Motor Sequencing Learning from Dance Step: A whole-body version of the Discrete Sequence Production Task

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Abstract

A major challenge in motor neuroscience is to understand the dynamics of motor learning and sequence acquisition in naturalistic settings beyond keyboard pressing tasks. A great deal of theory has been derived from established paradigms like the Discrete Sequence Production (DSP) task, yet it is largely unknown if applications beyond keyboard responses are feasible. In addition, further understanding of whole-body motor learning tasks would unravel other dimensions of motor coordination dynamics that contribute to learning. This leads to richer understanding of preparation, decision making, movement execution and optimisation processes when learning motor sequences. The current protocol describes how to conduct a modified DSP task by dance-stepping, allowing the study of whole-body dynamics. Firstly, we provide the necessary program in an E-Prime® script for replication and the DSP task is presented in a go/no-go method to further elucidate motor-specific execution. We explain a basic variant of the experiment with minimal and commercially available hardware, then scale the research possibilities and outline the integration of the Xsens motion capture systems for measuring kinematic variables like centre of mass displacement/ velocity changes. The additional measures allow researchers to investigate relationships between response times and movement kinematics for insight to learning processes. We showcase representative results to highlight possible ways data could be modelled. Finally, we cover the future opportunities and limitations of using such an approach. The goal is to make the experiment accessible for others to conduct that is supported by a publicly available video of the experimental procedure.

1. Introduction

The Discrete Sequence Production (DSP) task (Verwey, 1999, 2001) is a motor sequence learning research paradigm with well-established theoretical frameworks explaining the development of sequential learning behaviour (Abrahamse et al., 2013; Verwey et al., 2015). The DSP task is typically performed on a computer where learners use a keyboard to practice two short key pressing sequences of between 3–7 stimuli (scalable) separated with a clear break (Verwey et al., 2019). A series of placeholders (in the form of small squares) are displayed on a monitor, and each of the placeholders corresponds to one of the keys of the keyboard in a spatially compatible manner (see Abrahamse, Ruitenberg, de Kleine, & Verwey, 2013). When a placeholder lights up, learners rapidly press the compatible response key, and the next stimulus is displayed with virtually no time lag from the previous response. The keyboard DSP task has three distinctive features, firstly it starts typically with an extended practice phase of about 500 repetitions per sequence. With extensive practice leading to an over-learning situation, the DSP task becomes a two-choice reaction time task due a stable sequence representation, performed with automaticity. Each response consists of a familiar keying sequence that can be considered a building block of more complex motor movements (Arnold et al., 2017; Verwey et al., 2019). The second distinct feature of the DSP task is that sequences are usually counterbalanced for response sequence positions by performing a shift of keys for individual participants. Specific sequential positioning effects due to specific fingers can therefore be ruled out, as each finger contributes equally to the response times (RT) (Abrahamse et al., 2013). Counterbalancing also ensures that same sequences can be familiar and unfamiliar not because of control-order but due to underlying cognitive control processes. A third important feature is that the sequences remain discrete, i.e., limited to up to 7 key presses. This allows participants to prepare part of the sequence and, therewith, allow them to develop integrated sequence representations (Verwey et al., 2015).

Although key-press tasks are easy to conduct and the brief time to press individual keys give a good insight in the underlying sequence control processes, a broader ongoing challenge in motor sequence learning research is the strive for experimental paradigms to be more naturalistic and ecological like everyday whole-body movement activities. In daily activities and sports, multiple body parts are coordinated to successfully perform task-related movements. Current day theoretical motor sequence learning frameworks (Abrahamse et al., 2010; Cleeremans & Jimenez, 1998; Clegg et al., 1998; Keele et al., 2003; Verwey et al., 2015; Willingham et al., 2000) have been derived almost exclusively from keyboard-based tasks. One limitation is that these frameworks still may not fully explain the entire spectrum of the motor learning phenomena that result in different motor execution patterns. Heuer (1993) outlined that the task constraints typically drive the motor optimisation process, which means that one cannot assume the same outcomes and phenomena when using different limb modalities to respond to a centralised sequence structure. In some instances, indeed movements learnt in one modality showed limited transfer to other limbs even though sequences remained the same

(Barnhoorn et al., 2016). Therefore, it is important to design experiments that account for multilimbed coordination in sequence learning and current theoretical frameworks provide a strong foundation of learning phenomena, but also allow for extension of new cognitive and motor discoveries.

As a step towards investigating multilimbed motor sequence learning, Du and Clark (2018) ported another keying paradigm called the Serial Reaction Timed (SRT) task (Nissen & Bullemer, 1987), into a foot-step version to investigate centre of mass (CoM) changes prior to movement, as an objective indicator for explicit knowledge of sequence. Olivier et al. (2021) reported on the feasibility of the SRT task foot-step design, to understand its utility across different populations, thus backing the trend of increased interest of naturalistic motor sequence learning tasks. The DSP task has the same potential as the SRT task for transfer towards a dance-step version. Our goal was to create a dance-step DSP task that would encompass the same properties at the basic level to measure behavioural performances, with the ability to scale up for different experimental goals. There are three main points that we consider as new developments from the usual key-press DSP task: 1) Disassociation of cognitive and motor processes; 2) increased scalability of DSP task experiments to understand individualised body kinematics; 3) applications to ageing.

The first point is that cognitive processes involved in movement planning for finger-press execution are often embedded in RT when stimuli are continuous with immediate responding because finger-presses do not involve moving to new locations due to their fixed locations. RT is typically a summation of reaction time and movement time (Du & Clark, 2018; Du et al., 2017), and it is important to detangle these two important elements. In the current manuscript, the DSP task segregates both processes by firstly showing participants the sequence stimuli, and then collecting motor responses in a separate phase akin to a go/no-go task previously implemented in keyboard versions (De Kleine & Van der Lubbe, 2011). In the Method and Materials section, we provide the E-Prime® script which executes this clear separation of preparation and execution phases and explain the experiment setup in detail.

The second point is that the experiment should remain simple enough to be executed with minimal equipment but with the option to scale up other related measurements. The minimal option requires just a modern computer and a commercially available dance-pad to perform the experiment. Scalability is important for future work and the current manuscript focuses on the integration with an advanced body motion capture system called the Xsens MTw Awinda and the MVN Analyze software (Xsens, 2021). The Xsens MTw Awinda is a leading wearable, wireless inertial measurement system (IMS) that allows for three-dimensional (3-D) analysis of human movements (Blair et al., 2018). The IMS system combines the use of multiple inertial sensors in the form of 3D-accelerometers, gyroscopes and magnetometers, that are attached to various bodily segments and provide accurate kinematical estimations. Once the sensors (up to 20 sensors in one full suit) are set up, they provide accurate 3D positioning and orientation of each segment (forearm, shank, centre of mass etc.). Combined with the attached MVN Analyze software, precise estimations of segment/ sensor displacement (x, y, z axes), velocity and angular acceleration can be acquired and extracted to add a richness to movement aspects of motor sequence learning built upon the knowledge from the key-press DSP (KP-DSP) task.

In addition to RT performance, modern motion capture allows for further investigations in time-space factors that affect motor sequencing and understand whether coordinated body movements differences between individuals can explain task constraints imposed in the DSP task (Heuer, 1993). In the KP-DSP task, sequence learning characteristics are intentionally derived from a very low number of finger joints and their relative degrees of freedom (DoF) to unveil underlying sequencing properties. Each finger is paired with a single keyboard-press to respond to stimuli in a spatially compatible manner. In what we coin here as the dance-step DSP (DS-DSP) task, an uneven number of limbs (effectors) pairing with response locations result in dynamically changing DoFs to optimise sequence execution. This kind of motor execution allows for development into methods to differentiate individual ways that learners are acquiring motor sequences. For example, different participants may use different limbs for the same stimuli and/or use other ways to optimise their responses (i.e. jumps/ rotations etc.), which cannot be elucidated from key-press tasks with designated finger responses. This brings about new opportunities to understand motor learning driven by limb kinematics that predict RT/accuracy relationships. Above, we highlighted that anticipatory processes of CoM could indicate sequence knowledge (Du & Clark, 2018), and here hypothesise that other kinematical properties like CoM velocity and acceleration may reveal a more holistic understanding of sequence learning in whole body movements. We consider the present approach a contribution towards an ongoing paradigm shift in quantifying individual differences in motor learning, alongside group-level aggregation reporting. Explicitly, the DS-DSP task is different from the KP-DSP task in that: 1) feet are used instead of individual fingers, 2) sequence elements involve aimed movements to a target location (instead of just moving a finger down), and 3) there is freedom in choosing effectors (feet) to step on a target location.

The third and final point is that naturalistic motor sequence learning tasks can make training more interactive in diverse populations like the elderly which may reap additional peripheral benefits like improved dynamic balance and control. For example, Granacher et al. (2012) showed that participation in 8-weeks of progressive salsa dancing programme enhanced both static and dynamic postural control in the elderly. In general, the efficacy in dance or dance-like programs are positive and suggest that participation in these kinds of activity can lead to better management of dynamic mobility, overall physical performance and balance improvements (Fernández-Argüelles et al., 2015; Rodrigues-Krause et al., 2019). It is therefore possible that the DS-DSP task in an applied sense, act as a dynamic mobility motor learning program (with progressive training) that may lead to improvement of balance control. Elderly populations may benefit from this kind of motor learning, leading to a reduction in the risk of falls. Improvement of overall health and wellbeing for the elderly is an important global topic and the DS-DSP task may be a novel way to bridge fundamental science paradigms into modern and applied fields as part of health-based interventional programs for the elderly.

2. Method and materials

2.1. Dance-step Discrete Sequence Production Task in E-Prime®

We used E-Prime® as our stimulus presentation software due to its consistency in collecting reliable behavioural data (RT and accuracy) and relative ease in programming. The full script was programmed in E-Prime® Version 2.0.10.356, (download .es2 file from The Open Science Framework: https://osf.io/zmxay/download) and also curated on Github (https://github.com/Eggcite/DS_DSP) for adaptation and replication (Appendix 2). The main difference between the key-press DSP (KP-DSP) and the dance-step DSP (DS-DSP) tasks is the stimulus layout from a horizontal row of boxes, to the dance mat design that spatially corresponds to four areas (↑, ↓, → and ←) with a centre neutral position (see Fig. 1A). We used a high-quality commercially available dance mat (Nonslip Dance Pad Version 5 from D-Force) (See Appendix 1 for full equipment list). Participants start the DS-DSP task standing with both feet on the centre area of the dance mat whilst stimuli are presented on a wide screen television. We used LG model nr. OLED77CX6LA with a diagonal size of 77 inches, 3840 × 2160 pixel resolution in HDR colour, with a screen refresh setting of 120 Hz that was positioned approximately 1.20 m from the participant on the dance mat. The viewing angle of the display was approximately 120° and the visual angle dimension of each box was 2°×2 with an overall viewing of the stimulus area approximately 30°. The TV screen and the dance mat were connected to a Windows laptop that executed the DS-DSP task script (see Fig. 2 for connectivity of all devices). The setup requires a freeware application called JoyToKey (https://joytokey.net/en/), which converts input from the responses to assigned keys for E-Prime® to register the dance mat. Thereafter, E-Prime® recognises the directional keys as input from a traditional keyboard. We mapped the ↑, ↓, → and ← as W, S, D, A respectively as input for responses.

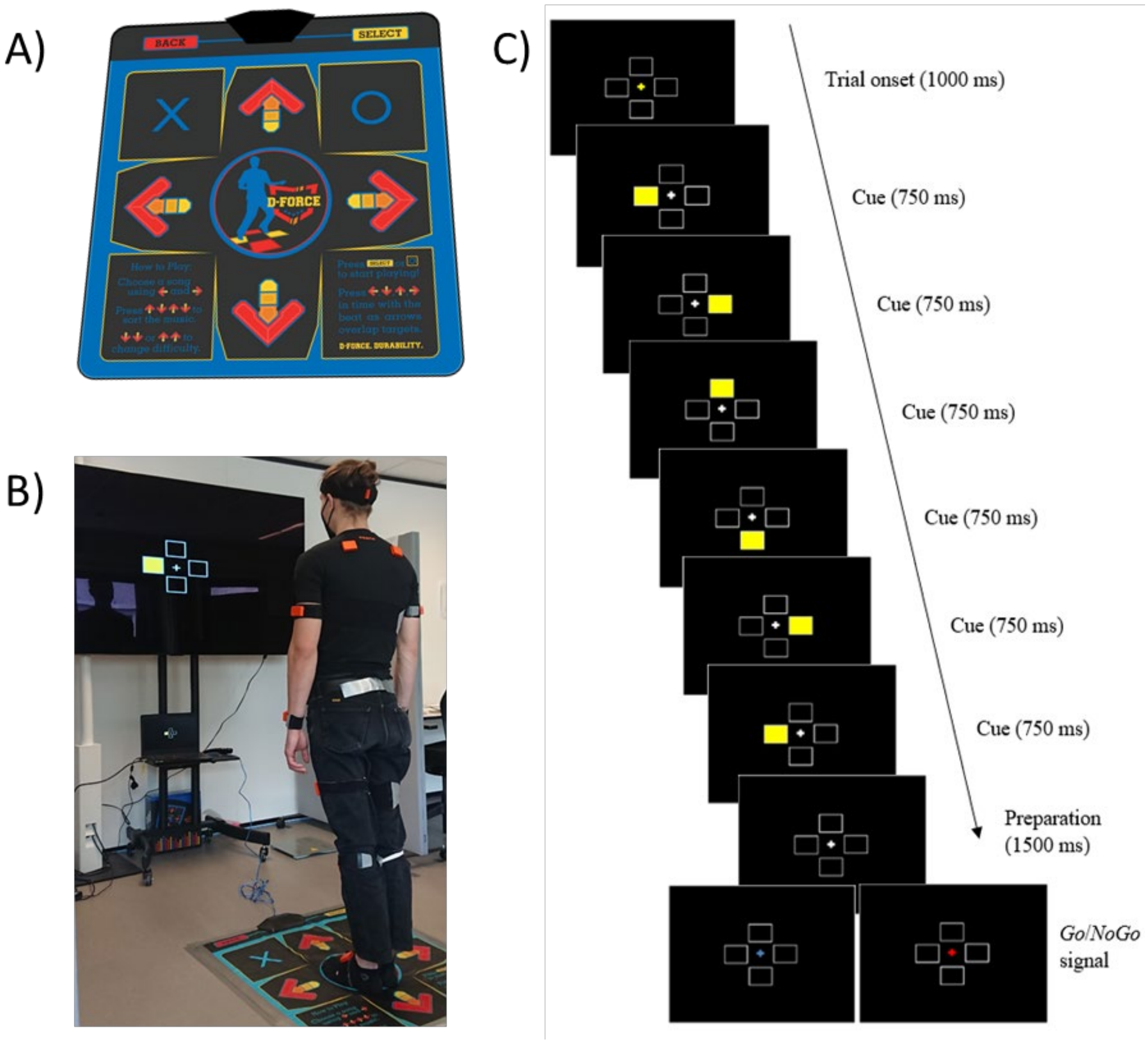


Fig. 1. Experimental set-up and stimuli. (A) An example of a commercially available dance mat. (B) During the dance step task participants stand with both feet in the centre of the dance mat that is 120 cm away with the overall viewing angle of the stimulus area of ~30°. After six stimuli have been presented, participants reproduce the sequence by stepping with one foot on the spatially corresponding areas on the dance mat. (C) An example of the Discrete Sequence Production task sequence that is presented from the onset of stimuli to the Go/NoGo signal. The duration of presentation is indicated for each phase.

Each trial consists of six stimuli (can be reduced/ increased) that are presented by the successive lighting up of the rectangular placeholders on the screen. As shown in Fig. 1 (C), first the default screen is presented with a cross in the middle lighting up in yellow for 1000 milliseconds (ms) upon which six rectangles take turns lighting up in yellow for 750 ms each (cf. De Kleine & Van der Lubbe, 2011). Next, participants see the default screen for another 1500 ms after which the cross in the middle lights up in either blue (Go) or red (NoGo). In the case of a Go stimulus, participants reproduce the sequence they just saw by taking six steps on spatially corresponding areas on the dance mat. In the case of a NoGo stimulus, the waiting time lasted three seconds until the next sequence was displayed. As outlined in De Kleine & Van der Lubbe (2011), the break during which participants wait for a signal makes it possible to separate sequence preparation and execution. The frequency of Go or NoGo stimuli was 92% and 8%, respectively. If the participant moved prior to the Go signal a "Too early!" message was displayed to halt the current trial, and then the next trial was shown. In the case of a mistake, feedback was presented which steps were wrong only after six steps were completed. When no mistakes were made, a 'good' word was displayed, and the next trial was shown.

In the provided script (see Appendix 2), participants would practise the following two sequences: ←→↑↓→← and →↑←↑→↓. The script has been commented for easy alteration to include more sequences and/or sequences with more stimuli and responses. To counterbalance target stimuli positioning, both sequences were rotated four times resulting in eight different counter-balanced sequences so that participants received the same sequences but with different positions. Possible variations in sequence difficulty or foot strength/preferences were not expected to effect participants' learning process. To give an example, the sequence ←→↑↓→← rotated once resulted in a different counter-balanced sequence ↑↓→←↓↑. Participants are given the liberty to organise their responses in the most naturalistic manner using any combination their two feet for correct execution.

The script is executed as a singular practice block which consists of 24 trials for each of the two sequences for a total of 48 trials with an additional 4 No-go trials. Halfway through each block (after completion of 24 trials) the script would execute a 30-second break before continuing to the second half. Both number of trials and break sessions/timing can be altered in the script. A completed block was indicated by a "This is the end of the session." message, followed by another feedback screen displaying the average response time and mistakes (%) for the block after completion. Between training blocks participants would be given a three-minute break, and after the fourth block, received a 10-minute break, in both cases controlled by the experimenter. Rest breaks are important to avoid physical and mental fatigue and participants were requested not to end breaks early. In one of our experiments (subject of a future manuscript) participants practiced over the course of eight training blocks yielding 192 practice trials per sequence. After this we conducted a test phase which comprised of two blocks of 48 trials (either familiar or unfamiliar) counterbalanced between the participants control for learning order.

2.2. Integration of Motion Capture Technology: Xsens MTw Awinda

If the main goal is to conduct this experiment with the minimal setup and/or the goal of an experiment is based on DS-DSP task-level manipulations and/or differences between populations, then there is no need to further integrate complexities in terms of hardware. The details in previous sections should be sufficient to conduct the DS-DSP task. However, if one is also interested in motion capture for additional research goals like understanding predictors of balance control or anticipatory effects of motor sequence learning and performance, then integration of the Xsens Awinda system is a natural extension with the DS-DSP task (for an extensive review of the Xsens technology see Paulich et al., 2018 & Schepers et al., 2018). Fig. 2 below shows a schematic overview of how the Xsens extension is integrated with the E-Prime® only setup.

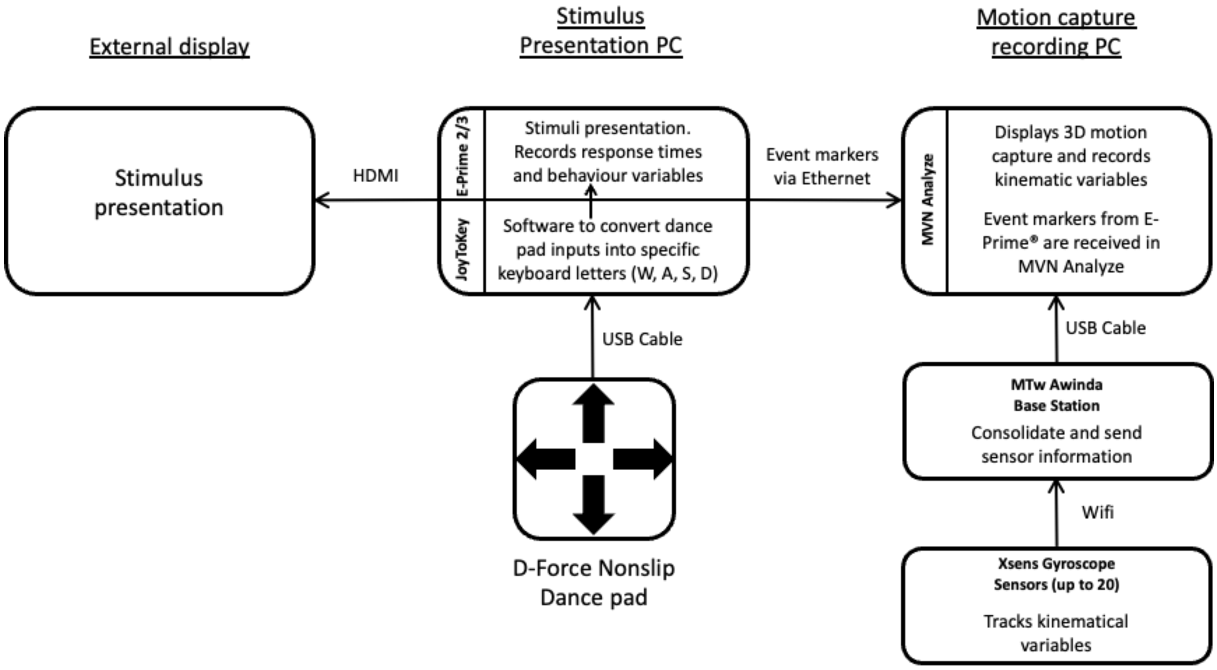


Fig. 2. Overview of equipment and respective connections. The basic setup only requires a stimulus presentation PC that can run E-Prime® and record behavioural variables including step-level accuracy and response times of participants. The bottom right side of the diagram shows that Xsens gyroscope motion capture sensors that can be configured up to 20 sensors in a full suit for recoding biomechanical kinematics such as limb segment, sensor vector displacement, velocity and acceleration. The sensors communicate through Wi-Fi with the MTw Awinda base station, which connects to the MVN Analyze recording software via a USB-A cable. Importantly, E-Prime® sends event markers through line code via a local ethernet to MVN Analyze for indexing different movement moments (e.g. each step).

The current protocol is focused on capturing measurements of CoM. We only outline the use of seven sensors which were the minimum required for accurate measures of lower body kinematics and CoM specified by Xsens MVN Analyze (Ver. 2021.0.1 build 6752). Should one require more sensors for investigating upper-body segments, up to 20 sensors can be used at once for a full suit. When recording with seven sensors (or between six to nine), MVN Analyze can have a maximum frame capture of 100 hertz, whilst using all 20 sensors the maximum output frame capture is 60 Hertz (Paulich et al., 2018). The sensors used in this manuscript were: centre on the pelvis, left and right thighs, left and right shins, left and right foot. Data from the sensors are wirelessly transmitted (through Wi-Fi) to an MTw Awinda base station – which represents one suit. A separate computer from the E-Prime® presentation is required to run the MVN Analyze software so that kinematical data can be recorded, processed and extracted for further analyses. To report on data latency, response onset delay between the initiation of responses on the dance-pad to when E-Prime® recorded the responses was on average 167.4 ms (± 20.8 ms; 2880 trials), in which E-Prime® accounts for as onset delays in its response time calculations. The network delay for receiving event markers in MVN Analyze after sent from E-Prime® was on average 7.3 ms (± 2.4 ms; 2880 trials) which falls within a normal range for local User Datagram Protocol (UDP) communications. Importantly, none of the participants reported any feeling of lag delays when responding to the stimuli.

2.3. Experimental procedure

The procedure and data outlined in the next sections was performed in accordance with Human Ethics guidelines approved by the University of Twente Ethics Committee filed as No. 210390.

2.3.1. Participant preparation together with Xsens

Participants in the lab were briefed about the purpose of the study, outlined their rights to leave at any time during the experiment. Participants then provide written informed consent to collect performance data and for body measurements like height, weight, arm span, hip height that were required and entered into the MVN Analyze software for accurate modelling of the CoM displacement. Participants were also asked to remove their shoes to measure their feet size and to attach sensors to each foot. Afterwards, a total of seven Xsens sensors were attached with the velcro tapes/binds from Xsens to one of each foot (2), shin (2), thigh (2) and one on the Pelvis (1), see Fig. 3 below (Xsens, 2022). This section is covered in the video component https://www.youtube.com/watch?v=DzjBRirkdqk.

Fig. 3. Xsens MTw Awinda seven sensor setup for minimal measurement of lower body kinematic performance (adapted from Xsens, 2022). The circles highlight the location of sensors attached to the

thighs, shins, feet and pelvis. This is a standardised minimal setting in the MVN Analyze software to estimate centre of mass changes.

2.3.2 Xsens calibration

With the sensors attached, a calibration procedure for the Xsens is required. The participant is instructed to stand straight, both arms hanging by the side (known as a N-pose) and wait for the researcher to start the procedure in MVN Analyze software. Once ready, the researcher signals to the participant to walk four meters in a straight line at normal walking speed to a predetermined marking on the ground, turn 180 degrees, and walk back to the starting position. MVN Analyze then processes the calibration procedure and notifies when a good calibration result is achieved – otherwise the calibration procedure is repeated.

2.3.3. Executing the Dance-Step Discrete Sequence Production task with Xsens

Once calibration is complete participants are instructed about the DS-DSP task in detail like explaining the number of trials, number of blocks, rest periods (shorter and longer rest), opportunity for bathroom breaks, drinks and offered to ask further questions. Participants watch a demonstration on how to perform the DS-DSP task and are explicitly shown to step with their whole foot during the task and not just with their toes. Participants are told to perform the DS-DSP as best they could with a goal to make the movement fast, accurate and smooth based on their own interpretation of the "dance" sequence presented. The participants were not controlled based on their chosen strategy (e.g. they could adopt spins or turnarounds as part of their sequence routine) or controlled which foot should be mapped to which response area on the dance mat.

When ready, the participants take position in the centre of the dance mat with both feet facing the screen (see Fig. 2B) and the researcher then starts the DS-DSP task. This was necessary prior to the start of each block to accommodate an additional procedure for the Xsens. Due to the mainly static space in which the participant is moving, signals from the Xsens sensors tend to drift (a normal occurrence of almost all analogue sensor technologies). This requires a locational reset for the sensors in the MVN Analyze software screen after each 24 trials (1/2 block) for more accurate capture of translational movement. The MVN recording starts before the E-Prime® script is executed. The participant starts the stimulus presentation by tapping their foot on the X panel on the top left corner (mapped in JoyToKey as spacebar) on the dance mat. The E-prime® script then executes the stimulus presentation and starts capturing response times and accuracy in the background. The provided script contains inline code to send event markers via a User Datagram Protocol (UDP ethernet) to MVN Analyze via a switch/ router. These event markers add information to the motion capture recording to index important phases like start and end of movement per sequence execution (refer to Appendix 2: Line 248 for example of these inline codes to send event markers). Each experiment block takes between 11 – 15 minutes for completion. Participants are given 3 minutes of rest between blocks and 10 minutes of rest after the half-way mark for recovery of energy. We captured subjective physical demand and effort via the commonly administered NASA-TLX (Hart & Staveland, 1988), to check if participants were overly fatigued from each training block before continuing. In a completed experiment, participants practised 192 trials per sequence (384 trials for two sequences) across eight practise blocks and two test blocks (96 trials) for a total of 480 trials. The experiment completed in approximately 2.5 hours.

3. Exemplar data analysis and results

3.1. Participants

Participants aged 18 to 35 were recruited and given course credits in exchange for their participation. Participants were healthy with no history of neurological, psychological or psychiatric disorders; no alcohol, tobacco or other drug addictions or dependencies; no signs of cognitive impairment as well as no obvious physical injuries or impairments that would affect their performance during the DS-DSP. Finally, they should not have taken part in similar sequence learning studies prior. 24 participants took part in the study (19 females, average age 20.5 ±2.3 years; 87.5% right-footed). Participants were also tested on their foot dominance by asking questions around ball-kicking and declaration of their lead leg if they skated or snowboarded and confirmed by having them perform a simple footedness test that involves first closing their eyes, standing straight and then pushing them from behind which typically caused them to take a step forward with their dominant foot (Staniszewski et al., 2016; van Melick et al., 2017). Those that identified as being right-footed would be assumed to react faster with preference of control using their right leg.

3.2. Dance step Discrete Sequence Production task results: Response time and Accuracy

Extraction of the data was merged at the participant level to form a completed data frame. Next, we show some exemplar results and visualisations based on the data of individual participants, and factorial level analysis on learning blocks to highlight basic data analysis.

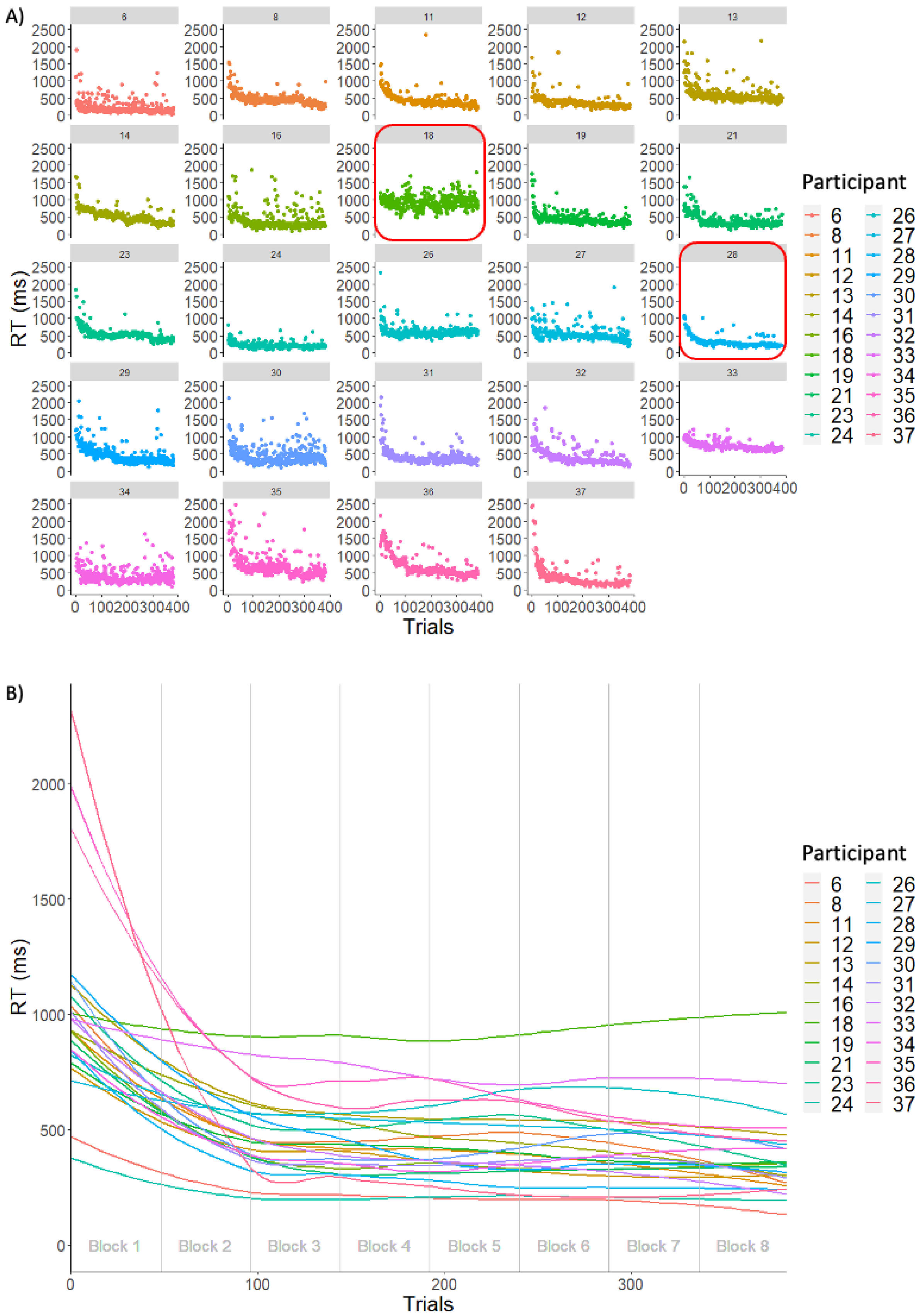


Fig. 4. Visualisation of (A) raw response time (ms) for 384 trials. Across the majority of participants, learning can be inferred from the decrease in response times from the repetition of trials and block

progressions. In (A) differences in response time changes between participants 18 and 28 (in red boxes) suggest different learning styles or strategies in DS-DSP task performance. It could be suggested that participant 18 was performance was more of a 'reacting' to the stimuli (cf. Verwey et al. 2015) and/or favouring accuracy than speeded responses. (B) Shows individual participant learning curve response times across 8 learning blocks.

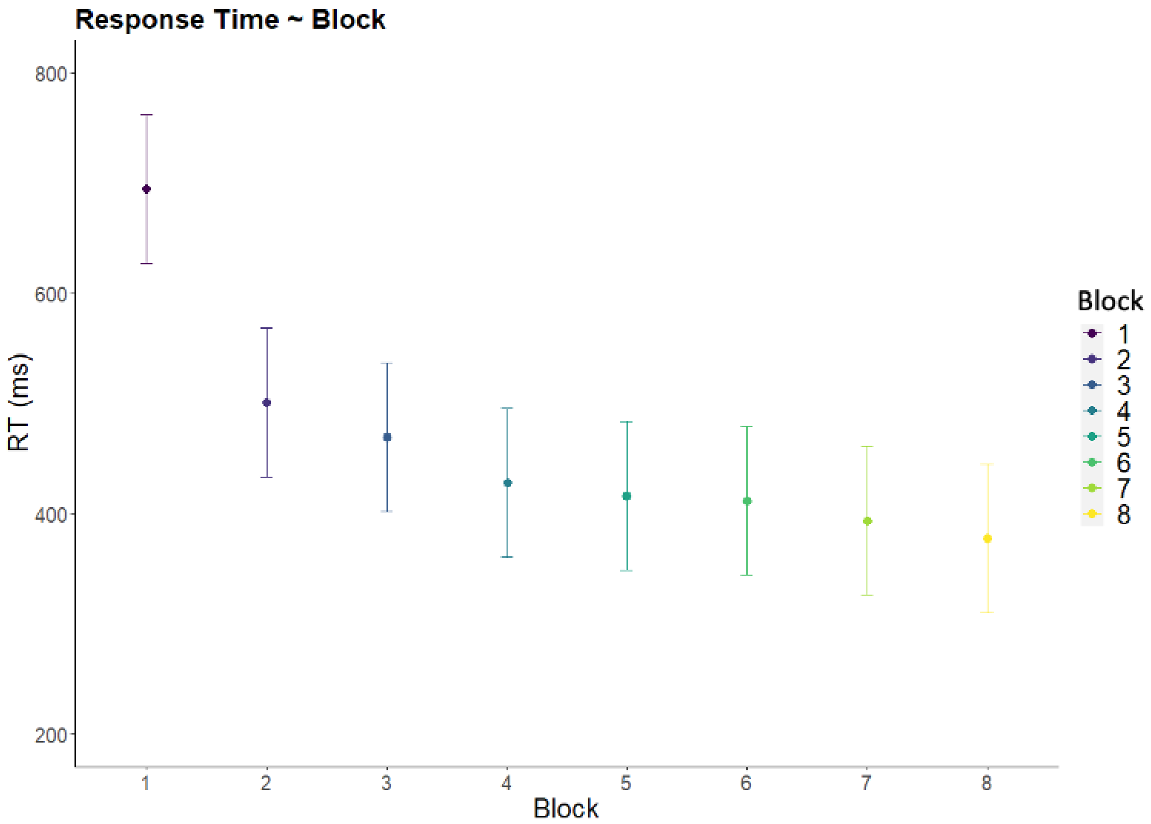


Fig. 5. Visualisation of linear-mixed effects model of mean step-level response times across blocks for accurate only sequence trials across 24 participants. This is one of the emerging methods to analyse the Discrete Sequence Production task. The mean response times for whole sequence execution in the dance-step are relatively short, considering that key-press responses are between the 200 to 400ms (Barnhoorn et al., 2019; Verwey & Abrahamse, 2012).

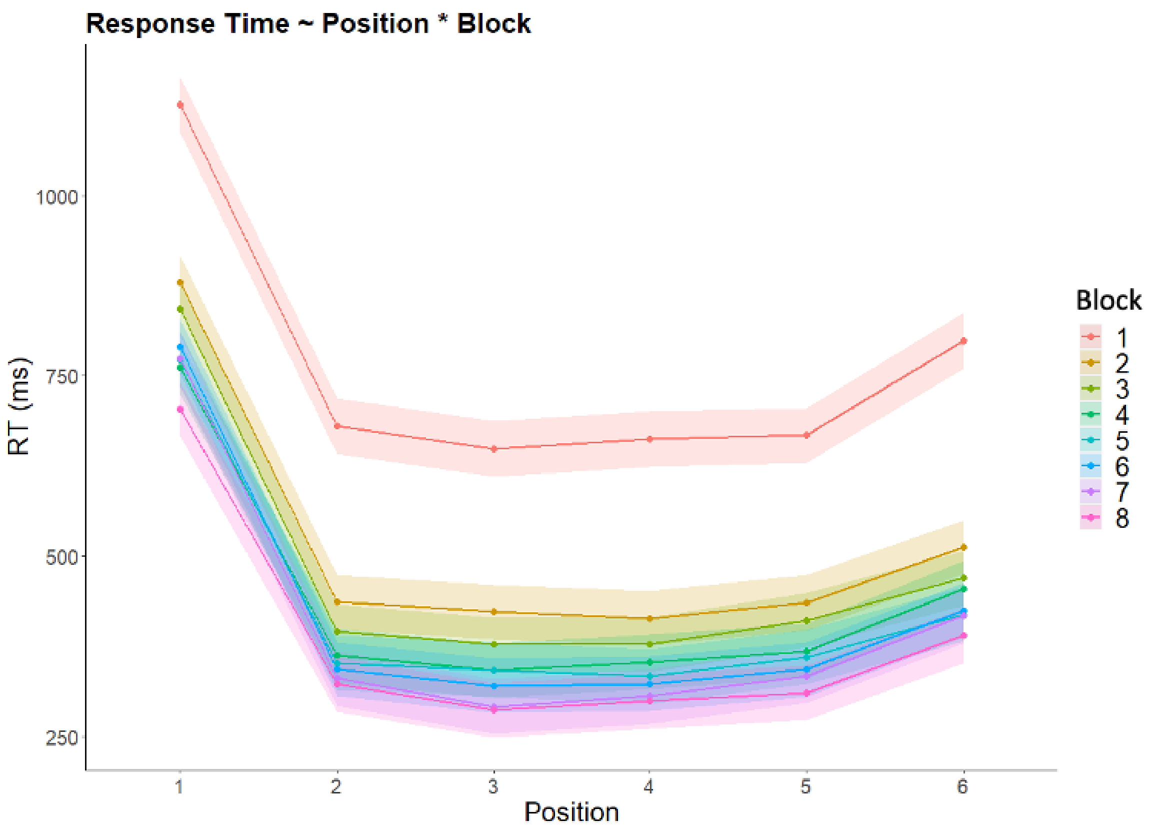
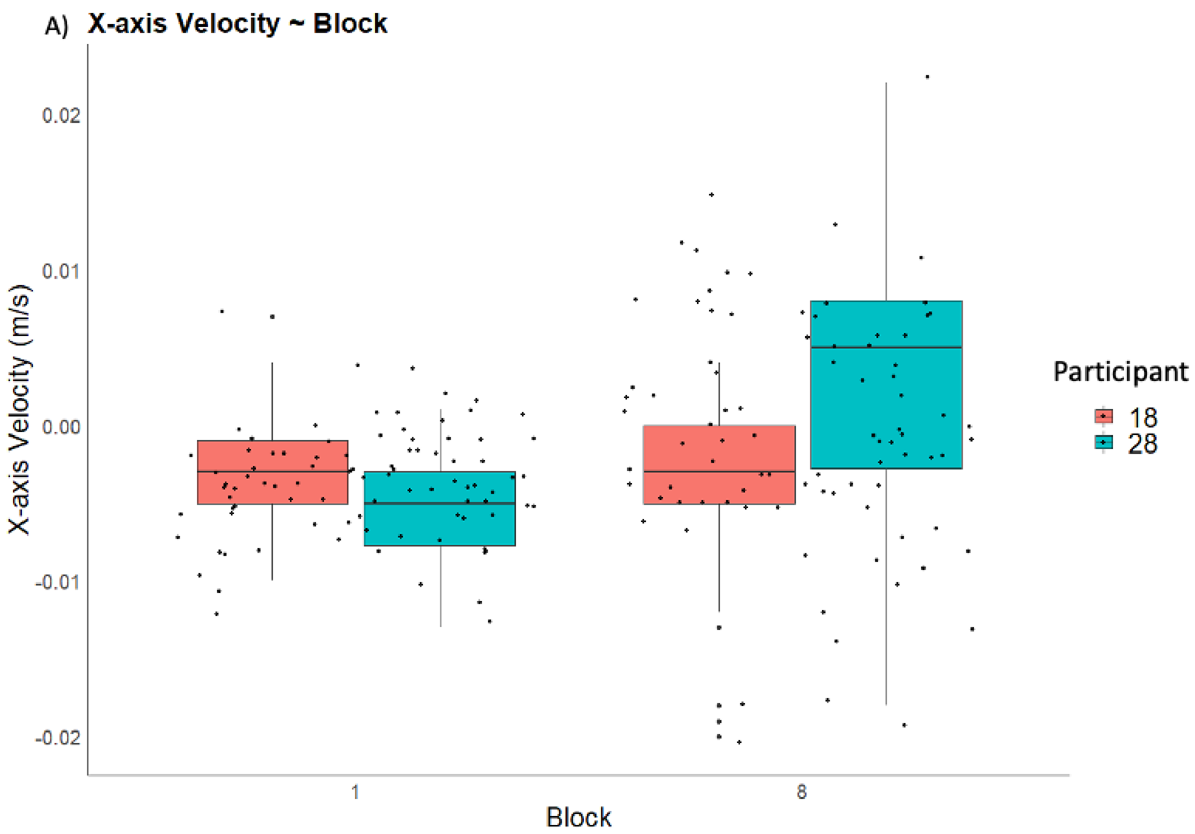


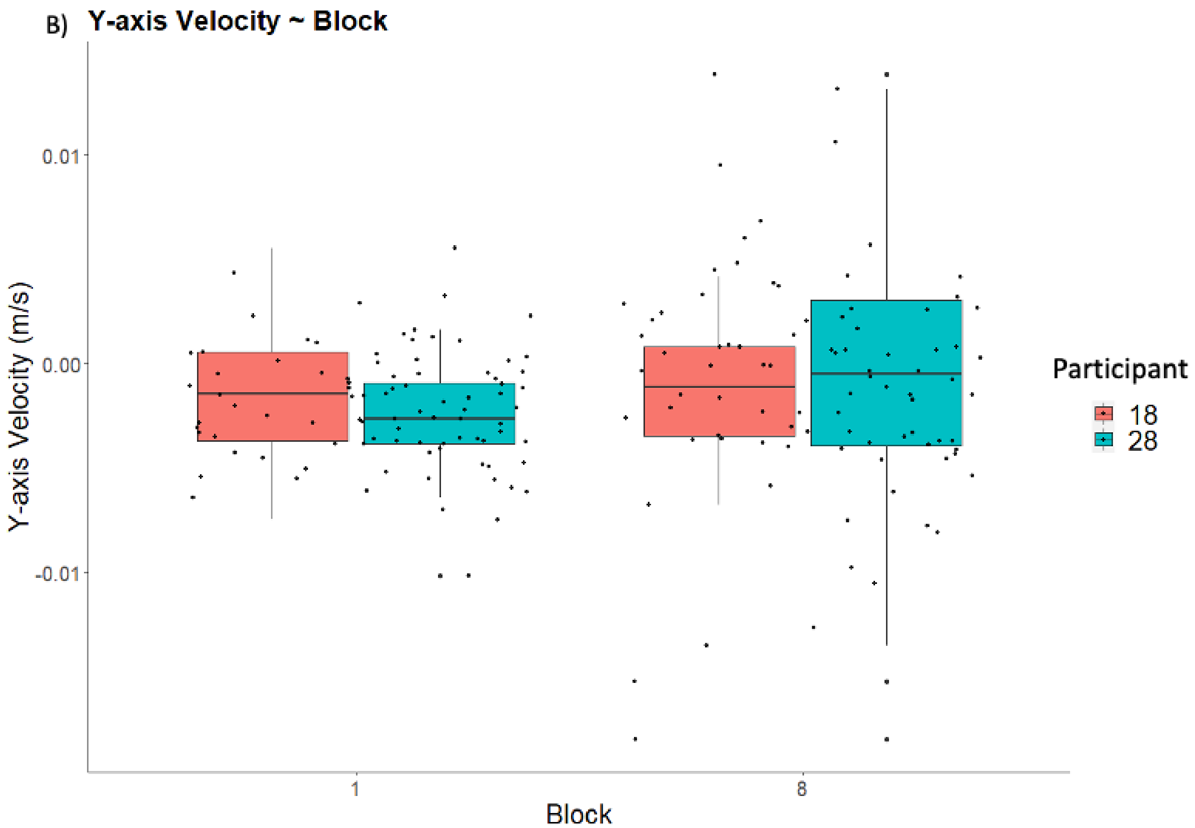
Fig. 6. Linear-mixed effect model of step-level response times across blocks of accurate only sequence trials across 24 participants. The DS-DSP task appears to showcase a different concatenation pattern in that the usual 3^{rd} or 4^{th} position slowing (indicating a chunk separation) usually observed in the key-press DSP is not evident. Instead, the slowing occurs in the 6^{th} position for the DS-DSP.

There are multiple ways that behavioural data could be analysed like aggregation methods for ANOVA repeated measures (Verwey, 2003) for within task factorial comparisons, or emerging linear-mixed effects models (Chan et al., 2020; Chan et al., 2018). There is a recent push towards accountability of individual performance whilst explaining group level phenomena. This has sparked a re-emergence for the use of latent growth curve analysis and exponential functions (Brown & Heathcote, 2003; Heathcote et al., 2000; Wiechmann, 2021). In-depth reporting of exemplar results remains the subject of a future manuscript.

3.2. Xsens results: Sequence-level Centre of Mass velocity changes with training

Extraction of Xsens data is performed via the MVN Analyze software package using the inbuilt export function for displacement, velocity, and acceleration variables. Since we recorded each block performance as an individual file – all 48 trials were captured, but with the help of event markers, clear segregation of individual dance-step/ sequence level performance is possible. We showcase CoM velocity between two exemplar participants (18 & 28) for sequence level execution across training blocks 1 and 8 to highlight learning differences.


A) X-axis Velocity ~ Block
X-axis Velocity (m/s)
0.02
0.01
0.00
-0.01
-0.02
1
8
Block
Participant
18
28


B) Y-axis Velocity ~ Block
Y-axis Velocity (m/s)
0.01
0.00
-0.01
1
8
Block
Participant
18
28

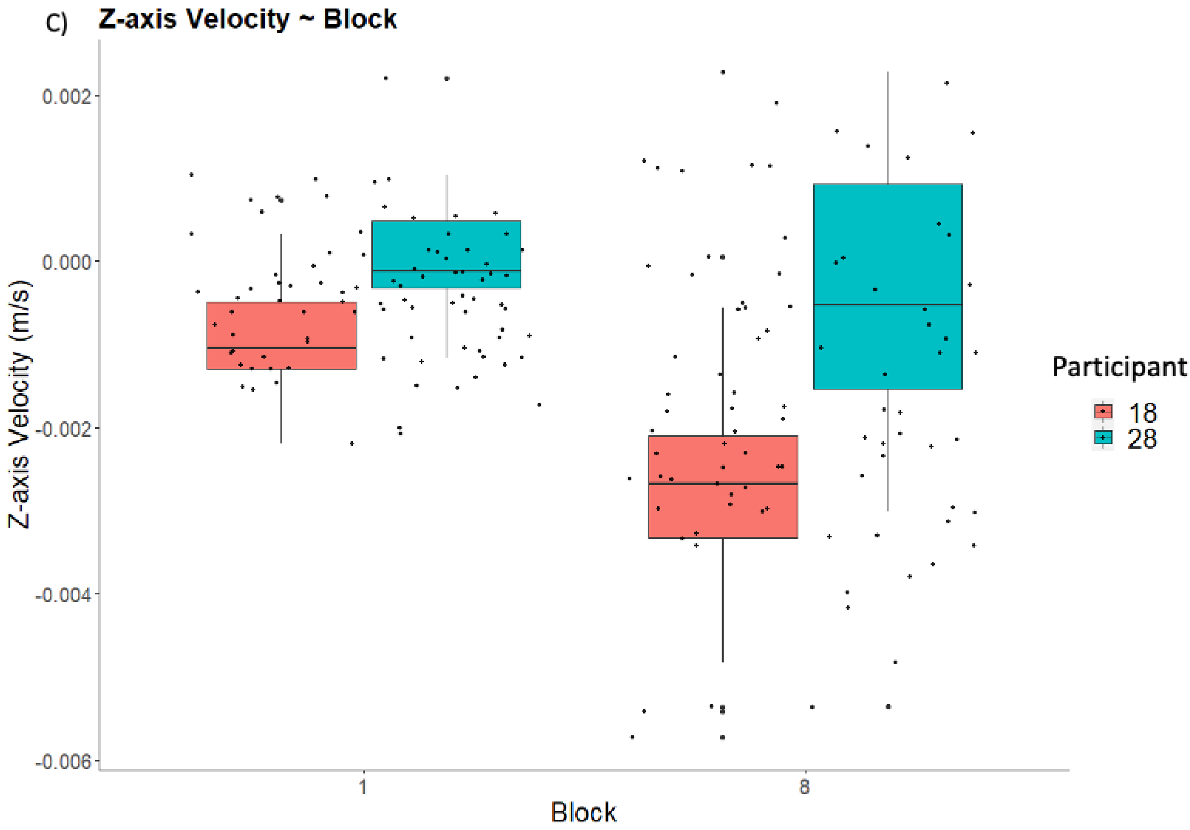


Fig. 7. Average sequence trial centre of mass velocity (m/s) in the A) x-axis, B) y-axis and C) z-axis for a comparison between participants 18 and 28. This data was obtained from the Xsens Awinda motion capture system. This is a follow up comparison of earlier learning curves in Fig. 4A. The figures show different patterns, in that participant 28 shows a development of more variability in the velocity of x, y and z-axes compared to participant 18 from block 1 to block 8. The changes between block 1 and 8 for participant 28 with regards to sequence performance, could be linked to Bernstein's classical theories of freeing of degrees of freedom alongside expertise development (Bernstein, 1947; Raap et al., 2009).

4. Discussion

The goal of this manuscript was to facilitate researchers that are interested in motor sequence learning and performance, of the implementation of a whole-body version of a usual DSP task, coined here as the DS-DSP task. We wanted to transfer the same task properties and general motor learning phenomenon in a more naturalistic format beyond keyboard-based laboratory settings and provided detailed methodology here. This was achieved whereby general learning patterns in Fig. 4 and Fig. 5 showcased trial-level and block-level RT decline, that were comparable to previous key-press iterations of DSP task (De Kleine & Van der Lubbe, 2011; Verwey, 1999). This backs the burgeoning trend of porting other motor sequence learning tasks that have been shown to be feasible (Olivier et al., 2021) and learning differences between different populations (Du et al., 2017).

The DS-DSP task provides an improvement to the usual keypress DSP task as a way to decern cognitive preparatory processes from motor execution processes because of the go/no-go approach. This was already evident in earlier work (De Kleine & Van der Lubbe, 2011), but the DS-DSP task provides new opportunities to test the limits of existing motor learning models like the C-SMB (Verwey et al., 2015). For example, evidence support that the concatenation/chunking phenomenon is resultant due to the combination of three to four individual keypresses executed as a single chunk to connect parts of a longer sequence together (Ruitenberg et al., 2015). In a typical six-key sequence, a significant increase in RT around the fourth keypress indicates that "split" of a sequence (Abrahamse et al., 2013). In the current work, participants performing the DS-DSP task (see Fig. 6) using two effectors (feet) and a constraint to develop an efficient strategy for fast responding, do not appear to slow at this middle point and execute the six-item sequence as if it were a single chunk. Further investigations are required to ascertain this point and understand if differences in effectors versus response positions indeed nullify the need for a concatenation, or that a dynamic relationship for multilimbed performance is evolving (Heuer, 1993). Another possible argument might be that coarticulation (Shah et al., 2013) of the lower body maybe much easier to utilise as there are less and larger joints to coordinate for responding to the task goal. These points all provide important directions that aim to further understand the cognitive and motor mechanistic actions in the DS-DSP task to push the science of optimisation processes in motor sequence learning.

Because the DS-DSP task is a full-body activity and there is increased motor coordination and complexity, it is valuable to incorporate the measurement of kinematical parameters using modern motion capture techniques. Whilst force-plates have been used in motor learning research (Du & Clark, 2018) and are technically considered the "gold standard" in biomechanics research (Basu, 2021), there is a significant disadvantage as it requires a laboratory and significant cost setup. Another advantage of the DS-DSP combined with the Xsens is that key indicators of anticipatory actions like CoM changes prior to movement can indicate cognitive processes that contribute to motor planning/preparation and execution processes in sequence learning (Kanekar & Aruin, 2014). In addition, kinematic parameter changes during planning or performance could be predictive of the response times and accuracy performance, which may be important factors to help model individual variations to performances (Chan et al., 2021).

The Xsens is also portable, robust, and designed to be operated in different environments. This means that investigations in diverse environments such as schools, hospitals, outdoors or rehabilitation centres are possible. Diverse populations like the elderly can therefore be supported by bringing the testing and training programs to them whilst maintaining the contextual integrity of a test environment. Furthermore, when investigating the elderly, biomechanical limitations of finger movement have been revealed (Barnhoorn et al., 2017) which contribute to finger-press RT slowing. We argue that what is more functional are postural effects in the elderly, such as CoM variability which could be an important parameter that be predictive of falls risk in the elderly population (Graham et al., 2017). In summary, we think that the DS-DSP will play a key role in applied psychology and motor neuroscience with the fields looking for more naturalistic and ecological testing paradigms.

4.1. Considerations and future directions

During the implementation of the DS-DSP task we noticed several differences from the KP-DSP task which we propose should be investigated as future work for the field of applied psychologists and motor neuroscientists. The first is the physiological requirements that differ from a mostly passive sitting posture to a whole-body movement. On the practical level, one must account for the amount of practice administered and enough rest for the recovery of energy. For example, some participants obviously performed the task with much effort from the start (even though instructions were standardised), whilst others paced themselves explaining that the experiment was ~2.5 hours long. Regardless, we followed a rule of giving participants approximately three-minute break between blocks, aiming to account for about >85% of recovery based on normal activity energetic systems utilisation and recovery (Rodríguez-Fernández et al., 2019). Halfway through the experiment (fourth block), we administered a longer break lasting 10 minutes and offered a sugary drink for recovery of glycose stores. Our younger participants did not report any adverse physical issues, but further investigation is needed for elderly population. Physiologists and ergonomists may provide an interdisciplinary view on the exertion and rest ratios for recovery and optimal learning performance.

A second direction that is important is the development of strategy over the course of learning. The DS-DSP task is interesting for this as instead of a single effector (i.e. finger) mapped to a single response key, the lower body has two effectors with four possible response positions. This means that effectors must be re-utilised again for future responses even when they have already been used earlier in the sequence. This gives rise to different strategies amongst participants as there is a need to reorganise limited effectors in the most efficient way to optimise performance of the sequence. For example, some participants choose to hop and use quick double step with both feet over certain parts of the sequence, whilst others chose to spin around even though their body does not face the screen anymore. The subject of how to best model these strategy adaptations (including classifiers) for a similar sequence is beyond the scope of the manuscript, but including kinematical variables is likely essential to further discern individual differences between participants. It is important to recognise that individual strategies exist in the DS-DSP task performances, and that aggregation of RT may only provide a limited scope for the understanding sequence learning performance.

4.2. Summary

Our goal was to modernize and convert a well-established motor sequence learning paradigm into a more ecological and applied methodology. This brings about new avenues of research, further testing of existing theoretical frameworks, integration of cutting-edge technology and further collaborations. This manuscript provided theoretical background, extensive instruction, and possible ways to visualise and analyse the data. We hope more researchers will utilise such paradigms and/or be inspired to adapt existing ones to further motor neuroscience research.

5. Procedural video component

The video component that is published alongside this manuscript is available here: https://www.youtube.com/watch?v=DzjBRirkdqk

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Appendix 1: Equipment list

Basic setup

Equipment name	Make	Model	Comment
E-Prime®	Psychology Software Tools	Minimum Ver. 2.0 (3.0 preferred)	For creating the stimuli executing the experiment
Display for stimuli	LG (in this experiment)	Model nr. OLED77CX6LA (77 inch display)	Any computer monitor/ TV that has at least 60Hz refresh rate
Dance mat USB device	D-Force	Nonslip Deluxe Dance Pad Ver. 5 (https://dancepadmania.com/deluxe/)	Multiple options from retailers but choose one that is non-slip and of higher quality
USB Input mapper	JoyToKey	Ver. 5.2.1	PC software used to map the dance mat as keyboard input
Personal computer (PC)	Any brand	Any model	Ensure PC has the minimum Windows OS requirement to run E-Prime® 2/3
Weighting scale and tape measure for height	Any brand	Any model	To record individual differences

Optional complexities:

Equipment name	Make	Model	Comment
3D Motion Capture	Xsens	MTw Awinda system (up to 20 sensors)	The motion capture system gives access to kinematics of limb positioning such as velocity, acceleration and displacement
3D Motion capture software	Xsens	MVN Analyze (on a yearly subscription)	The software allows for capture of 3D recordings, analysis and export of data files.

Ethernet router network hub	Any major brand e.g. Linksys, TP-Link etc.	Any model that has at least 4 ethernet slots (and an ethernet cable)	The hub is for communications between the motion capture computer and the stimuli computer for sending and receiving event markers
Personal computer (PC)	Any major brand	Ensure that the computer has the latest Windows 10/11 OS	This computer should have enough processing power (≥ Intel i7 in 2021), ram (≥16gb) and storage for motion capture

Appendix 2: E-Prime® Script

The file is an E-Prime® 2.0 file but can be upgraded to an E-Prime® 3.0 file easily and you can obtain them here: https://osf.io/zmxay/download. Here we outline the entire script and its execution. Please obtain the script that is freely available and curated at the following Github: https://github.com/Eggcite/DS_DSP/blob/main/ID1_script.

[See Supplementary Material]

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