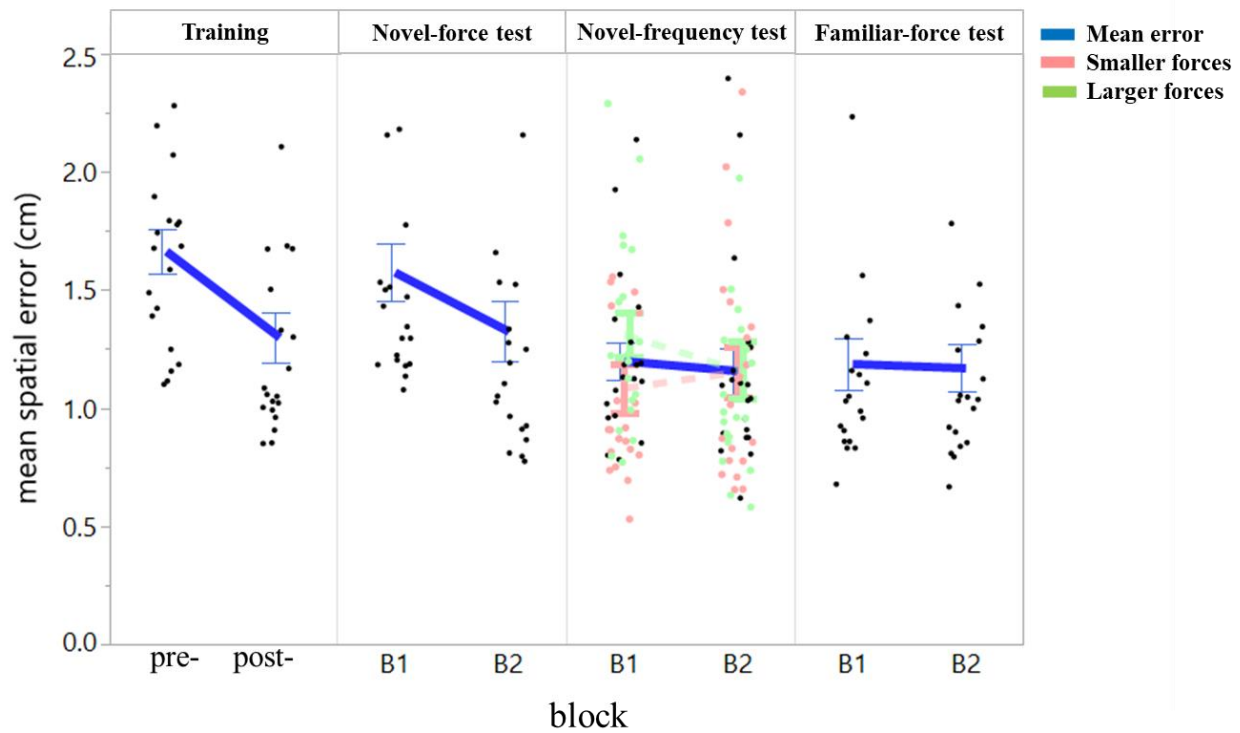


Fig 13. Mean spatial error during training and test phases in Experiment 1B: The figure shows the mean spatial error of participants' movements in the training and test conditions, in

separate panels. The first panel shows mean spatial error at the pre- and post-training blocks. From the test phases, the panel shows mean spatial error at Block 1 (B₁) and Block 2 (B₂) for *novel-force test*, *novel-frequency test*, and *familiar-force test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 3 (Familiar-force test): The ANOVA performed on the spatial accuracies at B₁ of training (mean = 1.663, SE = 0.094) and B_{1_T3} (mean = 1.186, SE = 0.110) revealed a significant reduction of spatial error at B_{1_T3} ($F(1,19) = 20.869$, $p < 0.0001$, $\eta^2 = 0.523$, see Fig 13). The ANOVA performed on average spatial error at B₁ of training and B_{2_T3} (mean = 1.169, SE = 0.101) also revealed a significant reduction of spatial error at B_{2_T3} ($F(1,19) = 31.076$, $p < 0.0001$, $\eta^2 = 0.621$, see Fig 13) indicating that participants improved their spatial error performance in the second block of the test as well, compared to their initial performance. The ANOVA on the spatial accuracies at B₈ (mean = 1.299, SE = 0.107) and B_{1_T3}, however, did not reveal a significant difference in performance ($F(1,19) = 0.899$, $p = 0.335$, $\eta^2 = 0.045$, see Fig 13). Comparison between the spatial accuracies at B₈ and B_{2_T3} also did not reveal any difference in performance ($F(1,19) = 1.995$, $p = 0.178$, $\eta^2 = 0.093$, see Fig 13). Even though participants did not significantly improve their performance in the test compared to their post-training performance, the results indicate that participants still maintained their learned performance, through the test, when exposed to already trained forces.

Temporal Accuracy

Training Phase: The ANOVA performed on the absolute asynchronies measured from the training data revealed a significant main effect of the Blocks, indicating that actors improved their temporal accuracy over time ($F(7, 133) = 2.544$, $p = 0.017$, $\eta^2 = 0.118$, see Fig 14). Although, post-hoc revealed that the first block (mean = 0.106, SE = 0.005) is only significantly different from B₆

(mean = 0.094, SE = 0.004) and B₈ (mean = 0.093, SE = 0.005), none of the other blocks were significantly different (all p s > 0.05).

Test 1 (Novel-force test): The temporal asynchrony between the actors at B₁ and B₂ of *Test1* was compared against their asynchrony measure at the first (B₁) and last blocks (B₈) of the training phase through four separate repeated measures ANOVAs. The analysis on the temporal asynchronies at B₁ of training (mean = 0.106, SE = 0.005) and B_{1_T1} (mean = 0.120, SE = 0.004) revealed a significant worsening of asynchrony at B_{1_T1} ($F(1,19) = 6.568$, $p = 0.019$, $\eta^2 = 0.257$, see Fig 14). The ANOVA ran on the asynchronies at B₁ of training and B_{2_T1} (mean = 0.116, SE = 0.004) did not reveal a significant main effect of Block ($F(1,19) = 1.972$, $p = 0.176$, $\eta^2 = 0.094$, see Fig 14). These results indicate that with time, actors managed to reduce their asynchrony to that of their initial performance in the task. However, the ANOVA ran on the post-training performance at B₈ (mean = 0.093, SE = 0.005) and B_{1_T1} showed a significant worsening of synchrony at B_{1_T1}, indicating actors could not maintain their temporal performance as in B₈, when required to generalize the movements to untrained conditions ($F(1,19) = 17.956$, $p < 0.0001$, $\eta^2 = 0.486$ see Fig 14). The ANOVA conducted on the absolute asynchronies at B₈ and B_{2_T1} also revealed a worsening of synchrony, suggesting that actors suffered an interference in their temporal dimension in the test phase ($F(1,19) = 15.192$, $p = 0.001$, $\eta^2 = 0.444$, see Fig 14).

Test 2 (Novel-frequency test): The average asynchronies at each of the two blocks in the test were compared to the actors' pre (B₁) and post-training (B₈) joint performances. The ANOVA conducted on the temporal asynchronies at B₁ of training (mean = 0.106, SE = 0.005) and B_{1_T2} (mean = 0.100, SE = 0.003), did not reveal any significant main effect ($F(1,19) = 1.116$, $p = 0.304$, $\eta^2 = 0.055$, see Fig 14). Similar results were obtained with analysis on B₁ and B_{2_T2} (mean = 0.105, SE = 0.005) indicating that participants maintained their initial temporal performance at the

throughout *Test2* ($F(1,19) = 0.071$, $p = 0.793$, $\eta^2 = 0.004$, see Fig 14). Comparison of the temporal accuracies at B_8 (mean = 0.093, SE = 0.005) and B_{1_T2} , also did not reach significance, ($F(1,19) = 0.984$, $p = 0.334$, $\eta^2 = 0.049$) and so was the case with B_8 and B_{2_T2} ($F(1,19) = 3.481$, $p = 0.078$, $\eta^2 = 0.155$, see Fig 14).

The within-test analysis with block and forces as factors, also did not reveal any main effects of the block, suggesting that the performance did not differ across blocks within Test 2 ($F(1,19) = 1.194$, $p = 0.288$, $\eta^2 = 0.059$). However, the temporal asynchrony was worse for the smaller force condition (mean = 0.106, SE = 0.004) compared to the larger force (mean = 0.106, SE = 0.004; $F(1,19) = 5.349$, $p = 0.032$, $\eta^2 = 0.220$). The interaction between the two factors was not significant ($F(1,19) = 0.573$, $p = 0.458$, $\eta^2 = 0.029$).

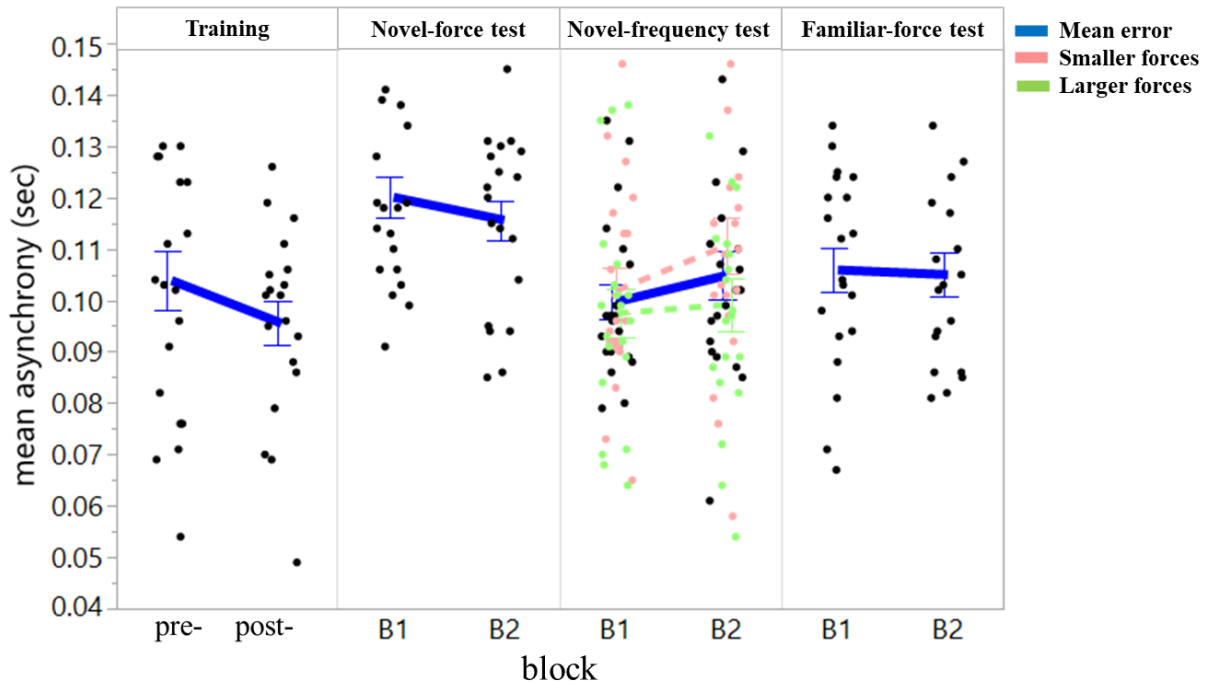


Fig 14. Mean temporal asynchrony during training and test phases in Experiment 1B: The figure shows the mean temporal asynchrony of the actors' landing times from the training and test phases in separate panels. The first panel shows mean asynchrony at the pre- and post-training blocks. From the test phases, figure shows mean asynchrony at Block 1 and Block 2 for *novel-*

force test, *novel-frequency test*, and *familiar-force test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 3 (Familiar-force test): The average temporal asynchronies of the actors at the two blocks of *Test3* was compared against the accuracies at the first (B_1) and last blocks (B_8) of the training phase through four separate repeated measures ANOVA. The analysis performed on the temporal asynchronies at B_1 of training (mean = 0.106, SE = 0.005) and B_{1_T3} (mean = 0.106, SE = 0.004) did not reveal any difference between the two performances, indicating that actors maintained their level of synchrony in the test as in their initial performance in the experiment ($F(1,19) = 0.008$, $p = 0.931$, $\eta^2 < 0.000$, see Fig 14). A similar comparison with B_{2_T3} (mean = 0.105, SE = 0.004) also showed no difference in the temporal accuracies ($F(1,19) = 0.060$, $p = 0.810$, $\eta^2 = 0.003$, see Fig 14). The analysis performed on B_8 (mean = 0.093, SE = 0.005) and B_{1_T3} was also non-significant, ($F(1,19) = 3.640$, $p = 0.072$, $\eta^2 = 0.161$, see Fig 14). Similar results were obtained from the comparison of absolute asynchronies at B_8 and B_{2_T3} ($F(1,19) = 3.798$, $p = 0.066$, $\eta^2 = 0.167$, see Fig 14).

3.3.3 Discussion

In Experiment 1B, we investigated whether individuals engaging in joint learning with a partner can successfully generalize the learned skill to novel and untrained action context, while the partner produces low variability in their movements. Participants were trained to perform discrete aiming movements and were later tested to perform sequential movements, under varying action contexts, as in Experiment 1A.

In Test 1, where individuals performed sequential movements under conditions of novel and larger forces, they slowly transferred their spatial performance at the cost of an interference in

their temporal performance, similar as observed in Experiment 1A. Again, individuals did not immediately adjust their motor parameters on their first exposure to the novel forces, as they only improved their spatial accuracy at B_{2_T1} compared to B_1 of training. As discussed earlier, it should be noted that this pattern of result could also be attributed to transient learning effect that happened over the first block of test, instead of any positive influence of the training. Also, the actors suffered an interference in the temporal performance during the test, indicating a spatiotemporal trade-off, as in Experiment 1A.

In Test 2, when tested for generalization under the influence of equal distribution of smaller and larger forces, individuals exhibited transfer in the spatial dimension with their overall performance, without suffering a trade-off cost in interpersonal temporal coordination. Interestingly, even though the within-test analysis revealed that participants' spatial performance was not different across the smaller and larger force conditions, their temporal synchrony was found to be worse when they received smaller forces. This result could be attributed to the novelty of the smaller forces for the participants (in Experiment 1A participants were pre-exposed to both smaller and larger forces). Even though one could assume that being trained under conditions of higher task difficulty (training only with larger force range) should be beneficial for performing in task with lower difficulty (smaller forces), our results suggests that this is not the case. This could indicate that the low variability from the partner might have limited their learning to larger forces alone, even though performing under the influence of smaller forces is relatively easier.

In Test 3, individuals showed a successful transfer in the spatial dimension by improving their accuracy from their initial performance level and maintaining their post-training performance in the test. Also, actors did not suffer an interference in the temporal dimension, meaning there was no spatiotemporal tradeoff.

Our results indicate that skill generalization during joint learning involving physical interaction, is not negatively impacted by variability. Participants in both experiments exhibited spatial skill generalization to novel movement scenarios, regardless of the partner's variability of movements during training. This is in accordance with the Ganesh et al., 2014 results that suggested that regardless of a partner's performance, physical interaction with another individual alone can improve motor learning. However, experiencing a higher variability of movements from a partner during the joint learning did seem to have some added benefit for skill generalization, observed as performance increments in test conditions involving lower task difficulty. It seems that a low variability from the partner might be limiting action exploration. Thus, despite the physical interaction, the lack of variability in the movements from the partner is not allowing individuals to augment their action repertoire in Experiment 1B. This is not to say that generalization was hindered. Rather, the low variability only limited any further improvement in performance. The lack of performance increment observed in Experiment 1B, indicates that even though learning and generalization is possible while training with a less variable partner, the dynamic model learned is less flexible in nature. This provides an indication that a partner's high variability during learning, involving physical interaction, allows one to learn a more flexible internal model of the task, which in turn fosters generalization. There was no indication that a lower variability has negative impact on performance. However, comparison of the performance against that of a SOLO condition would provide more insight into the impact of partner's variability on skill generalization in individuals. But for the reasons discussed under Study 1, we could not design a SOLO condition that could compliment our joint training condition.

3.4 Experiment 2A

The results of Experiment 1A and 1B suggest that when engaged in joint learning with an interactive partner, individuals can successfully transfer the learned skill to a novel movement context. Variability of the partner's movements did not seem to negatively impact generalization. If anything, a higher variability seems to have some performance benefit during generalization, especially when the movement parameters required for the task were known to the individuals, like pre-exposed force perturbations.

However, the order in which the various test phases were administered in both the experiments seems to be a potential confound in the study. Administering the test with the highest task difficulty, i.e., with novel and larger forces, first, can lead to a learning effect, which could influence performance in the later tests that has comparatively lower task difficulty. Moreover, in Test 2 of Experiment 1A, participants received the full range of forces they were exposed to during the training, i.e., [9-27] N. But, in Experiment 1B, participants were never exposed to the smaller forces during training, which make up 50% of Test 2 forces. Although it could be argued that even though the end-point forces were always larger forces in Experiment 1B during the training, participants still experience smaller forces while performing a sequence of movements we decided to rule out potential influences of the confound on the results. Therefore, we ran a follow-up control study, with the sequential movements with pre-exposed forces as Test 1, the novel and larger forces as Test 2 and the smaller and larger forces as Test 3.

3.4.1 Method

Participants

Twenty people participated in the study (13 Females, Mean_{age} = 29.23 years, SD_{age} = 3.264 years). Participants were recruited through the SONA online participation system. All participants were

right-handed and reported to have normal or corrected-to-normal vision. They received monetary compensation for their participation. One lab assistant volunteered as the confederate for the experiment.

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Procedure

The current experiment followed the experimental procedure as in Experiment 1A, in which a participant and the confederate performed the joint aiming task in a familiarization phase, followed by the joint training (see Table 5) and three test phases. However, the order of the test phases was rearranged in the current experiment, compared to the previous experiments (see Table 8). In *Test 1*, actors received the pre-exposed force configurations ranging from [9-27] N, in *Test 2*, actors received novel and larger force configurations in a sequence ranging from [27- 36] N and in *Test 3*, they received full range of forces from the training [9-27] N, in which 50% of the targets were picked from the smaller force bins, i.e., [9-24] N and 50% of the targets were picked from the largest force bin, [24-27] N.

Data processing and analysis

Participant's and confederates' kinematic data was segmented and analyzed following the same protocol as in Experiment 1A. The landing positions were obtained to measure the *spatial accuracy* of the actors and time points at these landing positions were obtained to measure the *accuracy of temporal coordination* between the actors. 0.875% trials from the training data and

0.166% from Test 2 in total were removed from the dataset as outliers. No outliers were found in Test 1 and Test 3.

Test Condition	Force Range (N)
Test 1	09.0 - 12.0
	12.0 - 15.0
	15.0 - 18.0
	18.0 - 21.0
	21.0 - 24.0
	24.0 - 27.0
Test 2	27.0 - 30.0
	30.0 - 33.0
	33.0 - 36.0
Test 3	09.0 - 24.0
	24.0 - 27.0

Table 8. Force Range for Test Phases: Test1 included pre-exposed forces from training, distributed across 6 different bins ranging from [09- 27] N. Test 2 included novel and larger forces selected from three different bins ranging from [27-36] N and Test 3 included equal distribution of smaller and larger forces separated into two bins, selected from the training range [09- 24] and [24- 27] N.

3.4.2 Results

Spatial Accuracy

Training Phase: The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.566$) revealed a main effect of Block, indicating that participants learned to reduce their spatial error over time ($F(7,133) = 3.506$, $p = 0.002$, $\eta^2 = 0.156$, see Fig 15). The post-hoc analysis revealed that spatial error at B1 (mean= 1.859, SE= 0.170) and B2 (mean= 1.762, SE= 0.140) was significantly higher compared

to B3, B5 and B8 (all $ps < 0.05$), none of the other blocks were significantly different from each other.

Test 1 (Familiar-force test): The ANOVA performed on the spatial accuracies at B₁ of training (mean= 1.859, SE= 0.170) and B_{1_T1} (mean= 1.316, SE= 0.118) revealed a significant reduction of spatial error B_{1_T1} ($F(1,19) = 15.169$, $p = 0.001$, $\eta^2 = 0.444$, see Fig 15). Similar reduction of error was observed at B_{2_T1} (mean = 1.056, SE= 0.094) when compared to B₁ ($F(1,19) = 34.134$, $p < 0.0001$, $\eta^2 = 0.642$, see Fig 15). The ANOVA on the spatial accuracies at B₈ (mean = 1.445, SE= 0.120) and B_{1_T1} revealed no significant difference, ($F(1,19) = 0.832$, $p = 0.373$, $\eta^2 = 0.042$, see Fig 15). However, comparison between the spatial accuracies at B₈ (mean = 1.445, SE= 0.120) and B_{2_T1} revealed a significant improvement in performance at B_{2_T1} ($F(1,19) = 9.028$, $p = 0.007$, $\eta^2 = 0.322$, see Fig 15).

Test 2 (Novel-force test): The ANOVA performed on the spatial accuracies at B₁ of training (mean=1.859, SE= 0.170) and B_{1_T2} (mean=1.691, SE= 0.123) revealed no significant main effect of Block, ($F(1,19) = 0.930$, $p = 0.347$, $\eta^2 = 0.047$, see Fig 15). Accuracy at B_{2_T2} (mean= 1.444, SE= 0.176) was also similar to the pre-training performance ($F(1,19) = 3.641$, $p = 0.072$, $\eta^2 = 0.161$, see Fig 15). The ANOVA performed on spatial accuracies at B₈ (mean= 1.316, SE= 0.082) and B_{1_T2} also showed no difference in performance ($F(1, 19) = 2.462$, $p = 0.133$, $\eta^2 = 0.115$, see Fig 15) and so was the case at B_{2_T2} ($F(1,19) = 0.000$, $p = 0.993$, $\eta^2 < 0.000$, see Fig 15).

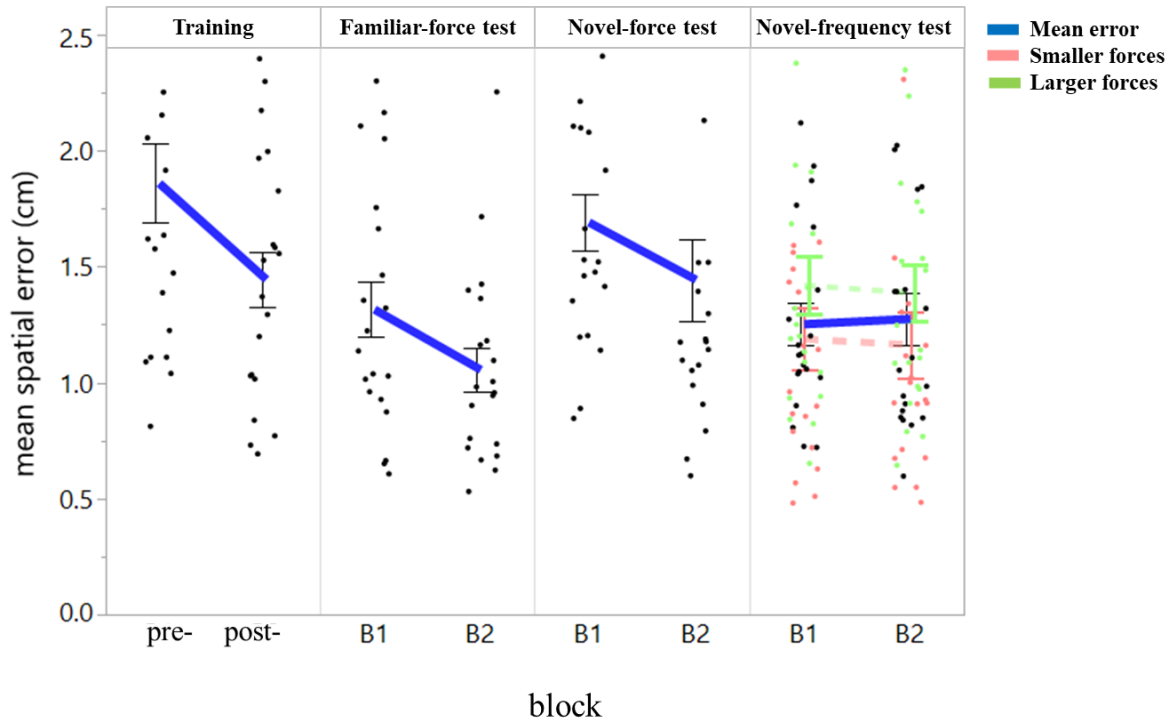


Fig 15. Mean spatial error during training and test phases in Experiment 2A: The figure shows the mean spatial error of participants' movements in the training and test conditions, in separate panels. The first panel shows mean spatial error at the pre- and post-training blocks. From the test phases, figure shows mean spatial error at Block 1 (B₁) and Block 2 (B₂) for *familiar-force test*, *novel-force test* and, *novel-frequency test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 3 (Novel frequency test): The ANOVA ran on the spatial accuracies at B₁ of training (mean = 1.859, SE= 0.170) and B_{1_T3} (mean = 1.252, SE = 0.092), revealed a significant reduction of errors across blocks, ($F(1,19) = 15.846$, $p = 0.001$, $\eta^2 = 0.455$, see Fig 15). Similar performance was found at B_{2_T3} (mean = 1.275, SE= 0.114) suggesting that participants further improved their spatial performance in the test ($F(1,19) = 14.024$, $p = 0.001$, $\eta^2 = 0.425$, see Fig 15). No difference in spatial accuracies was observed during comparison of the post-training performance, B₈ (mean = 1.445, SE = 0.120) and B_{1_T3} ($F(1,19) = 2.940$, $p = 0.103$, $\eta^2 = 0.134$, see Fig 15), B₈ and B_{2_T3} ($F(1,19) = 3.415$, $p = 0.080$, $\eta^2 = 0.152$, see Fig 15).

The within-test analysis did not reveal a block effect ($F(1,19) = 0.079$, $p = 0.782$, $\eta^2 = 0.004$), nor a main effect of force ($F(1,19) = 3.568$, $p = 0.074$, $\eta^2 = 0.158$), meaning participants' performance did not differ across blocks or the smaller and larger force conditions in Test 3. The interaction between the factors was also non-significant ($F(1,19) = 0.001$, $p = 0.970$, $\eta^2 = 0.001$).

Temporal Accuracy

Training Phase: The ANOVA performed on the absolute asynchronies did not reveal any significant reduction of asynchrony across the 8 blocks, ($F(7, 133) = 2.016$, $p = 0.058$, $\eta^2 = 0.096$, see Fig 16).

Test 1 (Familiar-force test): The ANOVA performed on the performance at B_1 of training (mean = 0.101, SE = 0.004) and B_{1_T1} (mean = 0.092, SE = 0.003) revealed a significant reduction of asynchrony, ($F(1,19) = 5.095$, $p = 0.036$, $\eta^2 = 0.211$, see Fig 16). This indicates that actors improved their synchrony from their initial performance when they performed sequential movements with pre-exposed forces. However, at B_{2_T1} (mean = 0.105, SE = 0.004), the asynchronies returned to the initial performance, ($F(1,19) = 0.744$, $p = 0.399$, $\eta^2 = 0.038$, see Fig 16). The post training performance, B_8 (mean = 0.096, SE = 0.006) was also found to be similar to B_{1_T1} , ($F(1,19) = 0.493$, $p = 0.491$, $\eta^2 = 0.025$, see Fig 16). The same was the case at B_{2_T1} , suggesting that actors maintained their floor synchrony achieved at the end of training, ($F(1,19) = 2.695$, $p = 0.117$, $\eta^2 = 0.124$, see Fig 16).

Test 2 (Novel-force test): The ANOVA performed on the temporal asynchronies at B_1 of training (mean = 0.101, SE = 0.004) and B_{1_T2} (mean = 0.119, SE = 0.006) revealed a significant worsening of asynchrony ($F(1,19) = 7.219$, $p = 0.015$, $\eta^2 = 0.275$, see Fig 16). A similar comparison at B_{2_T2} (mean = 0.113, SE = 0.005) against pre-training performance (B_1) showed no significant difference in asynchronies ($F(1,19) = 3.400$, $p = 0.081$, $\eta^2 = 0.152$, see Fig 16). The main effect of Blocks in

the ANOVA ran on B_8 (mean = 0.096, SE= 0.006) and B_{1_T2} revealed a significant worsening of asynchronies, ($F(1,19) = 11.942$, $p = 0.003$, $\eta^2 = 0.386$, see Fig 16), indicating that during the test, actors could not maintain the floor synchrony achieved at training. Similar results were obtained from the comparison of asynchronies at B_8 and B_{2_T2} , suggesting that actor's temporal coordination was overall worse in Test 2 compared to their post-training performance ($F(1,19) = 6.987$, $p = 0.016$, $\eta^2 = 0.269$, see Fig 16).

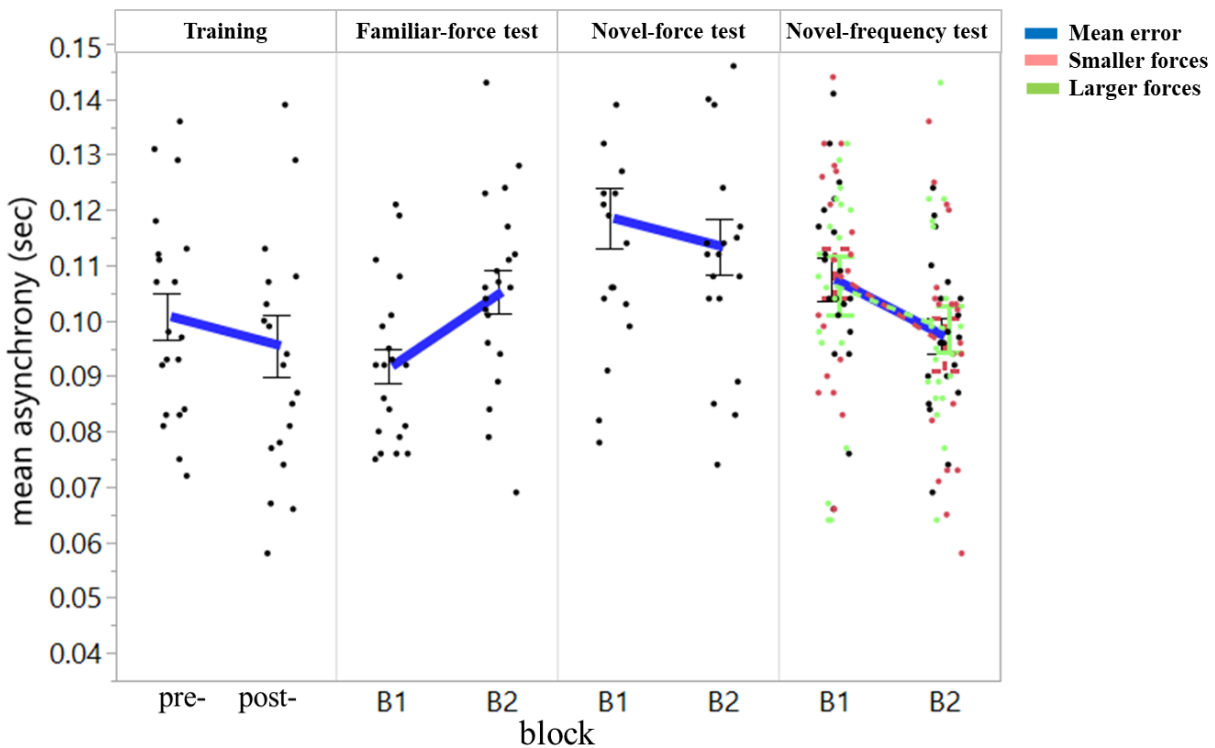


Fig 16. Mean temporal asynchrony during training and test phases in Experiment 2A: The figure shows the mean temporal asynchrony of the actors' landing times from the training and test phases in separate panels. The first panel shows mean asynchrony at the pre- and post-training blocks. From the test phases, figure shows mean asynchrony at Block 1 and Block 2 for *familiar-force test*, *novel-force test*, and *novel-frequency test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 3 (Novel-frequency test): The ANOVA conducted on the temporal asynchronies at B₁ of training (mean= 0.101, SE= 0.004) and B_{1_T3} (mean = 0.107, SE = 0.004), revealed no significant difference in asynchronies ($F(1,19) = 2.180, p = 0.156, \eta^2 = 0.103$, see Fig 16). Comparison between B₁ of training and B_{2_T3} (mean = 0.097, SE = 0.003) also did not reveal a main effect indicating that actors managed to maintain their initial temporal coordination throughout the test ($F(1,19) = 0.522, p = 0.479, \eta^2 = 0.027$ see Fig 16). Comparison of the asynchronies at B₈ (mean = 0.096, SE = 0.006) and B_{1_T3} revealed a significant worsening, indicating that participants could not maintain their post-training performance, in the first block of test ($F(1,19) = 5.110, p = 0.036, \eta^2 = 0.212$, see fig 16). However, actors returned to their floor performance achieved at Training, at B_{2_T3} ($F(1,19) = 0.070, p = 0.794, \eta^2 = 0.004$, see Fig 16).

The within-test analysis revealed a significant reduction of synchrony at B_{2_T3} (mean = 0.097, SE = 0.003) compared to B_{1_T3} (mean = 0.107, SE = 0.004), suggesting that participants improved their synchrony over blocks within the test ($F(1,19) = 4.404, p = 0.049, \eta^2 = 0.188$). However, there was no difference in performance in the smaller (mean= 0.102, SE= 0.003) and larger (mean= 0.103, SE= 0.004) force conditions ($F(1,19) = 0.011, p = 0.918, \eta^2 = 0.001$). The interaction between the factors were also not significant ($F(1,19) = 0.309, p = 0.585, \eta^2 = 0.016$).

3.4.3 Discussion

The current study aimed to rule out potential learning effects within test caused by the order of the test phases introduced in Experiment 1A. As in the original experiment, participants were trained to perform isolated aiming movements and later tested for the generalizability of their movement kinematics to sequential movements under the influence of different force ranges: pre-exposed forces as Test 1, novel and larger forces as Test 2 and the smaller and larger forces as Test 3.

Test 1 results replicated the results of the same test condition from Experiment 1A (Test 3). When tested under conditions of least task difficulty, producing sequential movements under the influence of pre-exposed forces from training, individuals transferred their skill in both the spatial and temporal dimension. Additionally, there was further improvement in their spatial accuracies, showing that generalizing to a novel action type while learning through physical interaction with a partner is easier when task difficulty is low.

In Test 2, when tested under conditions of highest task difficulty, i.e., novel and larger forces, there was no generalization observed in the spatial dimension, as performance was equivalent to the initial training throughout the test blocks. In Experiment 1A, novel and larger forces were introduced as Test 1, meaning they were exposed to the task demands of having to perform sequential movements and adapt to novel force range, all at once. Even though participants were surprised by the novel task demands at the first block, they managed to improve spatial accuracy already in the second block of test, compared to the training (slower generalization). In Experiment 2A, however, as novel and larger forces were introduced as Test 2, by the time they received these sequences, they were already exposed to the task demand of having to perform sequential movements (in Test 1), but with a familiar force range (pre-exposed forces). Hence, in Test 2, they might have suffered additional difficulty breaking the familiarity bias towards the force range while performing sequential movements. This would explain why they could not generalize their spatial performance. It needs to be noted that while there was no generalization observed in the spatial dimension, an interference in temporal coordination could be seen, as the asynchrony was higher in the test blocks.

In Test 3, under conditions of sequential movements in the influence of equal distribution of smaller and larger force range, individuals successfully transferred their spatial skill, without

suffering a trade-off at the temporal dimension, unlike the trade-off cost observed in Experiment 1A (Test 2). In the within-test analysis, the spatial performance did not differ across blocks or force ranges within the test. In Experiment 1A, when the current test condition was introduced as the second test phase, participants displayed worse spatial accuracy in the larger force range compared to the smaller force range. The present results suggest that changing the order of the test phase, allowed enough time for participants to adapt to the larger forces, hence, the absence of main effect of forces. Interestingly, a block effect was observed in the temporal performance, suggesting that actors exhibited a transient learning in their synchrony as well, across the two blocks in the test phase. The improvement in the spatial and temporal performance within test and across experiments suggest that participants continued to benefit from additional training when the task was more difficult.

3.5 Experiment 2 B

To control for the test order effects in Experiment 1B, we replicated Experiment 1B, only changing the order of the tests. As in Experiment 1B, here we explored how variability of partner's movements can influence skill generalization in individuals, during joint learning that involves physical interaction between the actors. In the current study, the confederate's target positions were manipulated to induce less variability in his movements. Following the training of aiming movement units, it was then tested whether generalization occurred to sequential movements that implied different force-range contexts; with pre-exposed forces as Test 1, the novel and larger forces as Test 2 and the smaller and larger forces as Test 3.

3.5.1 Method

Participants

Twenty people participated in the study (12 Females, Mean_{age} = 28.55 years, SD_{age} = 3.618 years). One participant's data had to be excluded from the analysis due to technical error during the recording. Participants were recruited through the SONA online participation system. All participants were right-handed and reported to have normal or corrected-to-normal vision. They received monetary compensation for their participation. One lab assistant volunteered as the confederate for the experiment.

Ethics Statement

The study was approved by the Hungarian ethics committee (United Ethical Review Committee for Research in Psychology- EPKEB). All participants gave informed consent in written form prior to the experiment.

Procedure

The current experiment followed the experimental procedure as in Experiment 1B, in which a participant and the confederate performed the joint aiming task through 3 different phases: the familiarization phase, followed by the joint-training and three test phases, in that order. Differently from Experiment 1B, the order of the tests was rearranged (see Table 9). In *Test1*, actors received pre-exposed force configurations from the training range, [24-27] N, in *Test2* they received larger and novel forces if the range [27-36] N and in *Test3* received 50% of the force configurations from the smaller force range, [9-24] N and remaining 50% of the force configurations were selected from the larger force range [24-27] N.

Experimental Condition	Force Range (N)
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Training	24.0 - 27.0
Test 1	24.0 - 27.0
Test 2	27.0 - 30.0 30.0 - 33.0 33.0 - 36.0
Test 3	09.0 - 24.0 24.0 - 27.0

Table 9. Force Range for different experimental conditions in Experiment 2B: Training included only a narrow range of forces, ranging [24 – 27] N. Test 1 included pre-exposed forces from the training, [24- 27] N, Test 2 included novel and larger forces selected from three different bins ranging from [27-36] N and Test 3 included equal distribution of smaller and larger forces separated into two bins, [09- 24] and [24- 27] N respectively.

Data processing and analysis

Participant's and confederates' kinematic data was segmented and analyzed following the same protocol as in previous experiments. The landing positions were obtained to measure the *spatial accuracy* of the actors and time points at these landing positions were obtained to measure the *accuracy of temporal coordination* between the actors. No outliers were observed in any of the data set.

3.5.2 Results

Spatial Accuracy

Training Phase: The ANOVA with a Greenhouse-Geisser correction ($\epsilon = 0.541$) revealed a main effect of Block, indicating that participants learned to reduce their spatial error over time ($F(7, 126)$

= 4.068, $p < 0.001$, $\eta^2 = 0.184$, see Fig 17). The post-hoc analysis revealed that spatial error at B₁ (mean= 2.145, SE= 0.190) was significantly higher compared to all other blocks except B₃ (all $ps < 0.05$).

Test 1 (Familiar-force test): The ANOVA performed on the spatial accuracies at B₁ of training (mean= 2.145, SE= 0.190) and B_{1_T1} (mean= 1.388, SE= 0.135) revealed a significant reduction in spatial error ($F(1,18) = 15.169$, $p = 0.001$, $\eta^2 = 0.444$, see Fig 17). Similar comparison with B_{2_T1} (mean = 1.393, SE= 0.109) also revealed a significant reduction of spatial error at B_{2_T1} ($F(1,18) = 19.732$, $p < 0.0001$, $\eta^2 = 0.523$, see Fig 17). The ANOVA on the spatial accuracies at B₈ (mean = 1.495, SE= 0.123) and B_{1_T1} revealed no significant difference, ($F(1,18) = 0.474$, $p = 0.500$, $\eta^2 = 0.026$, see Fig 17). Similarly, no difference in spatial accuracy was observed between B₈ and B_{2_T1}, ($F(1,18) = 0.625$, $p = 0.440$, $\eta^2 = 0.034$, see Fig 17).

Test 2 (Novel-force test): The ANOVA performed on the spatial accuracies at B₁ of training (mean= 2.145, SE= 0.190) and B_{1_T2} (mean=1.473, SE= 0.102) revealed, a significant improvement in accuracies when introduced to novel and larger forces ($F(1,18) = 13.970$, $p = 0.002$, $\eta^2 = 0.437$, see Fig 17). Accuracy at B₁ and B_{2_T2} (mean= 1.225, SE= 0.079) was also significantly different, indicating an improvement in performance during test compared to their initial performance in the task ($F(1,18) = 24.460$, $p < 0.0001$, $\eta^2 = 0.576$, see Fig 17). Spatial accuracy at B₈ (mean= 1.495, SE= 0.123) and B_{1_T2} was not different ($F(1, 18) = 0.025$, $p = 0.877$, $\eta^2 = 0.001$) and there was a marginal significance of effect at B_{2_T2}, with the test block having a smaller error compared to B₈, ($F(1,18) = 4.413$, $p = 0.05$, $\eta^2 = 0.197$, see Fig 17).

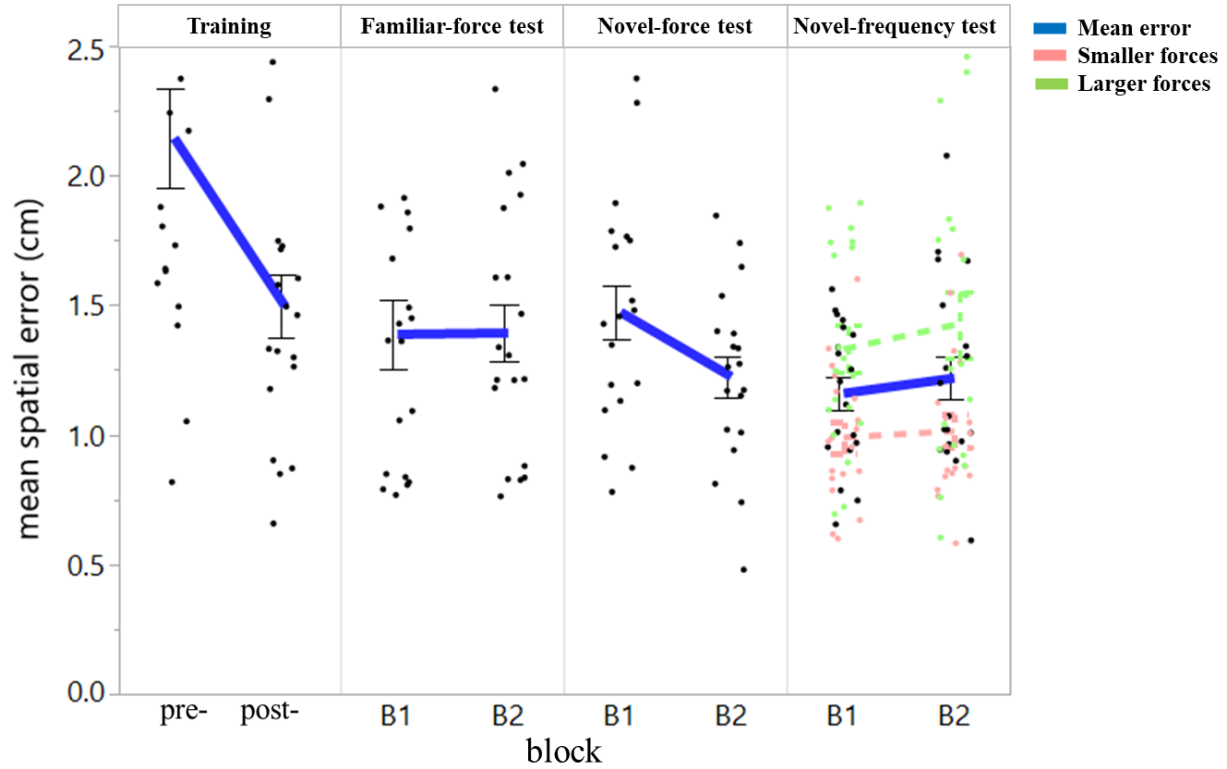


Fig 17. Mean spatial error during training and test phases in Experiment 2B: The figure shows the mean spatial error of participants' movements in the training and test conditions, in separate panels. The first panel shows mean spatial error at the pre- and post-training blocks. From the test phases, figure shows mean spatial error at Block 1 (B₁) and Block 2 (B₂) for *familiar-force test*, *novel-force test*, and *novel-frequency test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 3 (Novel-frequency test): The ANOVA ran on the spatial accuracies at B₁ of training (mean = 2.145, SE = 0.190) and B_{1_T3} (mean = 1.160, SE = 0.063), revealed a significant reduction of errors across blocks, ($F(1,18) = 39.714$, $p < 0.0001$, $\eta^2 = 0.688$, see Fig 17). Comparison of B₁ against B_{2_T3} (mean = 1.219, SE = 0.084) also revealed a significant reduction of spatial error, indicating that participants further improved their spatial performance in the test ($F(1,18) = 20.898$, $p < 0.0001$, $\eta^2 = 0.537$, see Fig 17). Analyses of the post-training performance, B₈ (mean = 1.495, SE = 0.123) and B_{1_T3}, also revealed a significant reduction in accuracies (10.461, $p =$

0.005, $\eta^2 = 0.368$, see Fig 17). A reduction of spatial error at B_{2_T3} was observed when compared against B₈, showing improved performance from training, across Test 3 ($F(1,18) = 3.897$, $p = 0.064$, $\eta^2 = 0.178$, see Fig 17).

The within-test analysis did not reveal a block effect ($F(1,18) = 0.453$, $p = 0.509$, $\eta^2 = 0.025$). However, a strong main effect of forces, revealed that the spatial error was higher in the larger force range (mean = 1.377, SE = 0.095) compared to the smaller force range (mean = 1.002, SE = 0.041; $F(1,18) = 19.234$, $p < 0.0001$, $\eta^2 = 0.517$). The interaction was not significant ($F(1,18) = 0.415$, $p = 0.527$, $\eta^2 = 0.023$).

Temporal Accuracy

Training Phase: The ANOVA performed on the absolute asynchronies measured from the training data did not reveal any significant reduction of asynchrony across the 8 blocks, ($F(7, 126) = 4.939$, $p < 0.0001$, $\eta^2 = 0.215$).

Test 1 (Familiar-force test): The ANOVA ran on the asynchronies at B₁ of training (mean = 0.107, SE = 0.005) and B_{1_T1} (mean = 0.098, SE = 0.004) revealed no difference, ($F(1,18) = 1.776$, $p = 0.199$, $\eta^2 = 0.090$, see Fig 18). The comparison of B₁ against B_{2_T1} was also not significant (mean = 0.099, SE = 0.005), ($F(1,18) = 2.500$, $p = 0.131$, $\eta^2 = 0.122$, see Fig 18). The post training performance, B₈ (mean = 0.087, SE = 0.006) was not significantly different from B_{1_T1}, ($F(1,18) = 3.634$, $p = 0.073$, $\eta^2 = 0.168$, see Fig 18). The same was the case at B_{2_T1}, suggesting that actors maintained their floor synchrony achieved at the end of training, ($F(1,18) = 3.340$, $p = 0.084$, $\eta^2 = 0.157$, see Fig 18).

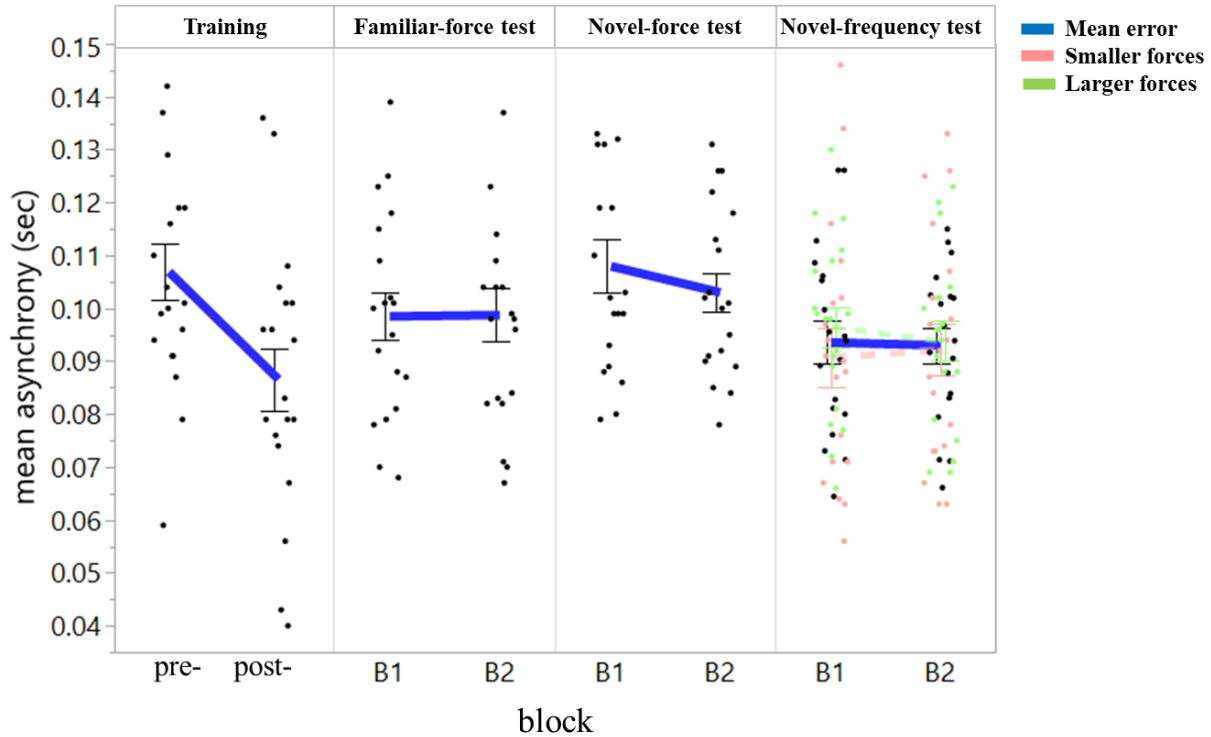


Fig 18. Mean temporal asynchrony during training and test phases in Experiment 2B: The figure shows the mean temporal asynchrony of the actors' landing times from the training and test phases in separate panels. The first panel shows mean asynchrony at the pre- and post-training blocks. From the test phases, figure shows mean asynchrony at Block 1 and Block 2 for *familiar-force test*, *novel-force test*, and *novel-frequency test* respectively. The red and green lines in the novel-frequency test panel shows the performances separately for smaller (Bin 1-5) and larger forces (Bin 6), respectively, for illustration purposes.

Test 2 (Novel-force test): The ANOVA performed on the temporal asynchronies at B₁ of training (mean= 0.107, SE= 0.005) and B_{1_T2} (mean= 0.108, SE= 0.005) showed no difference in temporal coordination ($F(1,18) = 0.028$, $p = 0.870$, $\eta^2 = 0.002$, see Fig 18). Similar comparison at B_{2_T2} (mean = 0.103, SE= 0.004) against B₁ also showed no difference ($F(1,18) = 0.383$, $p = 0.544$, $\eta^2 = 0.021$, see Fig 18). The main effect of Blocks in the ANOVA ran on B₈ (mean = 0.087, SE= 0.006) and B_{1_T2} revealed a significant worsening of temporal coordination at B_{1_T2}, ($F(1,18) = 8.922$, $p = 0.008$, $\eta^2 = 0.331$, see Fig 18). Analyses on asynchronies at B₈ and B_{2_T2}, also revealed a similar

worsening suggesting that actors' temporal performance was overall worse in Test 2 compared to their post-training performance ($F(1,18) = 4.743$, $p = 0.043$, $\eta^2 = 0.209$, see Fig 18).

Test 3 (Novel-frequency test): The ANOVA conducted on the temporal asynchronies at B_1 of training (mean = 0.107, SE = 0.005) and B_{1_T3} (mean = 0.094, SE = 0.004), revealed a significant improvement in performances ($F(1,18) = 4.925$, $p = 0.040$, $\eta^2 = 0.215$, see Fig 18). Actors improved their performance at B_{2_T3} (mean = 0.093, SE = 0.003) as well, compared to their initial performance in the task ($F(1,18) = 4.473$, $p = 0.049$, $\eta^2 = 0.199$, see Fig 18). The performance at B_{1_T3} did not differ from their post-training performance, B_8 (mean = 0.087, SE = 0.006; $F(1,18) = 1.062$, $p = 0.316$, $\eta^2 = 0.056$, see Fig 18). Asynchronies at B_{2_T3} also did not differ from B_8 , ($F(1,18) = 1.171$, $p = 0.294$, $\eta^2 = 0.061$, see Fig 18).

The within-test analysis did not reveal a main effect of block ($F(1,18) = 0.013$, $p = 0.911$, $\eta^2 = 0.001$), nor a main effect of force range ($F(1,18) = 1.135$, $p = 0.301$, $\eta^2 = 0.059$). The interaction between the factors also failed to reach a significance ($F(1,18) = 0.238$, $p = 0.631$, $\eta^2 = 0.013$).

3.5.3 Discussion

The current study aims to rule out any test-order effects in Experiment 1B. Our results replicated the effects observed in Experiment 1B. In Test 1, individuals showed a successful transfer of the spatial performance, without suffering a trade-off cost at the temporal performance, when they had to produce sequential movements under conditions of pre-exposed force perturbations. In Test 2, when individuals had to perform sequential movements under conditions of novel and larger forces, they successfully transferred their spatial performance at the cost of an interference in their temporal performance, as in Experiment 1B. In Test 3, when tested for

generalization under the influence of smaller and larger force conditions, successful transfer was observed in the spatial and temporal dimension. The within-test analysis revealed a main effect of forces in the spatial dimension, indicating that participants had a higher spatial error when they received larger forces. This suggests that learning was limited or slower in Experiment 2B, i.e., despite being trained in larger force range [24.0 - 27.0] and consecutively being tested in larger forces, participants did not flexibly adapt to novel action context, i.e., a novel distribution of force range that they were not previously exposed to, as easily as Experiment 2A participants. This suggest that low variability training limits the range of action possibilities one could learn in this task, even if they are trained in the highest task difficulty condition.

3.4 General Discussion

Joint action involves constant updating of the internal models encompassing both self and partner's movements, for an optimal task completion (Pesquita et al., 2018; Vesper et al., 2010, 2013). This includes maintaining and updating the joint action goal that is guiding the dyadic interaction, generating, and executing motor plans while taking into consideration both one's own and partner's contribution to the task. To coordinate successfully it is necessary to estimate sensory prediction errors by comparing the sensory outcome of the joint action to the predicted sensory states of own and partner's actions. Even though the mechanisms underlying action coordination have been discussed in the context of joint actions in general, less is known about joint action scenarios that involve motor learning through physical interaction with a partner. How does the dynamic internal model formulated during an interactive joint-motor learning incorporate information about one's own and partner's movements and how could these information be updated and generalized to accommodate any change in the interaction dynamic?

Our results show that successful skill generalization can be achieved in joint motor learning involving haptic coupling between the actors through modulation of the spatio-temporal dynamic of one's movements. Generalization to novel task context in joint learning, seems to be sensitive to the degree of task difficulty, as in individual learning contexts (Krakauer et al., 1999; Malfait et al., 2002, 2005). Depending on the difficulty of the task, participants generalized the learned skill differently in the various test conditions (see Table 10). If the difficulty in the novel task context was lower, individuals successfully transferred their spatial performance without suffering any decrement in the temporal synchrony with their partner. However, if the difficulty was higher in the novel task context, they transferred the spatial performance, by suffering a performance decrement or trade-off cost in the precision of their temporal coordination. These results indicate that skill generalization in a joint motor interactive task is mediated by the coupling dynamic involved in the task, i.e., generalization was compromised mostly when the task involved higher force perturbations.

Previous research on joint action coordination suggests that sensorimotor coupling between the actors can provide an additional benefit to one's performance that solo actions cannot provide, by generating new haptic channels with the partner to gather more information about the task (Van der Wel., 2011; Groten et al., 2012; Ganesh et al., 2014; Takagi et al., 2017; Batson et al., 2020). For example, Reed et al., 2008 showed that individuals performed a target acquisition task faster while haptically interacting with a partner compared to when they acted alone, even when the partners consider each other to be an impediment. However, dyadic interaction does not always entail a benefit in performance. Reed et al., 2008 suggests that sufficient interaction time is required for individuals to benefit from this haptic negotiation. Many studies did not find context

or task specific benefits of haptic interaction on individual motor performance (Beckers et al., 2018, 2020).

Test Conditions	Experiment 1A	Experiment 1B	Experiment 2A	Experiment 2B
Novel and Larger Forces	+* ^a	+* ^a	0*	+*
Familiar force and frequency	++	+	++	+
Novel frequency	++* ^b	+	+	+ ^b

Table 10. Summary of results of participant’s generalization from all four experiments: Generalization, transfer, or interference, is said to occur in the current task when the spatial accuracies in the test phase differs from the initial accuracy in training. An increment or a decrement in performance is marked by an improvement or worsening of accuracy in test compared to the final accuracy in training. “+” sign denotes a transfer of spatial accuracy in the test condition, “++” sign denotes a performance increment in the test compared to the floor accuracy in training and “0” denotes no generalization, meaning the test performance did not differ from the initial performance in training. The superscript “*” denotes an interference at the interpersonal coordination, i.e., a spatio-temporal trade-off. The superscript “a” denotes conditions in which the test performance, compared to the pre-training block, improved only in the second block of test, i.e., a slower generalization (see Discussion of Experiment 1A and 1B). In the test with ‘*novel-frequency*’, the superscript “b” denotes a main effect of force, with worst accuracy for larger forces, observed in the within-test analysis. It should be noted that the various test conditions are arranged as is in the table, for ease of tabulating- Experiment 1 and 2 received different order of tests.

In our study, we see that when individuals must counteract larger forces, the coordination dynamic breaks down and generalization is negatively affected. Having to counter larger forces, in physical terms, means actors experience a tighter physical coupling, therefore, their movements are more physically constrained. It could be that such hard mechanics of the interaction limits the

possibility of utilizing a haptic channel between the partner, as movements are less flexible now. In contrast, with smaller forces or trained forces, the sensorimotor information obtained through the dyadic interaction, might provide more flexibility to explore a wider range of action possibilities, which in turn allowed individuals to successfully update and adapt their joint action model, to generalize their learned skill without suffering a performance decrement.

Another relevant finding from the current study is that the partner's variability does not seem to be hindering generalization during joint learning. If anything, it provided some benefit in the individual performance when the task difficulty in the novel action context was limited. It could be assumed that training to produce aiming movements in isolation with a highly variable partner, allowed individuals to form a more generalized motor plan regarding aiming movements (Wu et al., 2014; Dhawale et al., 2017; Levac et al., 2019). This, in turn, could have aided them to combine the learned motor primitives to produce sequential movements.

The beneficial effect of variability observed in our task is in line with recent findings on human-robot interactions showing that promoting motor variability during robotic assistance enhances learning of dynamic motor tasks (Özen et al., 2021). Learning with a less variable partner, on the other hand, might only lead to limited exploration, despite the haptic interaction facilitating the process in the current task. Our results suggest that even if the training with a less variable partner is in a task involving higher task difficulty (larger force range, in our case), individual's learning will be limited to the trained force range during generalization, presumably due to a less flexible internal model learned during the training. This is the case even if the task context for generalization involves a lower difficulty level as indicated by the spatiotemporal trade-off observed for smaller forces in Test 2 of Experiment 1B. However, this does not imply that generalization was hindered. Rather, low variability reduced performance benefit in certain test

conditions. It should be noted that the beneficial effect of variability was also tied to the difficulty level of the novel task. As discussed before, the nature of the haptic interaction in our task limits the flexibility of individual's movements, while countering larger forces. This would negate the action exploration benefits that the partner's variability can provide- which is why a performance benefit with a highly variable partner was only observed in the novel action context involving lower task difficulty.

In our task, actors showed a prioritization of spatial accuracy over interpersonal temporal coordination, throughout the experiments. In our joint task, the various force configurations were achieved by manipulating the target positions of both actors. Smaller forces were achieved by cueing target positions closer to the start positions for both actors, and larger forces were achieved by cueing target positions that were further apart from the start positions. Moreover, the simultaneously cued targets do not mirror each other's positions; meaning, it is possible that in one configuration, when the participant had to move to a target closer to the start position, the confederate received a target farther away from the start position. In this case, the participant would tend to move faster to her target compared to the confederate, hence, implying different movement times. Thus, the spatial and temporal demands in our task were not equivalent.

In joint actions involving incongruent coordination demands, actors tend to engage in a complex trade-off between the spatial and temporal dimensions of their movements to optimize their performance (Richardson et al., 2015; Curioni et al., 2019). One could ask why did participants prioritize the spatial over the temporal dimension of the task? In our task, participants have more direct sensory access to their own movements compared to their partner's movements. The only access to the partner's movements is through the proprioceptive feedback they receive from the haptic coupling. Since a spatiotemporal trade-off was inevitable given the nature of the

task, it was easier to regulate the spatial parameter compared to the temporal parameter of the movements. Therefore, participants seem to have focused more on the spatial accuracy of their movements. One could assume that this spatiotemporal dynamic might be a general coordination strategy for such joint actions, involving haptic interaction. It remains to be investigated whether the trade-off would be reversed under different joint task constraints and instructions.

In conclusion, the dynamic action model one would build to achieve a successful task completion in a joint learning context could be enriched through haptic interaction, as it facilitates gaining of additional task information, provided, the difficulty of the interaction dynamic does not restrain the actors' movements too much. This, in turn, can promote skill generalizability in joint action, as the model then encompasses a wider range of action possibilities, from which one could choose to approach a novel task characteristic.

Future research could attempt to better isolate the differential effect of the training and test on final performance. The current experimental design could be improved with a baseline condition where we test participants performance at the sequential task before training. Further questions for future research include whether the spatiotemporal trade-off observed in the current study is reversible by changing the task demands or whether individuals always assign higher priority to individual accuracy than to the accuracy of joint action coordination when involved in physical interaction. Another issue that would be interesting to explore is whether skill generalization through joint learning can be observed over longer retention period as well.

Chapter 4. Conclusion

Returning to the example discussed in the beginning of the thesis, imagine that one of the two carriers had no experience with moving heavy objects on stairs. How fast would she learn and stabilize her movements to coordinate with her partner, so that they succeed in getting the mattress to the first floor? How do her partner's movement contribute to her learning? How do the physical coupling mechanics mediating their interaction, in this case through the soft mattress, impact her learning? Considering this is her first time doing this task, would her performance have been any different if they were carrying a harder furniture, say a table, which perturbs her movements less compared to a jiggly mattress? Also, how does learning with a partner support her ability to generalize the learned skills to a different context, say moving through a spiral stair instead of straight stairs, or carry a different piece of furniture, or even carrying the same object with a different partner? In this thesis, I addressed these questions by exploring how haptic interaction influences joint action learning. Specifically, I looked at how learning with a partner while haptically interacting with them allows one to acquire a motor skill and later transfer this skill to a novel task context. I also explored how the partner's motor variability influence the individual's learning during the dyadic interaction.

Haptic interaction between two individuals can be beneficial for joint action as the kinematic channel formed during haptic coupling provides more reliable information regarding a co-actor's movements, compared to any other sensory channel of information (Chackochan & Sanguineti, 2019). Therefore, I hypothesized that haptic interaction would foster skill acquisition in individuals during joint learning, when a partner exerts high variability on an individual's movements in a predictable manner; higher variability coming from a partner would facilitate action exploration in individuals and thus, foster the generation of a more flexible internal model

of motor control, which in turn would promote skill acquisition. Additionally, I hypothesized that a flexible internal model learned during the training of a skill through haptic interaction, would allow one to adapt to a novel task context easily, thus, allowing skill generalization. Given that the processes involved in skill acquisition and generalization are not the same (Seidler, 2010), it is possible that they are impacted differently during joint learning involving haptics.

The results of *Study 1* show that individuals involved in joint action learning selectively rely on either their own or their partner's variability (or both) for benefitting the individual and joint action performance, depending on the predictability of the partner's movements. In all three experiments, participants successfully regulated the variability of their own movements. However, individual performance was worse when the partner produced highly variable force perturbations in an unpredictable order. Interestingly, I found that predictability of force perturbations offset the detrimental effects of variability on individual performance. Participants in the high variability condition achieved higher flexibility and resilience for a wide range of force perturbations, when the partner produced predictable movements. Also, joint performance with a highly variable partner improved only when the partner produced (at least) partially predictable movements.

The results of *Study 2* showed that haptically coupled partners can achieve successful skill generalization in joint action learning through modulation of the spatiotemporal dynamic of their movements. The nature of generalization to novel task dynamics differed depending on the level of difficulty of the various novel task contexts. In my task, a higher difficulty involved countering force perturbations of higher magnitude, which in physical terms, translates into a tighter haptic coupling between the actors. The results suggest that skill generalization in a joint motor interactive task is mediated by the coupling dynamic involved in the task, i.e., generalization was interrupted or compromised most when the novel task involved higher task difficulty. These results

are in line with Takagi et al., (2016) suggesting that a softer coupling aids better learning performance as rigid coupling between the actors tends to break down the information channel formed during the interaction. Additionally, it was found that variability does not seem to hinder generalization in joint learning. If anything, as in skill acquisition, it provides some benefit, at least if the difficulty of a novel task is low. I propose that this is so because a higher force perturbation (higher task difficulty involved) tightly constrains the degree of freedom of one's movements, thus offsetting the ability to exploit varied action possibilities learned, which is otherwise possible with a flexible internal model in situ.

So, how is joint action learning and generalization mediated through haptic dyadic interaction? Haptic interaction seems to facilitate inter-personal coordination, even if co-actors have limited or no visual information about their partner's task. The specificity of the nature of this informational coupling is that actors are tightly linked through their biomechanics, which, unlike other sensory modalities, gives them the benefit of direct access to the partner's kinematic parameters. The error and the sensory-feedback delay involved in other sensory modalities are much higher compared to the instant feedback received through a haptic interaction. The speed with which sensorimotor feedback is received through haptic channels would provide room for a much faster online update of the movement plans. Thus, unlike other joint action scenarios that requires one to generate as consistent movements as possible to facilitate coordination, the mechanism adopted during haptic interactions might be different because they exploit the rich kinematic information available. Now for a detailed theoretical understanding of how joint action learning is mediated through haptic interaction, one could look at the predictive joint action model (PJAM)- a theoretical framework of human cooperative behavior (Pesquita et al., 2018). The PJAM assumes that during joint action, each actor maintains internal models of one's own and

partner's actions. The model comprises of three different hierarchical levels namely the *goal representation level*, where shared goals are maintained and updated, the *action planning level*, where motor commands are generated while considering own and partner's contribution to the interaction, and the *sensory routing level* which receives sensory inputs and compare it to internal model predictions. Each of these levels generates predictions of information that is expected to be found on the level below and the prediction errors generated at each level is fed back to the level above, to update the model. For a successful generation of these hierarchical models, one needs rich information regarding one's own and their partner's movements. And a close biomechanical coupling, like in our haptic interactive scenario, would only facilitate one's access to this information, and thus contribute to the three levels. Thus, learning under a constantly perturbing environment, facilitated by the haptic interaction, may allow one to widely explore a dynamic task environment through generating and executing multiple action plans and assessing the prediction errors caused by the joint movements, much faster. These estimations could be fed back to the higher levels to update one's model of the interaction. This would lead to generation of a more flexible internal model, encompassing a wider range of action possibilities, which facilitates skill acquisition. An additional benefit of a more generalized internal model is that it can be adopted in future performances, thus also aiding skill generalization.

Does partner's variability during a haptic interaction influence individual's learning the same way in skill acquisition and generalization? The results from the two studies shows that skill acquisition and generalization can be mediated by haptic interaction, regardless of the variability in the partner's movements, in joint action learning, i.e., *learning*- reduction of spatial error over time, was observed, in all training conditions from both studies when actors had to learn sequential

movements or discrete movements. And skill generalization was also observed in all experiments from Study 2.

However, the conditions under which the structure of partner's variability manifest to be beneficial, differed between skill acquisition and generalization. Variability reduction, as a means of making oneself predictable to the co-actor, is an important strategy adopted by individuals during joint action, as discussed before (Vesper et al., 2011, 2013). The skill acquisition study shows that one-way in which individuals exploit partner's variability for learning by not compromising the joint coordination is reducing their own variability, while simultaneously utilizing partner's variability transmitted through the haptic channels. However, for this to happen, the sequence of locations a partner's consecutive movements will visit must be predictable, so that movement variability could be utilized for performance benefit during learning. Thus, predictability of partner's action sequence seems to be a necessary pre-condition for variability to benefit joint skill acquisition of sequential movements.

In my skill generalization study the training condition did not involve a predictable sequence of movements from the partner, therefore participants could not have learned a particular structure in the unfolding of the variability (Sabu et al., 2020). Regardless, participants exhibited learning, suggesting that the mechanisms underlying joint action learning of sequential movements and discrete movements might be different. But more interestingly, there was not only generalization to sequential movements in all experiments of Study 2, but also some additional benefits of partner's variability in individuals' performance, although the partner's action sequence in the test phase was not predictable. This indicates that a predictable structure in the partner's movements for sequence production is only a requirement for skill acquisition and not for immediate performance during generalization to a novel task.

Together the findings are in line with previous research demonstrating that mechanisms involved in learning and retention of a skill through repetitive movements, are different from those supporting generalization of the skill to a novel task context. Generalization involves generating novel motor plans and muscle synergies to achieve the expected action outcome. Skill acquisition, improvement of motor performance over time through practice, utilizes exploration-to-exploitation strategies with the aim of reducing random movement variability in the exploitation phase (Shmuelof & Krakauer, 2011). If learning involves a haptic dyadic interaction, it then becomes necessary that there is some predictable structure to the partner's movement, so that one can achieve refined movements, without having to counter unforeseeable perturbations. For generalization, it is beneficial to develop motor programs that encompass many action possibilities and to adopt it to novel task contexts. Therefore, during a dyadic haptic interaction, a partner may introduce variability that is relevant to the task, that is, variability enhancing action exploration. Thus, predictability of a partner's movement might not be a necessary pre-condition for partner's variability to positively influence skill generalization.

An important aspect for future research that I did not address in this dissertation is the role of expertise or the skill-level matching of the actors in the dyad during joint learning. Novice - novice interactions have been found to be more beneficial for skill learning and transfer compared to novice-expert interactions, owing to the emergence of a collaborative learning where both actors explore the novel task dynamics together with equivalent effort (Saracbası et al., 2021; Nishimura et al., 2021). On the other hand, expert-novice interactions might hinder action exploration, as guidance from the expert might involve actively altering their movements to compensate for unexpected changes in the task dynamic, thus constraining the novices learning experience

(Mireles et al., 2017). It remains to be investigated how skill acquisition and generalization are influenced by movement variability in novice–novice interactions.

Another future direction for the present research is to investigate other kinds of generalization in dyadic interactions: for example, to different action contexts such as inter-limb transfer or transfer from one interaction partner to another. This kind of generalization would require one to engage new muscle synergies and to update the motor plans to successfully achieve the required action outcome, even more than adapting to a novel force range. Exploring generalization across limbs and partners would provide us with a clearer understanding about the nature of the information gathered during the dyadic haptic learning.

A further interesting question is how acquisition and generalization are affected while learning with a partner who is *naturally variable* in their movements, unlike the current task in which the variability was experimentally manipulated. Like in the Wu et al., (2014) studies, one could measure a baseline index of individual natural variability for each participant and then test the question of how two highly variable partners learn together, compared to less variable dyads, or to dyads where partners are not matched in natural variability. Addressing the question of how matched and non-matched partners learn during haptic dyadic interaction would complement the present project of inducing variability through task instruction.

Understanding the principles behind motor learning through dyadic interaction is relevant not only for application purposes involving rehabilitation techniques, sports training etc., but it is also relevant for the design of human-robot interfaces. Building robots that haptically interact with humans in intuitive and biologically meaningful ways requires a clear understanding of human-human interaction. On this ground, I believe the current thesis contributes to our understanding of the fundamental mechanics of human-human interaction involving haptics; to name a few, my

studies 1) shed light on the degree of haptic coupling that is useful in different joint learning contexts, 2) they address the role motor redundancy plays in the haptic cues and interaction between individuals, and 3) they capture an interactive scenario that involves a high degree of freedom of movement - the study of which is crucial for the design of haptic interfaces.

References

- Abeele, S., & Bock, O. (2003). Transfer of sensorimotor adaptation between different movement categories. *Experimental Brain Research*, 148(1), 128-132.
- Ashford, D., Bennett, S. J., & Davids, K. (2006). Observational modeling effects for movement dynamics and movement outcome measures across differing task constraints: A meta-analysis. *Journal of Motor Behavior*, 38(3), 185-205.
- Andrieux, M., & Proteau, L. (2014). Mixed observation favors motor learning through better estimation of the model's performance. *Experimental Brain Research*, 232(10), 3121-3132.
- Barbado Murillo, D., Caballero Sánchez, C., Moreside, J., Vera-García, F. J., & Moreno, F. J. (2017). Can the structure of motor variability predict learning rate?. *Journal of Experimental Psychology: Human Perception and Performance*, 43(3), 596.
- Basdogan, C., Ho, C. H., Srinivasan, M. A., & Slater, M. (2000). An experimental study on the role of touch in shared virtual environments. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 7(4), 443-460.
- Batson, J. P., Kato, Y., Shuster, K., Patton, J. L., Reed, K. B., Tsuji, T., & Novak, D. (2020, July). Haptic coupling in dyads improves motor learning in a simple force field. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 4795-4798). IEEE.
- Beckers, N., Keemink, A., Asseldonk, E. V., & Kooij, H. V. D. (2018, June). Haptic human-human interaction through a compliant connection does not improve motor learning in a force field. In *International Conference on Human Haptic Sensing and Touch Enabled Computer Applications* (pp. 333-344). Springer, Cham.
- Bernardi, N. F., Darainy, M., & Ostry, D. J. (2015). Somatosensory contribution to the initial stages of human motor learning. *Journal of Neuroscience*, 35(42), 14316-14326.

- Bernstein N. A. (ed.) (1967). *The Co-ordination and Regulation of Movements*. Oxford: Pergamon Press, 15–59.
- Bock, O., & Schneider, S. (2002). Sensorimotor adaptation in young and elderly humans. *Neuroscience & Biobehavioral Reviews*, 26(7), 761-767.
- Cardellicchio, P., Dolfini, E., Fadiga, L., & D'Ausilio, A. (2020). Parallel fast and slow motor inhibition processes in Joint Action coordination. *cortex*, 133, 346-357.
- Cardis, M., Casadio, M., & Ranganathan, R. (2018). High variability impairs motor learning regardless of whether it affects task performance. *Journal of Neurophysiology*, 119(1), 39-48.
- Chackochan, V. T., & Sanguinetti, V. (2019). Incomplete information about the partner affects the development of collaborative strategies in joint action. *PLoS Computational Biology*, 15(12), e1006385.
- Chauvigné, L. A., Belyk, M., & Brown, S. (2018). Taking two to tango: fMRI analysis of improvised joint action with physical contact. *PLoS One*, 13(1), e0191098.
- Cheng, X., Guo, B., & Hu, Y. (2022). Distinct Neural Couplings to Shared Goal and Action Coordination in Joint Action: Evidence Based on fNIRS Hyperscanning. *Social Cognitive and Affective Neuroscience*.
- Clarke, S., McEllin, L., Francová, A., Székely, M., Butterfill, S. A., & Michael, J. (2019). Joint action goals reduce visuomotor interference effects from a partner's incongruent actions. *Scientific Reports*, 9(1), 1-9.
- Curioni, A., Vesper, C., Knoblich, G., & Sebanz, N. (2019). Reciprocal information flow and role distribution support joint action coordination. *Cognition*, 187, 21-31.
- Dahms, C., Brodoehl, S., Witte, O. W., & Klingner, C. M. (2020). The importance of different learning stages for motor sequence learning after stroke. *Human Brain Mapping*, 41(1), 270-286.

- Dayan, E., & Cohen, L. G. (2011). Neuroplasticity subserving motor skill learning. *Neuron*, 72(3), 443-454.
- Dhawale, A. K., Smith, M. A., & Ölveczky, B. P. (2017). The role of variability in motor learning. *Annual Review of Neuroscience*, 40, 479-498.
- Doyon, J., & Benali, H. (2005). Reorganization and plasticity in the adult brain during learning of motor skills. *Current Opinion in Neurobiology*, 15(2), 161-167.
- Emken, J. L., & Reinkensmeyer, D. J. (2005). Robot-enhanced motor learning: accelerating internal model formation during locomotion by transient dynamic amplification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(1), 33-39.
- Emken, J. L., Benitez, R., Sideris, A., Bobrow, J. E., & Reinkensmeyer, D. J. (2007). Motor adaptation as a greedy optimization of error and effort. *Journal of Neurophysiology*, 97(6), 3997-4006.
- Feygin, D., Keehner, M., & Tendick, R. (2002, March). Haptic guidance: Experimental evaluation of a haptic training method for a perceptual motor skill. In *Proceedings 10th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. HAPTICS 2002* (pp. 40-47). IEEE.
- Furuki, D., & Takiyama, K. (2019). Decomposing motion that changes over time into task-relevant and task-irrelevant components in a data-driven manner: application to motor adaptation in whole-body movements. *Scientific Reports*, 9(1), 1-17.
- Ganesh, G., Takagi, A., Osu, R., Yoshioka, T., Kawato, M., & Burdet, E. (2014). Two is better than one: Physical interactions improve motor performance in humans. *Scientific Reports*, 4(1), 1-7.
- Gibb, R., Gray, R., & Scharff, L. (2016). *Aviation visual perception: Research, misperception and mishaps*. Routledge.

- Groten, R., Feth, D., Klatzky, R. L., & Peer, A. (2012). The role of haptic feedback for the integration of intentions in shared task execution. *IEEE transactions on haptics*, 6(1), 94-105.
- Hanson, J. V., Whitaker, D., & Heron, J. (2009). Preferential processing of tactile events under conditions of divided attention: effects of divided attention on reaction time. *Neuroreport*, 20(15), 1392.
- Harrison, S. J., & Richardson, M. J. (2009). Horsing around: spontaneous four-legged coordination. *Journal of Motor Behavior*, 41(6), 519-524. Chicago
- Herzfeld, D. J., & Shadmehr, R. (2014). Motor variability is not noise, but grist for the learning mill. *Nature Neuroscience*, 17(2), 149-150.
- Hilt, P. M., Badino, L., D'Ausilio, A., Volpe, G., Tokay, S., Fadiga, L., & Camurri, A. (2019). Multi-layer adaptation of group coordination in musical ensembles. *Scientific Reports*, 9(1), 1-10.
- Hodges, N. J., & Franks, I. M. (2002). Modelling coaching practice: the role of instruction and demonstration. *Journal of Sports Sciences*, 20(10), 793-811.
- Hodges, N. J., Williams, A. M., Hayes, S. J., & Breslin, G. (2007). What is modelled during observational learning? *Journal of Sports Science*, 25, 531-545
- Jin, X., & Costa, R. M. (2015). Shaping action sequences in basal ganglia circuits. *Current Opinion in Neurobiology*, 33, 188-196.
- Kager, S., Hussain, A., Cherpín, A., Melendez-Calderon, A., Takagi, A., Endo, S., ... & Campolo, D. (2019, June). The effect of skill level matching in dyadic interaction on learning of a tracing task. In *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)* (pp. 824-829). IEEE.

- Karlinsky, A., & Hodges, N. J. (2018). Turn-taking and concurrent dyad practice aid efficiency but not effectiveness of motor learning in a balance-related task. *Journal of Motor Learning and Development*, 6(1), 35-52.
- Kim, S., Ogawa, K., Lv, J., Schweighofer, N., & Imamizu, H. (2015). Neural substrates related to motor memory with multiple timescales in sensorimotor adaptation. *PLoS Biology*, 13(12), e1002312.
- Kiverstein, J., & Rietveld, E. (2021). Skilled we-intentionality: Situating joint action in the living environment. *Open Research Europe*, 1, 54.
- Knoblich, G., Butterfill, S., & Sebanz, N. (2011). Psychological research on joint action: theory and data. *Psychology Of Learning And Motivation*, 54, 59-101.
- Krakauer, J. W., Ghilardi, M. F., & Ghez, C. (1999). Independent learning of internal models for kinematic and dynamic control of reaching. *Nature Neuroscience*, 2(11), 1026-1031.
- Krakauer, J. W., Mazzoni, P., Ghazizadeh, A., Ravindran, R., & Shadmehr, R. (2006). Generalization of motor learning depends on the history of prior action. *PLoS Biology*, 4(10), e316.
- Krakauer, J. W. (2009). Motor learning and consolidation: the case of visuomotor rotation. *Progress In Motor Control*, 405-421.
- Levac, D. E., Huber, M. E., & Sternad, D. (2019). Learning and transfer of complex motor skills in virtual reality: a perspective review. *Journal Of Neuroengineering and Rehabilitation*, 16(1), 1-15.
- Little, D. Y. J., & Sommer, F. T. (2013). Learning and exploration in action-perception loops. *Frontiers In Neural Circuits*, 7, 37.
- Liu, L. Y., Li, Y., & Lamontagne, A. (2018). The effects of error-augmentation versus error-reduction paradigms in robotic therapy to enhance upper extremity performance and

- recovery post-stroke: a systematic review. *Journal Of Neuroengineering and Rehabilitation*, 15(1), 1-25.
- Loehr, J. D., & Vesper, C. (2016). The sound of you and me: novices represent shared goals in joint action. *Quarterly Journal of Experimental Psychology*, 69(3), 535-547.
- Lungu, O. V., & Debas, K. (2013). Motor learning during social interaction: the role of social interdependence. *Journal of Applied Social Psychology*, 43(10), 1984-1996.
- Magill, R., & Anderson, D. (2010). *Motor learning and control*. New York: McGraw-Hill Publishing.
- Malfait, N., Shiller, D. M., & Ostry, D. J. (2002). Transfer of motor learning across arm configurations. *Journal of Neuroscience*, 22(22), 9656-9660.
- Malfait, N., Gribble, P. L., & Ostry, D. J. (2005). Generalization of motor learning based on multiple field exposures and local adaptation. *Journal of Neurophysiology*, 93(6), 3327-3338.
- Masumoto, J., & Inui, N. (2013). Two heads are better than one: Both complementary and synchronous strategies facilitate joint action. *Journal of Neurophysiology*, 109(5), 1307-1314.
- Masumoto, J., & Inui, N. (2015). Motor control hierarchy in joint action that involves bimanual force production. *Journal of Neurophysiology*, 113(10), 3736-3743.
- McEllin, L., Knoblich, G., & Sebanz, N. (2018). Distinct kinematic markers of demonstration and joint action coordination? Evidence from virtual xylophone playing. *Journal of Experimental Psychology: Human Perception and Performance*, 44(6), 885.
- Melendez-Calderon, A., Komisar, V., & Burdet, E. (2015). Interpersonal strategies for disturbance attenuation during a rhythmic joint motor action. *Physiology & behavior*, 147, 348-358.

- Milanese, N., Iani, C., & Rubichi, S. (2010). Shared learning shapes human performance: transfer effects in task sharing. *Cognition*, 116(1), 15-22.
- Mireles, E. J. A., Zenzeri, J., Squeri, V., Morasso, P., & De Santis, D. (2017). Skill learning and skill transfer mediated by cooperative haptic interaction. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(7), 832-843.
- Mizuguchi, N., & Kanosue, K. (2017). Changes in brain activity during action observation and motor imagery: their relationship with motor learning. *Progress In Brain Research*, 234, 189-204.
- Nishimura, K., Saracbası, O. O., Hayashi, Y., & Kondo, T. (2021). Cooperative visuomotor learning experience with peer enhances adaptability to others. *Advanced Robotics*, 35(13-14), 835-841.
- Özen, Ö., Buetler, K. A., & Marchal-Crespo, L. (2021). Promoting motor variability during robotic assistance enhances motor learning of dynamic tasks. *Frontiers in Neuroscience*, 1436.
- Pacheco, M. M., & Newell, K. M. (2018). Search strategies in practice: Influence of information and task constraints. *Acta Psychologica*, 182, 9-20.
- Patton, J. L., Mussa-Ivaldi, F. A., & Rymer, W. Z. (2001, October). Altering movement patterns in healthy and brain-injured subjects via custom designed robotic forces. In *2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (Vol. 2, pp. 1356-1359). IEEE.
- Pesquita, A., Whitwell, R. L., & Enns, J. T. (2018). Predictive joint-action model: A hierarchical predictive approach to human cooperation. *Psychonomic Bulletin & Review*, 25(5), 1751-1769.
- Pekny, S. E., Izawa, J., & Shadmehr, R. (2015). Reward-dependent modulation of movement variability. *Journal of Neuroscience*, 35(9), 4015-4024.

- Pezzulo, G., Donnarumma, F., & Dindo, H. (2013). Human sensorimotor communication: A theory of signaling in online social interactions. *PloS One*, 8(11), e79876.
- Pezzulo, G., Donnarumma, F., Dindo, H., D'Ausilio, A., Konvalinka, I., & Castelfranchi, C. (2019). The body talks: Sensorimotor communication and its brain and kinematic signatures. *Physics Of Life Reviews*, 28, 1-21.
- Ranganathan, R., & Newell, K. M. (2013). Changing up the routine: intervention-induced variability in motor learning. *Exercise And Sport Sciences Reviews*, 41(1), 64-70.
- Reed, K., Peshkin, M., Hartmann, M. J., Grabowecky, M., Patton, J., & Vishton, P. M. (2006). Haptically linked dyads: are two motor-control systems better than one?. *Psychological Science*.
- Reed, K. B., & Peshkin, M. A. (2008). Physical collaboration of human-human and human-robot teams. *IEEE transactions on haptics*, 1(2), 108-120.
- Reinkensmeyer, D. J., Emken, J. L., Liu, J., & Bobrow, J. E. (2004, October). The nervous system appears to minimize a weighted sum of kinematic error, force, and change in force when adapting to viscous environments during reaching and stepping. In *Advances in Computational Motor Control III Symposium*.
- Reinkensmeyer, D. J., Akoner, O. M., Ferris, D. P., & Gordon, K. E. (2009, September). Slacking by the human motor system: computational models and implications for robotic orthoses. In *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 2129-2132). Ieee.
- Renart, A., & Machens, C. K. (2014). Variability in neural activity and behavior. *Current Opinion In Neurobiology*, 25, 211-220.
- Richardson, M. J., Harrison, S. J., Kallen, R. W., Walton, A., Eiler, B. A., Saltzman, E., & Schmidt, R. C. (2015). Self-organized complementary joint action: Behavioral dynamics of an interpersonal collision-avoidance task. *Journal of Experimental Psychology: Human Perception and Performance*, 41(3), 665.

- Sabu, S., Curioni, A., Vesper, C., Sebanz, N., & Knoblich, G. (2020). How does a partner's motor variability affect joint action?. *PloS One*, 15(10), e0241417.
- Sacheli, L. M., Tidoni, E., Pavone, E. F., Aglioti, S. M., & Candidi, M. (2013). Kinematics fingerprints of leader and follower role-taking during cooperative joint actions. *Experimental Brain Research*, 226(4), 473-486.
- Sallnäs, E. L., & Zhai, S. (2003). Collaboration meets Fitts' law: Passing virtual objects with and without haptic force feedback. In *IFIP Conference on Human-Computer Interaction* (pp. 97-104). IOS Press.
- Sánchez, C. C., Moreno, F. J., Vaíllo, R. R., Romero, A. R., Coves, Á., & Murillo, D. B. (2017). The role of motor variability in motor control and learning depends on the nature of the task and the individual's capabilities. *European Journal of Human Movement*, 38, 12-26.
- Saracbası, O. O., Harwin, W., Kondo, T., & Hayashi, Y. (2021). Mutual Skill Learning and Adaptability to Others via Haptic Interaction. *Frontiers in Neurorobotics*, 160.
- Sawers, A., & Ting, L. H. (2014). Perspectives on human-human sensorimotor interactions for the design of rehabilitation robots. *Journal Of Neuroengineering and Rehabilitation*, 11(1), 1-13.
- Schaal, S., Ijspeert, A., & Billard, A. (2003). Computational approaches to motor learning by imitation. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 358(1431), 537-547.
- Schmidt, R. C., & Richardson, M. J. (2008). Dynamics of interpersonal coordination. In *Coordination: Neural, Behavioral And Social Dynamics* (pp. 281-308). Springer, Berlin, Heidelberg.
- Schmidt, M. F., & Ding, L. (2014). Achieving perfection through variability: the basal ganglia helped me do it!. *Neuron*, 82(1), 6-8.

- Sebanz, N., & Knoblich, G. (2009). Prediction in joint action: What, when, and where. *Topics in Cognitive Science*, 1(2), 353-367.
- Sebanz, N., & Knoblich, G. (2021). Progress in joint-action research. *Current Directions in Psychological Science*, 30(2), 138-143.
- Seidler, R. D., Bloomberg, J. J., & Stelmach, G. E. (2001). Patterns of transfer of adaptation among body segments. *Behavioural brain research*, 122(2), 145-157.
- Seidler, R. D. (2007). Older adults can learn to learn new motor skills. *Behavioural brain research*, 183(1), 118-122.
- Seidler, R. D. (2010). Neural correlates of motor learning, transfer of learning, and learning to learn. *Exercise and sport sciences reviews*, 38(1), 3.
- Shadmehr, R., & Mussa-Ivaldi, F. A. (1994). Adaptive representation of dynamics during learning of a motor task. *Journal of neuroscience*, 14(5), 3208-3224.
- Shadmehr, R., Huang, H. J., & Ahmed, A. A. (2016). A representation of effort in decision-making and motor control. *Current biology*, 26(14), 1929-1934.
- Shea, C. H., Kohl, R., & Indermill, C. (1990). Contextual interference: Contributions of practice. *Acta Psychologica*, 73(2), 145-157.
- Shea, C. H., & Kohl, R. M. (1991). Composition of practice: Influence on the retention of motor skills. *Research Quarterly for Exercise And Sport*, 62 (2), 187-195.
- Shmuelof, L., & Krakauer, J. W. (2011). Are we ready for a natural history of motor learning?. *Neuron*, 72(3), 469-476.
- Smith, M. A., Ghazizadeh, A., & Shadmehr, R. (2006). Interacting adaptive processes with different timescales underlie short-term motor learning. *PLoS Biology*, 4(6), e179.
- Sofianidis, G., & Hatzitaki, V. (2015). Interpersonal entrainment in dancers: Contrasting timing and haptic cues. *Posture, Balance Brain Int Work Proc*, 34-44.

- Takagi, A., Beckers, N., & Burdet, E. (2016). Motion plan changes predictably in dyadic reaching. *PLoS one*, *11*(12), e0167314.
- Takagi, A., Ganesh, G., Yoshioka, T., Kawato, M., & Burdet, E. (2017). Physically interacting individuals estimate the partner's goal to enhance their movements. *Nature Human Behaviour*, *1*(3), 1-6.
- Takagi, A., Usai, F., Ganesh, G., Sanguineti, V., & Burdet, E. (2018). Haptic communication between humans is tuned by the hard or soft mechanics of interaction. *PLoS Computational Biology*, *14*(3), e1005971.
- Thoroughman, K. A., & Shadmehr, R. (2000). Learning of action through adaptive combination of motor primitives. *Nature*, *407*(6805), 742-747.
- Tumer, E. C., & Brainard, M. S. (2007). Performance variability enables adaptive plasticity of 'crystallized' adult birdsong. *Nature*, *450*(7173), 1240-1244.
- van der Wel, R. P., Knoblich, G., & Sebanz, N. (2011). Let the force be with us: dyads exploit haptic coupling for coordination. *Journal of Experimental Psychology: Human Perception and Performance*, *37*(5), 1420.
- van der Wel, R. P., & Fu, E. (2015). Entrainment and task co-representation effects for discrete and continuous action sequences. *Psychonomic Bulletin & Review*, *22*(6), 1685-1691.
- Vesper, C., Butterfill, S., Knoblich, G., & Sebanz, N. (2010). A minimal architecture for joint action. *Neural Networks*, *23*(8-9), 998-1003.
- Vesper, C., Van Der Wel, R. P., Knoblich, G., & Sebanz, N. (2011). Making oneself predictable: Reduced temporal variability facilitates joint action coordination. *Experimental Brain Research*, *211*(3), 517-530.
- Vesper, C., Schmitz, L., Sebanz, N., & Knoblich, G. (2013). Joint action coordination through strategic reduction of variability. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 35, No. 35).

- Vesper, C., & Richardson, M. J. (2014). Strategic communication and behavioral coupling in asymmetric joint action. *Experimental Brain Research*, 232(9), 2945-2956.
- Vesper, C., Schmitz, L., Safra, L., Sebanz, N., & Knoblich, G. (2016). The role of shared visual information for joint action coordination. *Cognition*, 153, 118-123.
- Vesper, C., Abramova, E., Bütepage, J., Ciardo, F., Crossey, B., Effenberg, A., ... & Wahn, B. (2017). Joint action: mental representations, shared information and general mechanisms for coordinating with others. *Frontiers in Psychology*, 7, 2039.
- Wolpert, D. M., & Flanagan, J. R. (2001). Motor prediction. *Current Biology*, 11(18), R729-R732.
- Wolpert, D. M., Ghahramani, Z., & Flanagan, J. R. (2001). Perspectives and problems in motor learning. *Trends in cognitive sciences*, 5(11), 487-494.
- Wolpert, D. M., Doya, K., & Kawato, M. (2003). A unifying computational framework for motor control and social interaction. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 358(1431), 593-602.
- Wu, H. G., Miyamoto, Y. R., Castro, L. N. G., Ölveczky, B. P., & Smith, M. A. (2014). Temporal structure of motor variability is dynamically regulated and predicts motor learning ability. *Nature Neuroscience*, 17(2), 312-321.
- Wymbs, N. F., Bastian, A. J., & Celnik, P. A. (2016). Motor skills are strengthened through reconsolidation. *Current Biology*, 26(3), 338-343.
- Ziegler, M. D., Zhong, H., Roy, R. R., & Edgerton, V. R. (2010). Why variability facilitates spinal learning. *Journal of Neuroscience*, 30(32), 10720-10726.

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