Full Length Article

Synchronous vs. non-synchronous imitation: Using dance to explore interpersonal coordination during observational learning

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ABSTRACT

Observational learning can enhance the acquisition and performance quality of complex motor skills. While an extensive body of research has focused on the benefits of synchronous (i.e., concurrent physical practice) and non-synchronous (i.e., delayed physical practice) observational learning strategies, the question remains as to whether these approaches differentially influence performance outcomes. Accordingly, we investigate the differential outcomes of synchronous and non-synchronous observational training contexts using a novel dance sequence. Using multidimensional cross-recurrence quantification analysis, movement time-series were recorded for novice dancers who either synchronised with ($n = 22$) or observed and then imitated ($n = 20$) an expert dancer. Participants performed a 16-count choreographed dance sequence for 20 trials assisted by the expert, followed by one final, unassisted performance trial. Although end-state performance did not significantly differ between synchronous and non-synchronous learners, a significant decline in performance quality from imitation to independent replication was shown for synchronous learners. A non-significant positive trend in performance accuracy was shown for non-synchronous learners. For all participants, better imitative performance across training trials led to better end-state performance, but only for the accuracy (and not timing) of movement reproduction. Collectively, the results suggest that synchronous learners came to rely on a real-time mapping process between visual input from the expert and their own visual and proprioceptive intrinsic feedback, to the detriment of learning. Thus, the act of synchronising alone does not ensure an appropriate training context for advanced sequence learning.

1. Introduction

Although some human learning can be understood as a direct experience of trial-and-error (Staddon & Cerutti, 2003), a larger proportion of human behaviour is learned indirectly via observation (Bandura, 2008). Accordingly, there is a significant amount of previous research demonstrating how observation can enhance learning, particularly with regard to complex motor skills, such as those demonstrated by athletes and other elite performers (Hodges, Williams, Hayes, & Breslin, 2007; Lago-Rodriguez, Lopez-Alonso, & Fernández-del-Olmo, 2013; McCullagh, Weiss, & Ross, 1989; Ste-Marie et al., 2012; Vogt & Thomaschke, 2007). While some

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learning of complex motor skills can occur by passive observation alone (Apšvalka, Cross, & Ramsey, 2019; Hargreaves & Lamont, 2017; Larssen, Ong, & Hodges, 2012; Mcgregor, Cashaback, & Gribble, 2018), physical practice involving active, imitative movement, whether immediate or delayed, is often required to ensure optimal acquisition of complex motor skills (Badets, Blandin, Wright, & She, 2006; Badets & Blandin, 2004, 2005; Blandin, Proteau, & Alain, 1994; Carroll & Bandura, 1990; Hodges et al., 2007; Maslovat, Hodges, Krigolson, & Handy, 2010; Wright, Coady, & Li, 1997). Indeed, the transformation of observed actions into produced actions not only facilitates motor performance (Hayes, Hodges, Scott, Horn, & Williams, 2006; Hayes, Ashford, & Bennett, 2008; Horn, Williams, Hayes, Hodges, & Scott, 2007), but also enhances a learner's ability to detect or correct for subtle errors in observed and produced actions (Lago-Rodriguez et al., 2013). Cognitive (Hommel, Müsseler, Aschersleben, & Prinz, 2001), neurological (Cross, Kraemer, Hamilton, Kelley, & Grafton, 2009), and self-organizing dynamical processes (Kelso, 1994) have been proposed to underlie both action observation and action production. Importantly, each of these theoretical approaches points to a source of shared information, implying that it is the inherent link between perception and action that makes observational learning possible (Davids, Williams, & Williams, 2005; Hecht, Vogt, & Prinz, 2001).

Of further relevance here, however, is the tacit understanding within the literature on observational learning that individuals can engage in such learning in one of two ways. First, a learner can passively observe an action or action sequence produced by another actor, expert, or *demonstrator*, and then following observation, attempt to actively reproduce the observed action or action sequence. This kind of observational learning corresponds to *non-synchronous* imitation, where there is a delay (small or large) between action observation and performance (i.e., practice). The second general form of observational learning involves learners actively attempting to reproduce an action or action sequence during action observation. This kind of "real-time" or concurrent practice observational learning corresponds to *synchronous* imitation. Human behavioural research suggests that successful interpersonal coordination may comprise a range of complex morphological and temporal synchronies (Cornejo, Cuadros, Morales, & Paredes, 2017). While research on perception-action coupling has focused on the role of synchrony in the spontaneous production of coordinated movement (Richardson et al., 2015; Schmidt, Carello, & Turvey, 1990; Schmidt & Fitzpatrick, 2016; Schmidt & Richardson, 2008), few studies to date have explicitly examined the dynamics of synchrony during the learning of coordinated movement (e.g., Buchanan, Ramos, & Robson, 2015). Moreover, the question remains as to whether non-synchronous and synchronous approaches to observational learning result in differential performance outcomes (Gordon et al., 2020; Weeks, Hall, & Anderson, 1996).

1.1. A dynamical systems approach to coordinated human behaviour

Synchronous and non-synchronous observational learning may be accounted for by a dynamical systems approach, in which the processes that govern human behaviour are understood in terms of self-organizing dynamics. Although there must exist some shared information which allows for the mapping of perception and action, this does not mean that stable behavioural patterns are solely the result of mental representations. Indeed, the dynamical systems approach posits that lawful, task-specific physical and informational constraints operate to generate and self-organize the context specific patterning of human behaviour (Haken, Kelso, Fuchs, & Pandya, 1990; Kelso, 1994). More specifically, the physical and informational properties of a task or agent-environment system define the possible stable states (i.e., states which attract the system) of behavioural organization and coordination, with control parameters that determine the particular behavioural states observed during ongoing task performance (Mark et al., 1997; Warren, 1984). At a critical value of a control parameter, a system's current state can become unstable, such that the system transitions to a more stable state (i.e., a bifurcation or a nonlinear phase transition occurs; Kelso, 1984; Patil, Nalepka, Kallen, & Richardson, 2020; Strogatz, 1994; Turvey, 1990). In the case of observational learning, learners must transform the relevant environmental and behavioural information into the space of order parameter dynamics (Buchanan, 2016; Kelso, 1994; Gregor Schöner, Zanone, & Kelso, 1992).

With regard to human behavioural synchrony specifically, such interpersonal coordination naturally emerges as an entrainment process of physically or biologically coupled behavioural rhythms. Accordingly, interpersonal coordinative behaviour can be modelled using simple coupled-oscillator dynamics (Kugler & Turvey, 1987; Newtson, Hairfield, Bloomingdale, & Cutino, 1987; Schmidt & Richardson, 2008), while taking into account the constraints of the task and any relevant social/psychological factors (Fitzpatrick, Schmidt, & Carello, 1996; Kelso, 1995; Turvey, Rosenblum, Schmidt, & Kugler, 1986). Indeed, previous research has demonstrated that pairs of individuals tend to synchronise the swinging of handheld pendulums, demonstrating a self-organised coupled-oscillator dynamic (Schmidt, Carello, & Turvey, 1990; Schmidt, Christiansen, Carello, & Baron, 1994; Schmidt, Fitzpatrick, Bienvenu, & Amazeen, 1998; Schmidt & Turvey, 1994) and further suggesting that this dynamic is visually-mediated, as unintentional synchronisation emerged even when pairs were explicitly asked to maintain their own swinging pace (Schmidt & O'Brien, 1997). More recent research has also examined the applications of this dynamic in more ecologically valid interpersonal paradigms in which intentional coordination is inhibited, such as when completing an interpersonal puzzle task (Richardson, Marsh, & Schmidt, 2005). Unintentional synchronisation of oscillatory movements consistently emerged not only during pendulum swinging (Richardson, Lopresti-Goodman, Mancini, Kay, & Schmidt, 2008), but also during activities such as walking (van Ulzen, Lamoth, Daffertshofer, Semin, & Beek, 2008), rocking chairs (Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007), and free limb movement (Issartel, Marin, & Cadopi, 2007). In sum, the dynamics of synchronisation occur not only in laboratory studies, but also in naturalistic social interactions.

Although governed by coordination dynamics, interpersonal synchrony is thought to serve as a foundation for successful social exchange. Synchronous behaviours are associated with increased cooperation among adults (Wiltermuth & Heath, 2009) and children (Kirschner & Tomasello, 2010) as well as with greater conformity (Wiltermuth, 2012), altruism (Valdesolo & DeSteno, 2011), and trust (Launay, Dean, & Bailes, 2013). Namely, the functional benefit of synchronised social interaction is to facilitate a perception of connectedness between interaction partners, which promotes affiliation, cooperation, and joint action (Miles, Griffiths, Richardson, & Macrae, 2009). Recent research suggests that behavioural synchrony may also underlie collaborative learning (Malmberg, Haataja,

Seppänen, & Järvelä, 2019). When individuals undertake learning in groups (or pairs), the degree to which individuals temporally synchronise their behaviours determines the effectiveness of joint output and quality of work (Erkens, Jaspers, Prangsma, & Kanselaar, 2005). Individuals undertaking successful collaborative learning exhibit greater synchronicity of mutual gaze (Schneider & Pea, 2013), joint visual attention (Schneider et al., 2018), and physiological arousal (Ahonen, Cowley, Hellas, & Puolamäki, 2018), and these signals are increased with increased task difficulty (Järvelä, Hadwin, Malmberg, & Miller, 2019; Malmberg et al., 2019; Mønster, Håkonsson, Eskildsen, & Wallot, 2016). Individuals are thought to regulate shared learning through construction of joint meaning and goals for a task (Järvelä et al., 2019) and to monitor these outcomes through behavioural synchrony (Järvelä, Malmberg, & Koivu-niemi, 2016; Volet, Vauras, Salo, & Khosa, 2017). However, few studies to date have examined these phenomena in the learning of coordinated movement.

1.2. Empirical research on synchronous and non-synchronous observational learning approaches

Non-synchronous imitation is perhaps the most ubiquitous form of observational learning (Fryling, Johnston, & Hayes, 2011). It is employed in the learning of simple everyday behaviours, such as shoelace and knot tying (Cross, Hamilton, Cohen, & Grafton, 2017; Roshal, 1961), ball throwing (Al-Abood, Bennett, Hernandez, Ashford, & Davids, 2002; Hall & Erffmeyer, 1983; Williams, 1989b), and racket swinging (Gray, 1990), as well as in the learning of complex behavioural and motor sequences, such as those involved in juggling (Hodges et al., 2007), rugby throws and kicks (Faelli et al., 2019; Sani & Khan, 2017), gymnastics (Magill & Schoenfelder-Zohdi, 1996), and dance (Cross, 2012). Such observational training is often employed to systematically investigate a learner's ability to reproduce the spatiotemporal characteristics of various movement sequences (Ashford, Bennett, & Davids, 2006). For instance, studies using serial reaction time tasks, bimanual tasks, and keypress sequencing consistently demonstrate that participants who first undertake observational practice exhibit better performance during physical practice replications of task sequencing (Badets, Blandin, & Shea, 2006; Buchanan & Dean, 2010; Heyes & Foster, 2002). Similarly, studies assessing sequencing tasks involving full-body motor movement (e.g., sports, gymnastics, dance) find that participants who undertake observational practice in addition to subsequent physical practice perform better than participants who undertake only observational practice (Williams, 1989a) or physical practice in the absence of observation (i.e., learning occurs via written or verbal instruction and feedback only; Faelli et al., 2019). Thus, collectively, previous research on non-synchronous imitation has provided clear and consistent evidence that such observational training can enhance both the learning and performance of complex motor sequences and actions.

Although observational learning involving synchronous imitation is perhaps less ubiquitous than non-synchronous observational learning, such learning is often employed when learning complex, skilled motor sequences, particularly during dance and musical instrument instruction. Indeed, research has demonstrated that novice dancers were better able to perform dance sequences they had physically practiced by synchronising with a video avatar compared to dance sequences they had only observed, which were in turn performed better than novel sequences they had never practiced (Kirsch, Diersch, Sumanapala, & Cross, 2018). Likewise, novice guitar players were better able to perform music sequences they had practiced by synchronising with a video game over the previous three days compared to sequences they had only observed, which were in turn performed better than sequences never observed (Gardner, Aglinskas, & Cross, 2017). Additionally, synchronous physical practice of a motor skill (e.g., single limb coordination) alters the self-evaluation of one's performance capabilities consistent with the dynamics of action production and is dependent on shared information about relative phase (Buchanan et al., 2015). Thus, similar to non-synchronous training approaches, synchronous imitation with physical practice can lead to better end-state performance or reproduction of motor sequences.

Although both forms of imitation (i.e., non-synchronous and synchronous) may enhance motor reproduction and learning of movement sequences, synchrony may play a larger role in observational learning than is currently understood. Recent research on synchronous imitation in observational learning has demonstrated associations between physiological synchrony and learned behavioural outcomes. Using a skin conductance measure of physiological arousal, Parnamets, Espinosa, and Olsson (2018) found that greater physiological synchrony of the autonomic nervous system between a demonstrator and an observer during threat response led to greater observational learning of threat-based cues. Another recent study using fMRI demonstrated that a greater degree of neurophysiological synchrony between a blindfolded demonstrator and novice observers learning to fold origami led to better learning outcomes (Kostorz, Flanagin, & Glasauer, 2020). Although behavioural and physiological synchrony may operate independently (Gordon et al., 2020), previous work suggests that physiological synchrony can emerge concurrently during cooperative or joint-action behavioural tasks (Palumbo et al., 2017). Thus, these synchrony-driven improvements for learned behavioural outcomes might also be reflected following an interpersonal coordination task, in which greater behavioural synchrony might lead to improved end-state task performance (i.e., post-learning proficiency).

Not surprisingly, synchronous imitation is also more common for behavioural tasks that require interpersonal and multi-agent coordination (i.e., joint-action tasks; Eerola, Jakubowski, Moran, Keller, & Clayton, 2018; McEllin, Knoblich, & Sebanz, 2018; Wolf, Sebanz, & Knoblich, 2018) or that involve improvised perceptual-motor sequences (Chauvigné, Belyk, & Brown, 2018; Issartel, Gueugnon, & Marin, 2017). Interestingly, evidence from studies observing experts during improvised motor learning tasks suggests that a greater degree of synchrony may lead to better end-state performance. Although these paradigms do not include a delayed, independent replication component, end-state performance on novel or improvised tasks may act as an example of learning. For instance, when compared to novices, martial arts experts exhibited a stronger dynamical synchronisation during an improvised sword-swinging task (Schmidt, Fitzpatrick, Caron, & Mergeche, 2011). Likewise, expert dancers exhibited more movement complexity and interpersonal coordination compared to novices during tasks involving improvised movement in dyads (Issartel, Marin, & Cadopi, 2006) or when performing movements of increasing complexity with a confederate (Washburn et al., 2014). Noy, Dekel, and Alon (2011) found that expert improvisers (e.g., actors and musicians) demonstrated more synchronisation, better precision, and were able

to perform at higher levels of complexity when compared to novices during a mirror game task in which pairs of participants created complex movements while intentionally staying as synchronised as possible. Using the same mirror game task, Gueugnon et al. (2016) further demonstrated that novice participants exhibited a greater ability to synchronise over time, and participants who engaged in an additional unintentional synchronisation task between improvisation trials also produced more complex movements. Consistent with evidence from expert performers, a greater degree of interpersonal synchronisation among novices can lead to better end-state performance during intentional coordination tasks such as improvisation. If we consider end-state performance as indicative of learning for novel or improvised tasks, these studies suggest that a synchronous imitation approach may allow for greater success in performing novel movements and improving at the task *during* the learning process (i.e., learning rate).

1.3. Current study

Although research has demonstrated that both synchronous and non-synchronous observational learning can enhance motor skill acquisition, the question remains as to whether they result in the same performance outcomes (Gordon et al., 2020; Weeks et al., 1996), both in terms of learning rate and post-learning proficiency. Accordingly, the aim of the current study was to investigate whether synchronous and non-synchronous observational training approaches differentially influence performance outcomes. Research with dancers suggests that an ability to reproduce previously unknown movements in real time is key to learning movement sequences (Brown & Meulenbroek, 2016; Thullier & Moufti, 2004). Additionally, successful learning of choreographed dance sequences is often a joint action that depends on the interaction of sensory, motor, and cognitive processes (Bläsing & Schack, 2012; Bläsing, Tenenbaum, & Schack, 2009; Brown & Meulenbroek, 2016). Thus, the task of learning a dance routine provides an ideal platform to evaluate the role of interpersonal coordination during observational learning of a full-body movement sequence. We therefore employed a novel dance sequence to assess the degree to which synchronous versus non-synchronous imitation influences learning and performance. That is, novice dancers were asked to reproduce a movement sequence by either synchronising with an expert dancer (synchronous imitation) or by observing and then imitating the expert's movements (non-synchronous imitation). Of particular interest was whether individuals who learned via synchronous imitation exhibited better end-state performance than individuals who learned via non-synchronous imitation. We also assessed whether exhibiting higher performance across training trials (i. e., better synchronous and non-synchronous imitation) influences end-state performance, with the expectation that better imitative performance during training trials would transfer to better end-state, non-imitative performance.

2. Methods

2.1. Participants

First-year undergraduate psychology students ($N = 42$) from Macquarie University were recruited from the online research participant pool, and two additional volunteers from the university elected to participate in this study. Undergraduate psychology students received course credit in exchange for participation in the 1-h study. The study was approved by the Macquarie University Human Research Ethics Committee (code: 5201800393), and all participants provided voluntary, informed consent before undertaking research procedures. Participant characteristics are summarised in Table 1.

2.2. Procedure

Twenty-two participants were randomly selected from the university population and assigned to the synchronous imitation condition. Later, an additional twenty participants were randomly selected and assigned to the non-synchronous imitation condition. In the synchronous condition, participants were asked to synchronise their movements to the best of their ability with a confederate (first author), who was a professional dancer with 26 years of dance experience. In the non-synchronous condition, the confederate first performed the movement sequence while the participant only observed. The participant was then asked to replicate the sequence

Table 1
Participant characteristics by condition.

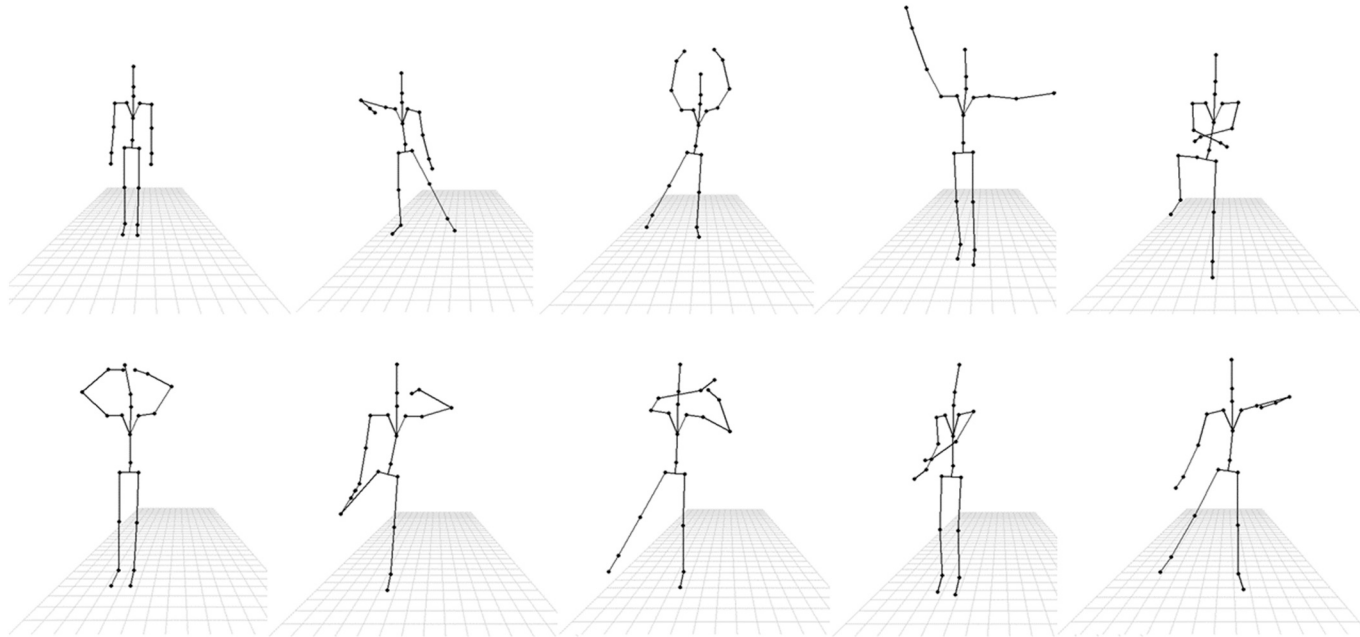| Measure	Synchronous	Non-synchronous
	M (SD) or %	*M (SD)* or %
	n = 22	*n* = 20
Age	20.26 (6.20)	21.35 (5.10)
Proportion female	59.10%	50.00%
Proportion right-handed	68.20%	90.00%
Dance experience		
Dance classes	50.00%	50.00%
Years of training	2.30 (3.96)	2.35 (4.34)
Social dancing (per month)	1.57 (0.99)	1.80 (2.08)
Dance video games	50.00%	55.00%
Learning ability	2.50 (0.80)	2.55 (1.05)
Dance ability	2.46 (0.80)	2.50 (1.00)

Fig. 1. Illustrations of the key steps of the 16-count dance choreography shown sequentially from top left to bottom right. Postures as performed on the first (right-hand) side are shown up to the halfway mark. The same steps were repeated and mirrored on the second (left-hand) side.

without the assistance of the confederate, and this process was repeated for each learning trial. After completing 20 training trials, participants were asked to perform the sequence by themselves for the final (21st) trial. The confederate performed the movement sequence at 70 bpm for the first 10 trials and at 80 bpm for the last 10 trials. The tempo was increased midway to replicate the way in which dancers tend to gradually increase the speed of their movements as they become more comfortable with a learned sequence. To regulate tempo across trials, the confederate provided a vocal four-count preparation at the start of each trial and wore wireless Bluetooth headphones connected to a metronome that was set to the respective trial tempo. Following completion of the study, participants were asked to complete a post-experimental demographics and dance experience survey (see Table 1).

2.3. Materials

2.3.1. Movement sequencing

An original 16-count movement sequence was developed for this study, which involved bodily weight shifts and coordination of limbs. The sequence was designed to be repeated on the right and left sides, taking 32-counts in total to complete one trial. The sequence was conceived to suit a basic level of movement capability but to be performed by both expert and novice movers. Movement involved minimal direction changes and no rotational changes, such that the confederate and learner remained facing the anterior wall throughout execution. A mild degree of complexity was introduced through synchronisation of unidirectional lower limb movements with symmetrical but opposing upper limb movements. The movements involved in the dance sequence are displayed as an illustration in Fig. 1. This illustration was created using motion data recordings of the confederate. A data playback video of the full movement sequence can be seen here: https://youtu.be/_5t0KBcVhb8

2.3.2. Room setup

To enhance ecological validity, a set of body-length dance studio mirrors were placed at the anterior wall and dancers performed the movement sequence facing these mirrors throughout the study. To indicate the confederate's starting position, a marker was placed on the floor 1.9 m in front of the mirror and 1.4 m from the right wall. A second marker for the participant's starting position was placed to the left and behind the confederate's marker, such that it was 3 m in front of the mirrors and 2.7 m from the right wall. This was to allow participants to clearly see the confederate's movements reflected in the mirror as well as directly from behind and to the side. Although participants were instructed to stand on their marker facing directly forward, they were not explicitly told to focus on either the confederate or the mirror. Mirror placement, position markers, and other room setup conditions were identical for both the synchronous and non-synchronous conditions.

2.3.3. Motion capture

The Rokoko Smartsuit Pro (Rokoko, Copenhagen, Denmark) was used to capture the positional and angular data of the confederate and participants during the study. This system uses full-length bodysuits containing 19 embedded inertial measurement units with nine degrees of freedom and wirelessly records motion data at 100 Hz up to a range of 100 m. Rokoko Studio Software was used to record and export data, with data recordings scaled to participant height. An HTC Vive positional tracker was affixed to the centre back of both suits to provide minor corrections for global position. These trackers use six degrees of freedom positional tracking of a rigid body in three-dimensional space to record pitch, yaw, and roll (rotational motion) in addition to linear motion in the sagittal, frontal, and transverse planes. Two Vive base stations 2.0 were mounted to the anterior and posterior walls to track the position and orientation of the Vive trackers.

2.3.4. Post-experimental survey

Participants were asked about their age, gender, handedness, and previous dance experience, including whether they took any dance classes, years of experience, how often they dance in social settings (e.g., clubs, parties), and if they have ever played dance-based video games. Participants also reported on their perceived ability to learn movement sequences and their perceived dance ability on a Likert-type scale from 1 (*very bad*) to 5 (*very good*).

2.4. Data processing of whole-body motion trajectories

Three-dimensional Cartesian coordinates for the pelvic, shoulder, wrist, and ankle joint centres were extracted from the motion capture data for each trial. Relative positions of the joint centres were calculated using the pelvic centre coordinates as a reference to control for whole-body motion and to control for the relative position of participants in space. This resulted in each trial having an 18-dimensional trajectory that describes whole-body motion. The start of motion was marked by identifying any movement from either the confederate's or participants' right ankle joints, as all sequences began by moving the right lower limb.

2.5. Calculating measures of similarity (generation of dependent variables)

A Multidimensional Cross-Recurrence Quantification Analysis (MdCRQA; Wallot, 2018) was used to calculate a similarity measure to compare confederate and participant trajectories. Using the MdCRQA approach, participant performance was quantified by pairing the participant's motion data from each trial with the confederate's motion data from the same trial, except for the 21st trial when the confederate did not perform the sequence. In this instance, the participant's motion data from trial 21 was paired with the confederate's motion data from trial 20.

The confederate's performance was quantified for use as a baseline reference measure by pairing slow-tempo (70 bpm) trials (i.e., trials 1–10) with consecutive trials of the same tempo and by pairing the final slow-tempo trial with itself. This process was then repeated for fast-tempo (80 bpm) trials (i.e., trials 11–20).

MdCRQA generates a recurrence matrix that represents the repetition of patterns in two multivariate time-series datasets. This analysis detects whether similar patterns were repeated in both datasets and records the temporal recurrence of these patterns. The recurrence matrix generated from the MdCRQA is a two-dimensional recurrence plot of binary elements, where each time-series is represented by each of the dimensions. Values of one represent recurrence, and values of zero represent the absence of recurrence. Thus, the higher the proportion of ones in the recurrence matrix, the higher the recurrence between the datasets (i.e., multivariate movement trajectories). The ratio of the number of ones to the total number of elements in the recurrence matrix is called the *recurrence rate*. If the recurrence rate is kept constant, a high concentration of ones around the counter-diagonal (i.e., the line of incidence) signifies a high level of temporal recurrence between the time-series, as shown in Fig. 2a. In other words, the values along the line of incidence index the degree to which the two time-series recur or repeat the same pattern at the same time (i.e., occur synchronously). Recurrences occurring away from the line of incidence indicate the same pattern occurring at a temporal offset or lag, and the magnitude of that lag is proportional to the distance away from the line of incidence. A low level of recurrence between the time-series is shown in Fig. 2b, in which there is a low concentration of ones around the counter-diagonal and a greater concentration of zeros. In the present study, MdCRQA was performed by first normalising the datasets (motion trajectories explained in Section 2.4) by using the respective z-scores, while the radius for calculating the recurrence was normalised by using maximum distance between the two datasets. The recurrence matrix was then calculated for each trial by varying the normalised radius to get a recurrence rate of 2% (Wallot & Leonardi, 2018). The resulting recurrence matrices were upscaled to 1000×1000 using the resize function from OpenCV, which interpolates the elements of the matrices to control for variation in time-series length between datasets (Bradski, 2000).

The recurrence matrix can further be used to create a diagonal cross-recurrence profile (DCRP), in which all elements of the recurrence matrix within a given window along the line of incidence are summed together and normalised with the total number of elements in the window while sliding the window along the leading diagonal of the recurrence matrix (Wallot, 2018). A window size of 25 was used with the resized recurrence matrix to calculate DCRP. The values for the height and location of the peak of the DCRP can be used to quantify the degree of recurrent structure (i.e., similarity of movement patterns) and lag between the time-series. Accordingly, normalised DCRP peak height and location values served as the two outcome variables representing quality of performance for our quantitative analyses. In other words, when using the confederate's performance as the baseline reference measure, the normalised *DCRP peak height* represents the degree to which participants produced the *correct movement sequence*, and *DCRP peak location* represents the *temporal lag*, or the degree of synchrony, with which participants performed the sequence.
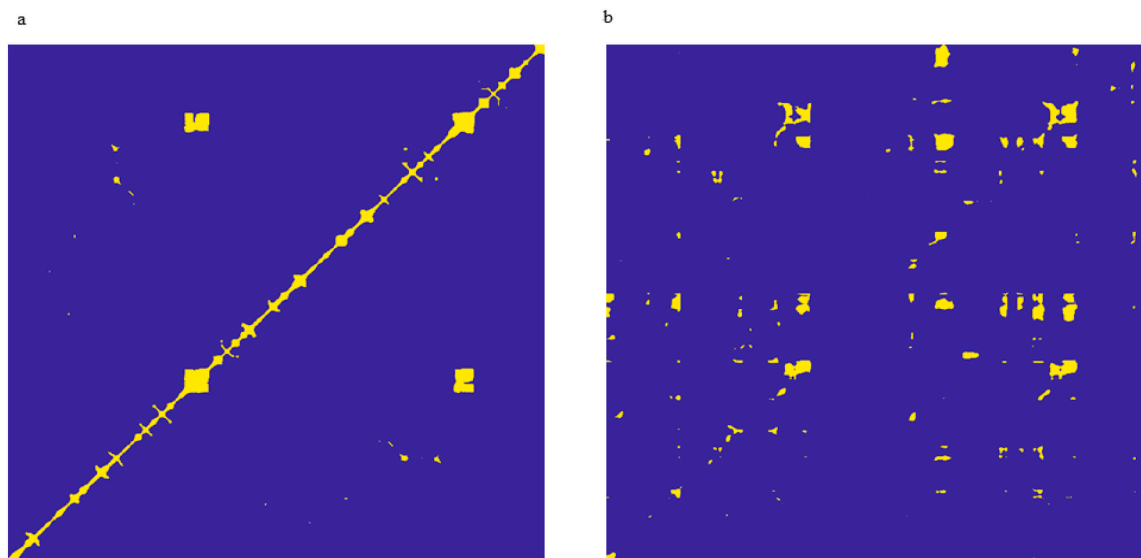

Fig. 2. a) high temporal recurrence; b) low temporal recurrence. The higher density of points along the line of incidence in Fig. 2a would be reflected by a higher peak value in the DCRP, indicating a higher degree of accuracy in movement sequencing.

2.6. Statistical analyses

Analyses were conducted using IBM SPSS Statistics version 25. As the motion capture program failed to accurately record movement output on some trials, data generated by the MdCRQA were examined for missing values. These observations were assumed to be missing at random because they were attributable to recording failure rather than participants' performance on the movement task. Little's missing completely at random (MCAR) test was conducted to confirm this assumption (Little, 1988). Correct movement

sequencing and timing[1] as measured by DCRP peak height and time lag (i.e., peak location), respectively, served as the dependent variables for the following analyses.

First, we conducted a series of linear mixed models to assess within-subjects changes in performance from trial 1 to trial 21, using trial 1 as the baseline reference group. Because we were interested in the longitudinal effect of trial on performance outcomes within each condition and a singular model could not be specified, two models for each condition (i.e., synchronous and non-synchronous) were generated to assess the two dependent variables of interest (i.e., peak height and time lag). This model allows for random subject-specific effects, fixed effects, non-constant variability, and varied correlational patterns and was chosen over a repeated-measures ANOVA as it accounts for missing values by estimating missing observations from the recorded observations at each timepoint, which increases power while reducing bias (Schober & Vetter, 2018). We used a scaled identity covariance structure to allow for an assessment of a random intercept in the model, as participants exhibited varying performance ability at baseline. Following the recommendations of Maric, Haan, Hogendoorn, Wolters, and Huizenga (2015), trial was treated as categorical and entered into the model as a repeated measure and fixed effect. 95% confidence intervals (*CI*) are reported as a measure of effect size for parameter estimates (Cumming, 2014). As we wanted to assess whether there was an effect of trial on performance between specific timepoints, pairwise comparisons with Bonferroni corrections were specified within the mixed model. Specifically, we were interested in comparing performance between trials 10 and 11, when the tempo was changed, and between trials 20 and 21, when the participant was required to perform the movement sequence without the assistance of the confederate[2].

Next, we conducted a series of independent samples *t*-tests to assess differences in end-state performance (i.e., trial 21) between synchronous and non-synchronous conditions. We also assessed whether the change in performance from trial 20 (i.e., with the confederate) to trial 21 (i.e., without the confederate) differed between synchronous and non-synchronous conditions. Cohen's *d* is reported as a measure of effect size, with 0.20, 0.50, and 0.80 representing small, medium, and large effects, respectively (Cohen, 1988).

Finally, we conducted a series of multiple regression analyses to assess whether condition and average performance across the first 20 trials predicted end-state performance for both peak height and lag. Multiple R-squared (R^2) is reported as a measure of effect size, representing the percentage of variance in the dependent variables that can be explained by the predictors in each model.

3. Results

3.1. MdCRQA

Fig. 3 displays recurrence plots highlighting examples of good versus poor performance. The recurrence plots for the confederate's trials exhibit consistently high concentrations of recurrence around the line of incidence. In cases of good participant performance, the recurrence matrix does not initially exhibit any pattern along the line of incidence, signifying lower performance in the initial trials. However, a clearer pattern emerges as the trials progress, with plots displaying a higher concentration of recurrence around the line of incidence for later trials. In cases of poor participant performance, no pattern emerges along the line of incidence throughout the trials, suggesting little improvement in performance. Additional DCRP peak height versus time lag plots are presented in Fig. 3 and demonstrate changes in performance for good versus poor performers. For confederate baseline performance, recurrence values remain consistently high while the time lag of the peak is zero. In comparison, recurrence values for good performers increase across the trials and the time lag settles at zero, whereas recurrence values for poor performers remain low across the trials and demonstrate inconsistent time lag.

3.2. Longitudinal effects of performance over time

Results of missing value analyses using Little's test were not statistically significant for synchronous (peak height: $X^2_{(182)} = 166.13$, $p = 0.794$; lag: $X^2_{(182)} = 132.38$, $p = 0.998$) or non-synchronous conditions (peak height: $X^2_{(208)} = 195.03$, $p = 0.731$; lag: $X^2_{(208)} = 181.49$, $p = 0.908$), suggesting that our data were missing at random and appropriate for assessment using linear mixed models.

For the synchronous condition, the overall fixed effects model assessing changes in peak height across trials was statistically significant ($F_{(20, 412)} = 18.43.68$, $p < 0.001$). An examination of the fixed effects demonstrated a similar level of performance across the first 20 trials performed with confederate, indicating that participants reproduced the movement sequence with a consistent degree of accuracy throughout the training trials. However, participants exhibited poorer movement accuracy for trial 21 ($M = 0.08$, $SE = 0.01$) compared to their trial 1 baseline performance ($M = 0.13$, $SE = 0.01$; $b = -0.05$, $SE = 0.01$, $t_{(412)} = -7.32$, $p < 0.001$, *95% CI*: -0.08, -0.04), suggesting that participants' ability to reproduce the movement sequence across trials did not improve, but instead became worse when no longer imitating the confederate. These results are represented in Fig. 4a. The random intercept was statistically significant ($Z = 3.27$, $p = 0.001$), suggesting substantial variation in movement sequencing accuracy among participants. Conversely, the overall model assessing changes in lag across trials was not statistically significant ($F_{(20, 413)} = 1.38$, $p = 0.129$). This is illustrated in

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[1] In the following sections, timing refers, generally, to the correct movement being produced at the correct time. Specifically, timing is synonymous with synchrony in the synchronous condition, whereas timing in the nonsynchronous condition captures how accurately participants matched the timing demonstrated by the confederate during observation. Timing, here, is used in favour of the term synchrony to delineate between our use of synchrony as an observational training condition and synchrony as an outcome variable.

[2] Model equation: $y_{ij} = b_0 + b_1 * u_i + b_2 * \delta_j + \varepsilon_{ij}$ in which u represents the random factor *participant* and δ represents the fixed factor *trial*
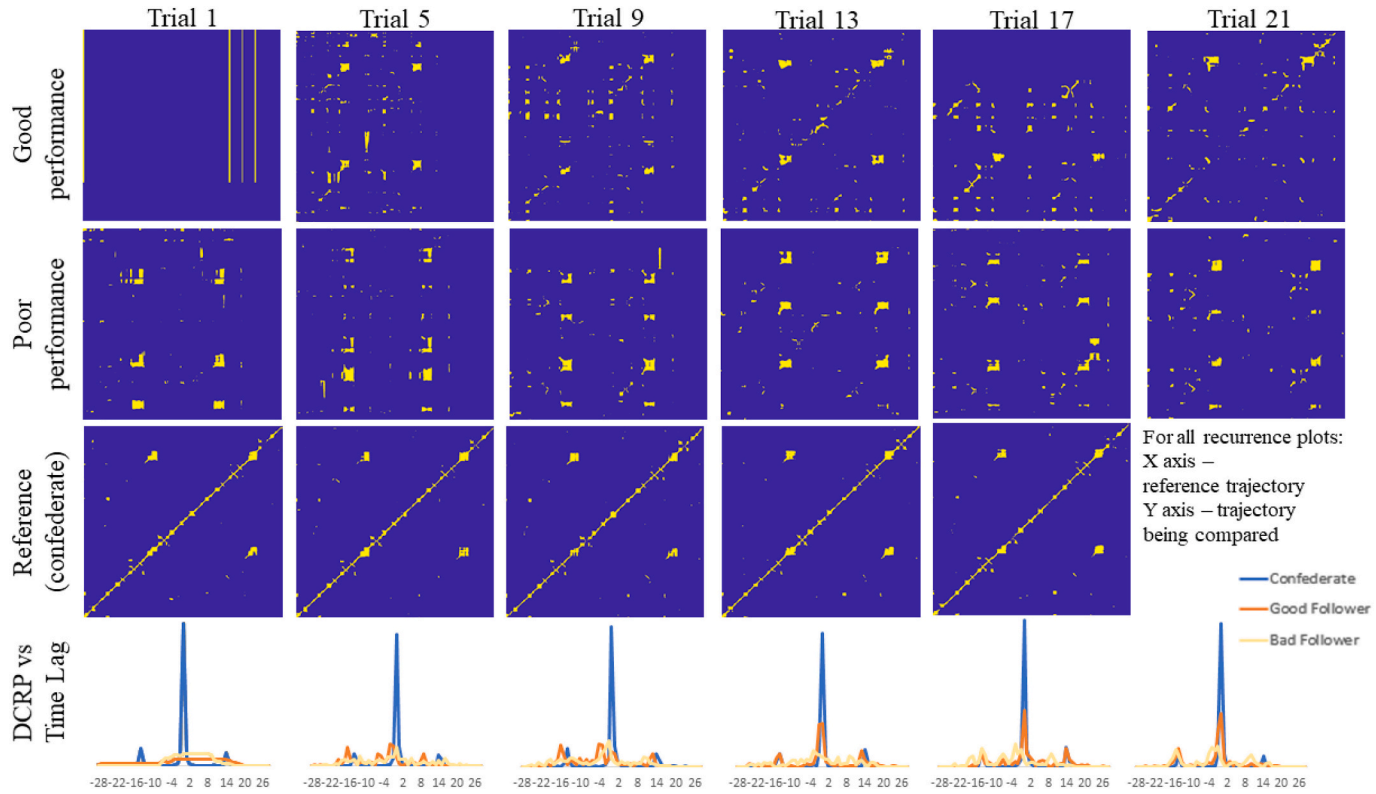
Fig. 3. Good versus poor performance over 21 trials with reference to confederate baseline performance.
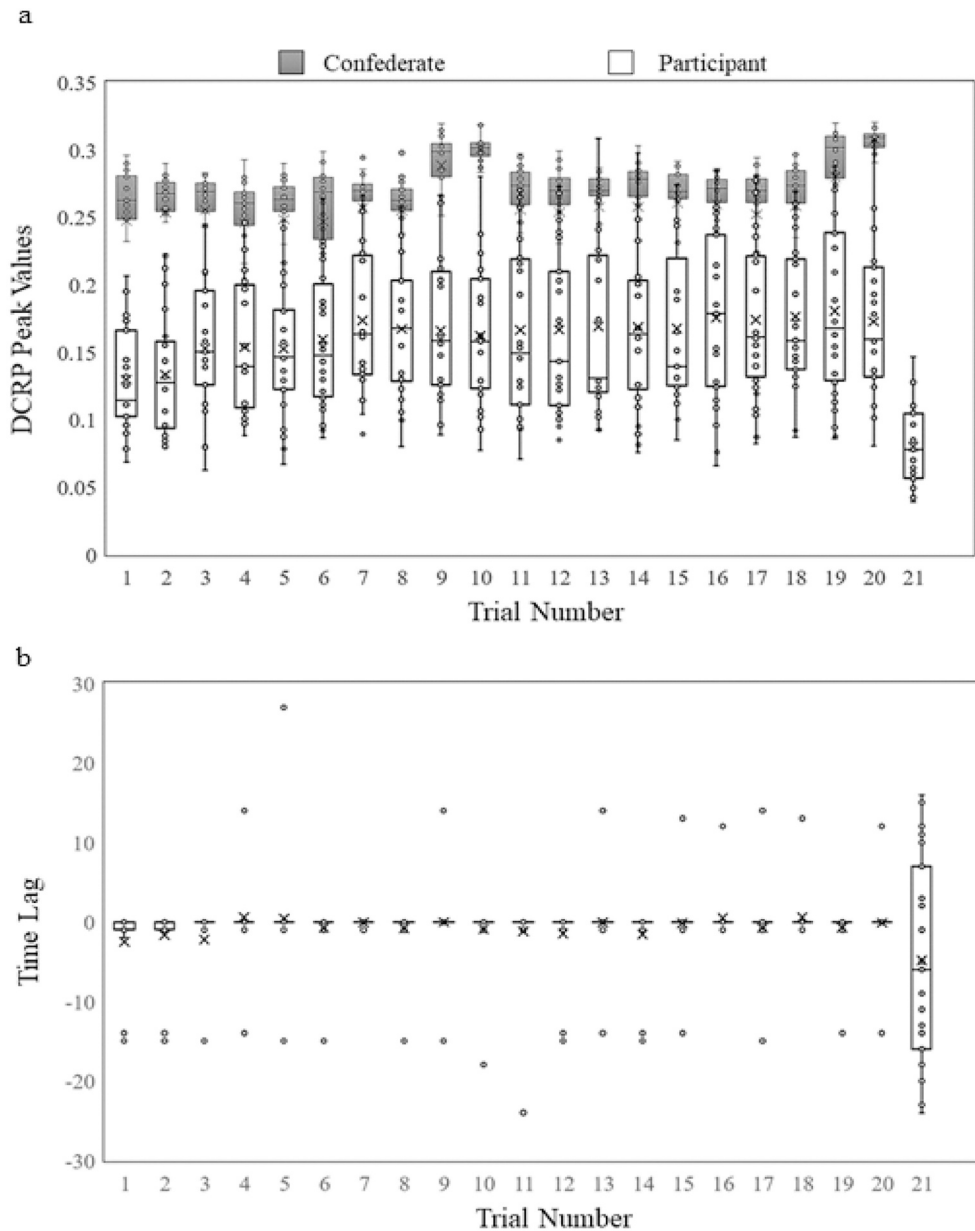
a

b

Fig. 4. a) synchronous condition peak height with reference to baseline confederate performance; b) synchronous condition lag.

Fig. 4b and indicates that participant timing did not significantly differ across any of the trials.

For the non-synchronous condition, the overall fixed effects model assessing changes in peak height across trials was not statistically significant ($F_{(20, 376)} = 0.83$, $p = 0.676$). An examination of the fixed effects demonstrated a somewhat increasing but inconsistent pattern in the accuracy of movement sequencing across all 21 trials, as represented in Fig. 5a. However, trial 21 ($M = 0.10$, $SE = 0.01$) was not significantly different to baseline trial 1 ($M = 0.12$, $SE = 0.01$; $b = -0.02$, $SE = 0.02$, $t_{(376)} = -1.05$, $p = 0.294$, *95% CI:* $-0.05, 0.02$), suggesting that participants' ability to correctly reproduce the movement sequence did not significantly improve across trials. The random intercept for this model was not statistically significant ($Z = 1.87$, $p = 0.061$), suggesting that participant variability was not influential in this condition. The overall model assessing changes in lag across trials was not statistically significant ($F_{(20, 375)} = 1.33$, $p = 0.157$), suggesting participants' timing did not improve across trials, as represented in Fig. 5b.

Pairwise comparisons further demonstrated that for the synchronous condition, peak height at trial 21 was significantly lower than peak height at trial 20 ($\Delta M = -0.10$, $SE = 0.01$, $p < 0.001$), but for the non-synchronous condition, peak height at trial 21 was not significantly different from peak height at trial 20 ($\Delta M < 0.01$, $SE = 0.02$, $p = 1.000$). These results suggest that synchronous participants performed worse on the final trial, whereas non-synchronous participants exhibited a similar degree of movement sequencing accuracy on the final non-imitative performance trial compared to the previous learning trial. Furthermore, there was no effect of
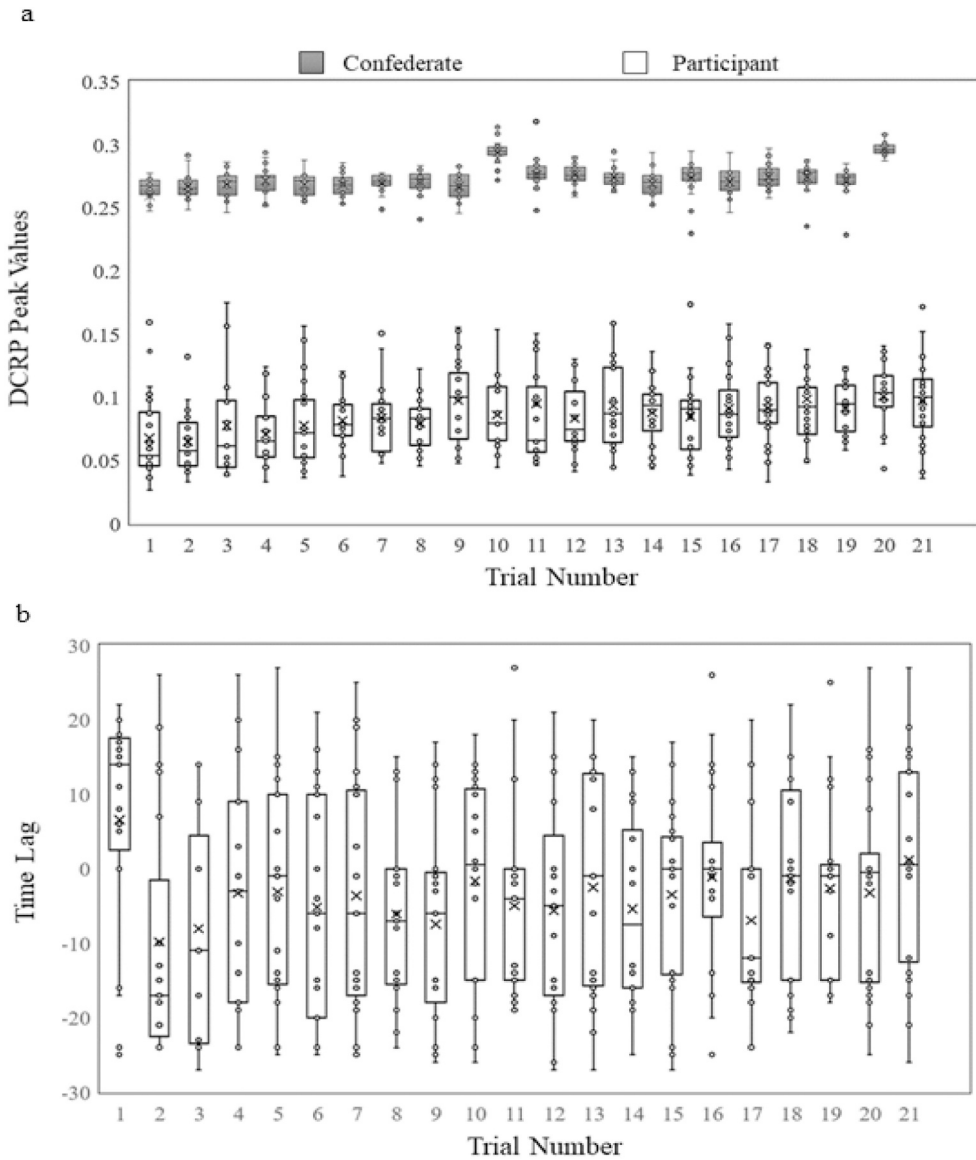
a

b

Fig. 5. a) non-synchronous condition peak height with reference to baseline confederate performance; b) non-synchronous condition lag.

tempo change on peak height, as there were no significant differences between trials 10 and 11 for the synchronous condition ($\Delta M < 0.01$, $SE = 0.01$, $p = 1.000$) nor for the non-synchronous condition ($\Delta M = -0.01$, $SE = 0.02$; $p = 1.000$), suggesting that tempo change did not have an influential effect on participants' movement sequencing accuracy. As there was no substantial effect of trial on time lag for either condition, we did not investigate any further pairwise comparisons associated with these models.

3.3. Group differences in end-state performance

Results of the independent samples t-tests did not demonstrate a significant difference between synchronous ($M = 0.08$, $SD = 0.03$) and non-synchronous conditions ($M = 0.10$, $SD = 0.04$) for end-state peak height ($t_{(39)} = -1.71$, $p = 0.095$, $d = 0.57$) nor for end-state lag (synchronous: $M = -4.86$, $SD = 13.14$; non-synchronous: $M = 1.20$, $SD = 14.76$; $t_{(39)} = -1.39$, $p = 0.173$, $d = 0.43$), although effect sizes were moderate. However, the change in peak height from trial 20 to trial 21 was significantly different between synchronous ($M = 0.10$, $SD = 0.05$) and non-synchronous conditions ($M = 0.01$, $SD = 0.04$; $t_{(34)} = 6.60$, $p < 0.001$, $d = 1.99$), such that synchronous participants exhibited a decrease in movement accuracy compared to non-synchronous participants. As Levene's test for equality of variances suggested variances were unequal for this analysis ($F = 4.43$, $p = 0.042$), degrees of freedom were adjusted accordingly. The change in lag from trial 20 to trial 21 was also significantly different between synchronous ($M = -4.70$, $SD = 12.58$) and non-synchronous conditions ($M = 4.45$, $SD = 14.15$; $t_{(38)} = -2.16$, $p = 0.037$, $d = 0.68$), such that synchronous participants also

exhibited a decrease in their ability to reproduce the correct sequence timing during the final trial compared to non-synchronous participants. These results indicate that although both synchronous and non-synchronous participants exhibited a similar degree of movement sequencing accuracy and timing on the final trial (see Fig. 6a, b), non-synchronous participant performance remained consistent during the transition from assisted, observational training to non-imitative performance, while synchronous participant performance did not (see Fig. 7a, b).

3.4. Associations between average performance and end-state performance

Results of multiple regression analyses indicated that for end-state peak height, the three-way interaction between condition, average peak height, and average lag was not statistically significant ($b = 0.05$, $SE = 0.09$, $t = 0.59$, $p = 0.562$) nor were the interactions between condition with average peak height ($b = 0.58$, $SE = 0.39$, $t = 1.48$, $p = 0.149$) and condition with average lag ($b < 0.01$, $SE = 0.01$, $t = -0.08$, $p = 0.767$). As such, all interactions were removed from the model resulting in a statistically significant overall model ($F_{(3, 37)} = 3.10$, $p = 0.038$, $R^2 = 0.20$) with condition ($b = 0.03$, $SE = 0.01$, $t = 2.01$, $p = 0.052$), average peak height ($b = 0.23$, $SE = 0.13$, $t = 1.82$, $p = 0.078$), and average lag ($b < -0.01$, $SE < 0.01$, $t = -1.81$, $p = 0.078$) predicting end-state peak height. These results suggest that both a greater degree of movement sequencing accuracy and a greater degree of synchrony across training trials are associated with a better ability to reproduce the correct movement sequence at end-state, when controlling for type of imitation. Additionally, non-synchronous participants exhibited better movement sequencing accuracy compared to synchronous participants, controlling for average performance across trials. However, while the individual predictors approached the nominated statistical significance ($a = 0.05$), they were not statistically significant.

For end-state lag, the three-way interaction between condition, average peak height, and average lag was not statistically significant ($b = 11.56$, $SE = 38.63$, $t = 0.30$, $p = 0.767$) nor were the interactions between condition with average peak height ($b = 219.61$, $SE = 169.91$, $t = 1.29$, $p = 0.205$) and condition with average lag ($b = 3.07$, $SE = 2.46$, $t = -0.83$, $p = 0.414$). After interactions were
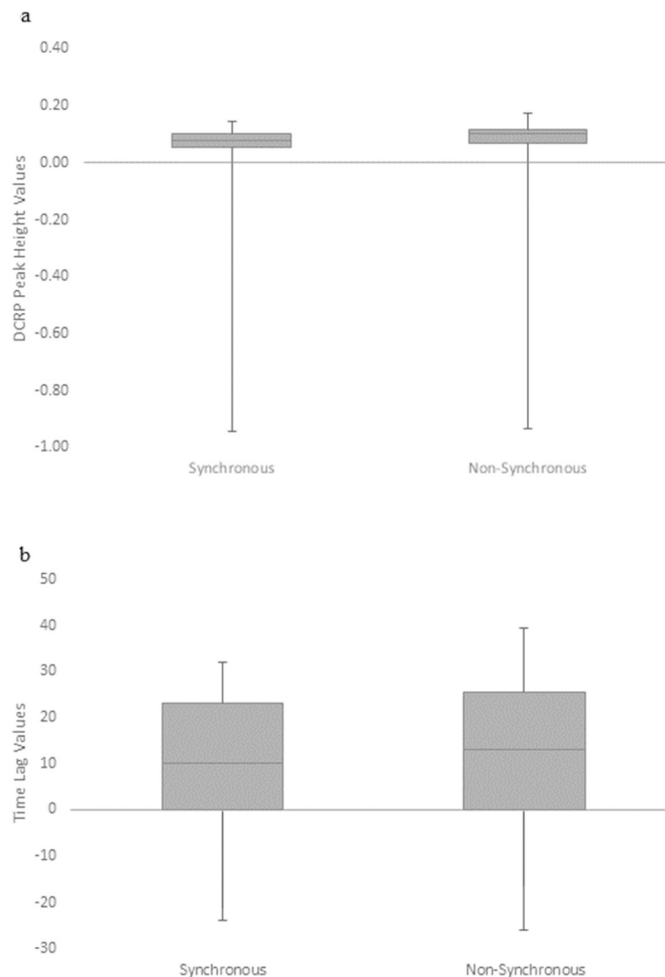

Fig. 6. a) between group differences in end-state peak height; b) between group differences in end-state lag.
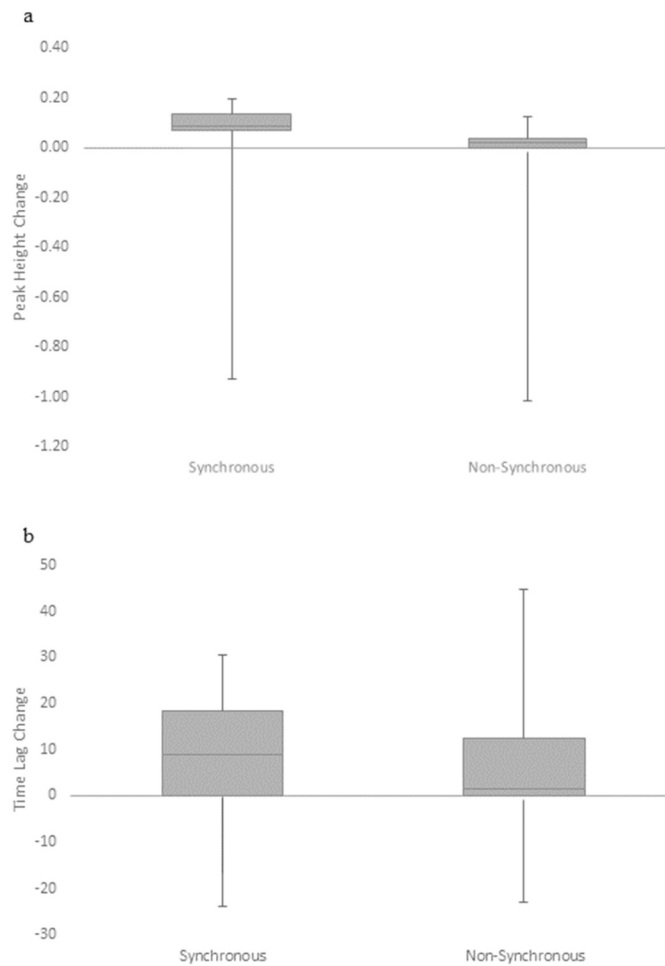
Fig. 7. a) between group differences in peak height change from trial 20 to 21; b) between group differences in lag change from trial 20 to trial 21.

removed from the model, the overall model remained statistically non-significant ($F = 1.73$, $p = 0.178$, $R^2 = 0.05$), suggesting that condition ($b = 8.03$, $SE = 6.42$, $t = 1.25$, $p = 0.219$), average peak height ($b = -14.49$, $SE = 57.35$, $t = -0.25$, $p = 0.802$), and average lag ($b = 0.93$, $SE = 0.52$, $t = 1.78$, $p = 0.083$) did not predict lag at end-state. In other words, the degree of synchrony or correct timing exhibited at end-state was not influenced by type of imitation nor average performance across training trials.

4. Discussion

Previous research has shown that both synchronous and non-synchronous observational learning can enhance motor skill acquisition (Faelli et al., 2019; Gardner et al., 2017; Kirsch et al., 2018; Williams, 1989a). We aimed to elucidate whether these observational training approaches can differentially influence the learning rate and post-learning proficiency of performing a novel movement sequence by asking novice dancers to reproduce a dance movement sequence. We found that end-state performance did not significantly differ between individuals who synchronised with an expert demonstrator (synchronous imitation condition) and those who first observed and then imitated the expert's movements (non-synchronous imitation condition). However, the change in performance from the last learning trial to the final solo performance trial was more pronounced between groups, such that, contrary to our hypotheses, synchronous learners exhibited poorer performance when no longer assisted by the expert (i.e., non-imitative) compared to non-synchronous learners, who exhibited similar imitative and non-imitative performance. We also found that, consistent with our hypotheses, better imitative performance across training trials led to better end-state, non-imitative performance ability, but only with respect to the accuracy, and not the timing, of movement reproduction. In other words, participants were better able to produce the correct movement sequence when they exhibited better performance across the imitative trials, but this did not impact participants' ability to perform these movements at the correct tempo.

Taken together, our results suggest that neither synchronous nor non-synchronous learners exhibited evidence of learning at end-state. We found that participant end-state performance was equally poor for both synchronous and non-synchronous approaches when compared to the expert's performance. As might be expected from novice dancers, participant end-state performance did not reach the

same level of quality as the expert for either synchronous or non-synchronous training conditions. This was highlighted in the DCRP vs time lag plots in Fig. 3, but moreover, paired *t*-tests demonstrated no differences in end-state performance when comparing the two learning approaches. Additionally, our assessment of the longitudinal effects of practice across training trials demonstrated that non-synchronous imitation led to similar performance across trials and during the final trial, whereas synchronous imitation exhibited a negative effect, such that participants performed worse during the final trial when no longer assisted by the expert. These effects were confirmed by paired t-tests with a large effect size (i.e., $d > 1$), which demonstrated a significant difference between learning approaches when comparing the change in performance from the last learning trial to the final solo trial. As shown in Figs. 4 and 5, participants in the synchronous training condition performed the movement sequence more similarly to the expert during training trials with respect to both accuracy and synchrony, but this was not sustained during end-state performance. In comparison, non-synchronous participants exhibited consistently poor performance throughout training trials and at end-state.

Although synchronous imitation did not lead to better end-state performance outcomes when compared to non-synchronous imitation, participants in the synchronous condition did exhibit a higher degree of accuracy and synchrony with the expert during training trials than did participants in the non-synchronous condition. Given participants' poor end-state performance, this finding can be better understood when we consider the roles of task-intrinsic and augmented feedback in motor skill learning. Task-intrinsic feedback refers to the internal sensory information received through visual, auditory, haptic, and proprioceptive modalities, whereas augmented feedback is information typically received via an external source, such as verbal correction or encouragement from a teacher or coach (Anderson, Magill, Mayo, & Steel, 2019). Indeed, successful observational learning requires a change from unstable to stable coordination patterns through an appropriate training context and reliance on memory (Schöner & Kelso, 1988). Research has shown that consistent augmented feedback (i.e., *guidance effect*) may be detrimental to the learning process (Ronsse et al., 2011; Salmoni, Schmidt, & Walter, 1984). Namely, when visual information is highly available, visuo-spatial, but not motor representations of the desired action are formed (Buchanan & Wang, 2012). Our results suggest that reliance on visual input and intrinsic feedback alone may also result in this same detrimental outcome, consistent with the idea that individually tailored and varied augmented feedback is necessary to ensure optimal skill acquisition (Anderson et al., 2019). That is, to encourage functional perception-action coupling when acquiring a motor skill, practice tasks should facilitate varied movement behaviours that are oriented toward specific goals but which are tailored to an individual's action competencies (Araújo, Davids, & Passos, 2007; Davids, Araujo, Vilar, Renshaw, & Pinder, 2013; Pinder, Davids, Renshaw, & Araújo, 2011).

In the present study augmented feedback was not provided, and thus, participants were forced to rely on intrinsic feedback alone. Although synchronous participants were able to perform the movement sequence with the expert, they could not reproduce the sequence at end-state, while non-synchronous participants performed poorly across all trials. This suggests that synchronous, but not non-synchronous participants were able to develop a visuo-spatial representation of the movement sequence. However, synchronous participants may have become overly reliant on the visual and proprioceptive feedback provided by matching the expert's movements across trials. Consistent with previous work (Buchanan & Wang, 2012; Kovacs, Buchanan, & Shea, 2009, 2010), this reliance can allow for more rapid and stable performance of a motor skill, but only when visual information remains available, and may come at the expense learning if task constraints do not allow for motor representations of the desired behaviour.

This finding is further consistent with previous research on synchronous imitation during coordinated improvisation tasks (Chauvigné et al., 2018; Gueugnon et al., 2016; Issartel et al., 2006; Issartel et al., 2017; Noy et al., 2011; Schmidt et al., 2011; Washburn et al., 2014). This previous research suggested that a higher degree of synchrony during the improvisation of complex perceptual-motor sequences was associated with an improved ability to both synchronise and produce more complex movements at end-state (e.g., Gueugnon et al., 2016). However, these previous studies did not include an explicit measure of learning. That is, participants were never asked to commit the movement sequences to memory nor were they asked to reproduce them without assistance. Although some learned replication of motor sequences is suggested by previous fMRI studies (Gardner et al., 2017; Kirsch et al., 2018), these neurological studies assessed performance across multiple training days and employed training sessions of 54–64 trials, whereas the present study employed only one training session of 20 trials. Taken together with this previous research, our findings suggest that acute synchronous imitation may allow for a higher degree of imitative performance, but this does not necessarily transfer to non-imitative/solo performance consistent with the idea of learning.

Finally, regression results suggested that a higher degree of accuracy (i.e., peak height) and a lower degree of synchrony (i.e., lag) with the expert across training trials predicted higher end-state accuracy, but that there was no effect on participants' ability to maintain proper timing at end-state. Results also showed no effect of tempo (70 vs 80 bpm) on performance outcomes, further suggesting that timing had little to no influence on sequence learning, although these results are not surprising as this tempo change was minimal. Consistent with research by Weeks et al. (1996), the association between a lower degree of synchrony and better end-state movement replication may reflect participants' increased efforts in committing the sequence to memory by reducing task complexity (i.e., removing the task demand of synchronising). This may also explain why participants in the non-synchronous condition exhibited better end-state movement accuracy than participants in the synchronous condition when controlling for both accuracy and lag over training trials. Taken together, regression results suggest that the ability to accurately replicate movement impacts performance while an ability to synchronise or perform within a certain timeframe does not. However, the overall regression model was statistically significant while the individual predictors were not, and thus, these results require replication and should be interpreted with caution.

Given the somewhat increasing (but statistically non-significant) pattern in performance accuracy for the non-synchronous group as highlighted in Fig. 5a, further investigation regarding the effect of a non-synchronous imitation approach is also required. Given the pattern of results in Fig. 3 for good versus poor performers, it may be necessary to assess performance between sub-groups of participants based on underlying performance ability (i.e., aptitude, previous training, greater capacity for movement tasks) within a larger sample. Comparative studies are also required to clarify the role of expertise among synchronous and non-synchronous training

approaches, as previous research suggests that visuo-motor familiarity with specific types of movement is associated with better performance of novel movements of the same kind (Cross et al., 2009; Diersch et al., 2013; Gardner et al., 2017; Schmidt & Lee, 2005). Although we asked participants to report on their previous movement experience, we did not include a comparison of novice versus expert dancers as an independent variable in our analyses, as the majority of participants reported little to no previous dance training. Despite a lack of statistical significance between synchronous and non-synchronous groups, the pattern of results for non-synchronous learners suggests that they might exhibit greater movement accuracy over time than synchronous learners. Consistent with previous work (e.g., Buchanan et al., 2015; Gardner et al., 2017; Kirsch et al., 2018), however, a greater number of training trials across multiple training days may be required to better elucidate the roles of synchronous versus non-synchronous imitation in observational training contexts.

4.1. Limitations and conclusion

Results of this study should be interpreted with respect to the following limitations. First, we did not include a non-imitative comparison group. Although this study is unique in its comparisons of synchronous and non-synchronous imitation, future research should include an observational practice only control group (i.e., with no concurrent or later physical performance) to better integrate these new findings with recent observational learning studies that use control groups (e.g., Buchanan & Park, 2017; Faelli et al., 2019; Gardner et al., 2017; Kirsch et al., 2018). Second, as we aimed to assess the unique influence of synchronous and non-synchronous imitation approaches on end-state non-imitative performance, the expert did not use verbal cues during training trials. However, dancers, athletes, and most other learners typically experience verbal instruction and feedback in addition to the physical and visual components of observational practice (Cross, 2012; Faelli et al., 2019; Magill & Schoenfelder-Zohdi, 1996; Sani & Khan, 2017). Further, the availability of speech during observational learning may offer additional benefits to learning and task success than visual observation alone, as evidenced by the beneficial impact of verbal instruction during manual or bimanual tasks (Buchanan, 2019; Pagnotta, Laland, & Coco, 2020). Thus, future studies may seek to extend these previous findings by comparing the learning of full-body movement sequences undertaken with and without verbal instruction and/or feedback, which would also allow for the provision of augmented feedback. Third, eye-tracking measures were not included in this study. Given our assertion that synchronous participants came to rely on intrinsic visual feedback to produce accurate movement during imitation trials, future research may benefit from a dedicated assessment of visual attention during observational learning. Finally, we found moderate effect sizes for non-significant *t*-tests. Thus, future studies might seek to replicate our results in a larger sample that is appropriately and specifically powered to detect small to moderate effect sizes.

Despite these limitations, our findings offer novel contributions to the existing body of observational learning research. The current study is the first to compare synchronous and non-synchronous imitative approaches to observational learning of a full-body, complex motor-movement sequence. As such, this task demanded a high reliance on executive function (e.g., attention, memory) in addition to full-body motor movement that included challenges such as integrating opposing upper and lower limbs, which may be more representative of the observational learning approaches employed in the training of athletes, dancers, and gymnasts (Cross, 2012; Faelli et al., 2019; Magill & Schoenfelder-Zohdi, 1996; Sani & Khan, 2017). Additionally, the novel use of the MdCRQA approach allowed for a unique assessment of the temporal and spatial characteristics of the movement sequence as a detailed description of the co-evolution of two time-series (Marwan, Carmen Romano, Thiel, & Kurths, 2007; Webber & Zbilut, 2005). Furthermore, using MdCRQA across all trials allowed us to visualize the progression of temporal and spatial performance as participants performed more trials. Thus, the form of MdCRQA detailed here could provide a generalized method of assessing the sequential structure and synchrony of complex motor sequences. Finally, although we found that performance at end-state did not differ between synchronous and non-synchronous learners, the change from imitative to non-imitative performance was substantially poorer for synchronous learners, while performance for non-synchronous learners remained consistently poor across trials. Thus, the main finding of this study suggests that, like the guidance effect (i.e., consistent augmented feedback), consistent intrinsic feedback in the absence of variable augmented feedback is detrimental to learning. That is, learners cannot develop motor representations of the target sequence if they come to rely on a real-time mapping process between visual input from a model and their own visual and proprioceptive feedback. Although a dynamical systems approach suggests that spontaneous or intentional synchrony can enhance interpersonal coordination, the act of synchronising alone does not appear to ensure an appropriate training context for advanced sequence learning.

Declarations of interest

The authors have no conflicts of interest to disclose.

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All authors have contributed to and have approved the final manuscript.

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