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Breaking the Barriers to Designing Online Experiments: A Novel Open-Source Platform for Supporting Procedural Skill Learning Experiments

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Corresponding Author:	Chandramouli Krishnan University of Michigan Michigan Medicine Ann Arbor, Michigan UNITED STATES
First Author:	Luis Hernan Cubillos, B.Sc.
Order of Authors:	Luis Hernan Cubillos, B.Sc.
	Thomas Edmund Augenstein, M.S.E.
	Rajiv Ranganathan, Ph.D.
	Chandramouli Krishnan, P.T., Ph.D.
Abstract:	Background Motor learning experiments are typically performed in laboratory environments, which can be time-consuming and require dedicated equipment/personnel, thus limiting the ability to gather data from large samples. To address this problem, some researchers have transitioned to unsupervised online experiments, showing advantages in participant recruitment without losing validity. However, most online platforms require coding experience or time-consuming setups to create and run experiments, limiting their usage across the field. Methods To tackle this issue, an open-source web-based platform was developed (https://experiments.neurro-lab.engin.umich.edu/) to create, run, and manage procedural skill learning experiments without coding or setup requirements. The feasibility of the platform and the comparability of the results between supervised (n=17) and unsupervised (n=24) were tested in 41 naive right-handed participants using an established sequential finger tapping task. The study also tested if a previously reported rapid form of offline consolidation (i.e., microscale learning) in procedural skill learning could be replicated with the developed platform and evaluated the extent of interlimb transfer associated with the finger tapping task. Results The results indicated that the performance metrics were comparable between the supervised and unsupervised groups (all p's > 0.05). The learning curves, average tapping speeds, and micro-scale learning were similar to previous studies. Training led to significant improvements in mean tapping speed (2.22 ± 1.48 keypresses/s, p < 0.001) and a significant interlimb transfer of learning (1.22 ± 1.43 keypresses/s, p < 0.05). Conclusions The results show that the presented platform may serve as a valuable tool for conducting online procedural skill-learning experiments.

Highlights

- A new web-based open-source app was developed to conduct motor learning experiments.
- The platform requires no coding experience and can be used to create and manage online experiments.
- Feasibility and replication experiments were also conducted to validate the platform.
- Performance improvements were similar between supervised and unsupervised learning.
- Results also replicated prior results, including a rapid form of micro-scale learning.

Breaking the Barriers to Designing Online Experiments: A Novel Open-Source Platform for Supporting Procedural Skill Learning Experiments

Authors: Luis H. Cubillos[a,b], Thomas E. Augenstein[a,b], Rajiv Ranganathan[c,d], Chandramouli Krishnan*[a,b,e,f]

a. Neuromuscular and Rehabilitation Robotics Laboratory (NeuRRo Lab), Physical Medicine and Rehabilitation, Michigan Medicine, Ann Arbor, MI-48108, USA

b. Robotics Institute, University of Michigan, Ann Arbor, MI-48109, USA

c. Department of Kinesiology, Michigan State University, East Lansing, MI- 48824, USA

d. Department of Mechanical Engineering, Michigan State University, East Lansing, MI-48824, USA

e. Department of Biomedical Engineering, University of Michigan, Ann Arbor, MI-48109, USA

f. School of Kinesiology, University of Michigan, Ann Arbor, MI,

Corresponding Author*

Chandramouli Krishnan, PT, PhD

University of Michigan

325 E Eisenhower Parkway, Suite 3013

Ann Arbor, MI - 48108

Phone: (319)-321-0117

Fax: (734)-615-1770

Email: mouli@umich.edu

Abstract

Background

Motor learning experiments are typically performed in laboratory environments, which can be time-consuming and require dedicated equipment/personnel, thus limiting the ability to gather data from large samples. To address this problem, some researchers have transitioned to unsupervised online experiments, showing advantages in participant recruitment without losing validity. However, most online platforms require coding experience or time-consuming setups to create and run experiments, limiting their usage across the field.

Method

To tackle this issue, an open-source web-based platform was developed (https://experiments.neurro-lab.engin.umich.edu/) to create, run, and manage procedural skill learning experiments without coding or setup requirements. The feasibility of the platform and the comparability of the results between supervised (n=17) and unsupervised (n=24) were tested in 41 naive right-handed participants using an established sequential finger tapping task. The study also tested if a previously reported rapid form of offline consolidation (i.e., microscale learning) in procedural skill learning could be replicated with the developed platform and evaluated the extent of interlimb transfer associated with the finger tapping task.

Results

The results indicated that the performance metrics were comparable between the supervised and unsupervised groups (all p's > 0.05). The learning curves, average tapping speeds, and micro-scale learning were similar to previous studies. Training led to significant improvements in mean tapping speed (2.22 ± 1.48 keypresses/s, $p < 0.001$) and a significant interlimb transfer of learning (1.22 ± 1.43 keypresses/s, $p < 0.05$).

Conclusions

The results show that the presented platform may serve as a valuable tool for conducting online procedural skill-learning experiments.

Keywords: Key pressing; offline gains; micro-offline; micro-online; cloud computing; machine learning

Introduction

Motor learning is a fundamental and essential part of human behavior, characterized by acquiring new motor skills and enhancing the performance of old ones. Investigations probing the mechanisms that underlie the way we learn and adapt movements (i.e., motor learning studies) have increased dramatically over the past two decades. These studies typically use motor learning tasks that can be broadly categorized into one of the following: motor adaptation (Izawa, Rane, Donchin, & Shadmehr, 2008; Wei & Kording, 2009) or skill acquisition (Higgins, 1991; Krakauer, 2006; Newell, 1991).

Motor learning experiments are typically conducted in person in a laboratory environment to control experimental parameters, but creating this controlled environment comes at a cost (Tsay, Lee, Ivry, & Avraham, 2021). In-person experiments require specialized equipment and dedicated personnel to recruit participants and administer experiments. They also impede the ability to conduct experiments with a large sample size because only one participant can be tested at any given time and some participants may be unable to attend in-lab sessions due to various constraints (e.g., time, cost, transportation). Additionally, in-person experiments typically recruit highly selective participants (e.g., lab members or college students), inducing bias and minimizing the generalizability of the study results (Tsay et al., 2021). Furthermore, lab environments may not always be feasible, such as restrictions imposed by the current global pandemic. Thus, especially given that motor learning studies suffer from issues related to small sample size and publication bias (Lohse, Buchanan, & Miller, 2016), there is an increasing need to look beyond lab experiments.

To address these issues, researchers have turned to online experiments (Anglada-Tort, Harrison, & Jacoby, 2022; Bonstrup, Iturrate, Hebart, Censor, & Cohen, 2020; Listman, Tsay, Kim, Mackey, & Heeger, 2021; Tsay et al., 2021). Running experiments online makes study recruitment easier for researchers and involvement easier for participants. As a result, investigators can recruit several participants who are more representative of the general population (Paolacci & Chandler, 2014). Online experiments have had great success in the social sciences, with platforms such as PsychoPy (Peirce, 2007), PsyToolkit (Stoet, 2017), Gorilla (Anwyl-Irvine, Massonnié, Flitton, Kirkham, & Evershed, 2020), and lab.js (Henninger, Shevchenko, Mertens, Kieslich, & Hilbig, 2022) allowing researchers to both create and conduct their studies online. The field of motor learning has also begun conducting online experiments, both by developing new platforms for motor adaptation studies (Tsay et al., 2021) and by using existing platforms for skill learning studies (Bonstrup et al., 2020; Listman et al., 2021). These studies have shown that online experiments are valid and replicate findings from in-person experiments (Bonstrup et al., 2020; Tsay et al., 2021). However, a primary limitation of most current platforms is that they require researchers to code the experiments themselves; thus, users need to have some programming experience. This requirement creates a barrier to the widespread use of these platforms, ultimately limiting the impact of these online tools on the motor learning research community.

The field of motor learning is broad and uses a diverse set of experimental paradigms (Ranganathan, Tomlinson, Lokesh, Lin, & Patel, 2021). However, an important requirement for running online experiments successfully is that the experimental paradigms must be simple and should not require equipment or resources beyond those typically available in a participant's home (e.g., computer, mouse, keyboard). One paradigm that fits this need and has been used over the past decade by numerous motor learning researchers is the sequential finger tapping task (Bonstrup et al., 2020; Bonstrup et al., 2019; Korzeczek, Cholin, Jorschick, Hewitt, & Sommer, 2020; Van Der Werf, Van Der Helm, Schoonheim, Ridderikhoff, & Van Someren, 2009; Witt, Margraf, Bieber, Born, & Deuschl, 2010). In this paradigm, a participant repeatedly taps with their hand a 5-element (or more) sequence (e.g., 41324) of finger movements as quickly and accurately as possible. Performance in this task is typically quantified by the improvements in speed (measured in keypresses/s) and/or accuracy (measured by the number of correct sequences tapped during each trial or block). The sequential finger tapping task has been well-characterized and used extensively in the study of procedural memory formation in the motor learning literature (Bonstrup et al., 2020; Censor, Sagi, & Cohen, 2012). For example, this task has been used to analyze the role of the hippocampus in sequential learning and consolidation of skill (Buch, Claudino, Quentin, Bonstrup, & Cohen, 2021; Diekelmann & Born, 2007), to investigate the mechanisms of offline motor learning at a microscale of seconds (Bonstrup et al., 2020; Bonstrup et al., 2019), and to study the hemispheric lateralization and interlimb transfer of sequence learning (Grafton, Hazeltine, & Ivry, 2002). Researchers typically rely on their own custom scripts to run these experiments in the lab or online (e.g., using the Amazon Mechanical Turk Platform). However, as mentioned previously, there is a critical need for developing a testing platform that provides flexible options to perform sequential finger tapping tasks without the need for coding experience to minimize barriers to designing and conducting online experiments.

Therefore, the purpose of this paper was to develop and test a new open-source, web-based platform that allows researchers to design, set up, run, and manage sequential finger-tapping experiments. No coding experience is required, and the experiments can be shared in any crowdsourcing platform to recruit participants online. Notably, the platform requires no specialized equipment or resources, including the need for web hosting. The experimental process is also highly time-efficient because of the ability to quickly create and run online experiments and the availability of pre-processed data immediately after the completion of the experiment. Additionally, a feasibility study was performed to show that 1) the results of in-person and online experiments are similar on the platform and 2) these results are similar to those from a previous seminal paper on a rapid form of offline consolidation in skill learning (Bonstrup et al., 2019). The interlimb transfer (Grafton et al., 2002; Japikse, Negash, Howard, & Howard, 2003; Lefumat et al., 2015; Parlow & Kinsbourne, 1989; Perez, Wise, Willingham, & Cohen, 2007; Jinsung Wang & Robert L Sainburg, 2004) of learning and offline consolidation is also reported, to showcase an example of the new possibilities that this platform gives to interested researchers.

Methods

Web-based Experimental Platform

An open-source web-based platform (https://github.com/lhcubillos/motorlearningapp) was developed to allows researchers in the motor learning field to create and run different types of sequential finger tapping task experiments online without any coding or scripting requirement. The sequential finger tapping task was chosen because this is one of the most commonly used motor learning paradigms that require no specialized equipment for testing purposes, thereby making it most suitable for online experiments (Bonstrup et al., 2020; Bonstrup et al., 2019; Censor et al., 2012; Friedman & Korman, 2016; Korzeczek et al., 2020; Van Der Werf et al., 2009; Witt et al., 2010). The short sequences used in this task also meant that the learning was focused on how participants improve motor performance, as opposed to other features of learning such as sequence acquisition (Ghilardi, Moisello, Silvestri, Ghez, & Krakauer, 2009).

The platform was developed using the frameworks Django (version 4.0, Django Software Foundation) and Vue (version 3.0, Evan You). Django is a Python-based open-source framework typically used for the back-end development of web applications (i.e., reading and writing to the database, general data processing, etc.). On the other hand, Vue is an open-source JavaScript framework for front-end development that was used to develop the user interfaces (both researcher and participant). The web application is currently hosted on the Google Cloud Platform (GCP) and can be publicly accessed at https://experiments.neurro-lab.engin.umich.edu on any browser. A sample experiment to test the platform is available online at https://experiments.neurro-lab.engin.umich.edu/experiment/5FYA. Due to the platform's open-source nature, researchers with some programming experience can also run the application locally and add any new features they need for their specific studies.

The platform has two user interfaces: the researcher interface (Figure 1 top) and the participant interface (Figure 1 bottom). The investigators can access the researcher interface after logging in with their username and password created during their profile registration. After logging in, the researcher interface displays the investigator's profile that contains their current studies and options for creating new ones. Within each existing study, the investigator can view the number of responses, download recorded data, publish the study (make it available to participants), or even delete it when necessary. Existing studies are classified as unpublished or published. A study that is unpublished means that its study parameters are still being decided upon. In this stage, the study can be edited and tested but is unavailable to participants. After the investigator is satisfied with their study, they can publish it. When the study is published, it is available to participants and can no longer be edited by the investigator. Once the investigator is satisfied with the number of participants, or they wish to pause data collection for whatever reason, they can disable the study, making it unavailable to participants. A disabled study can be re-enabled at any time if the investigator wishes to resume data collection.

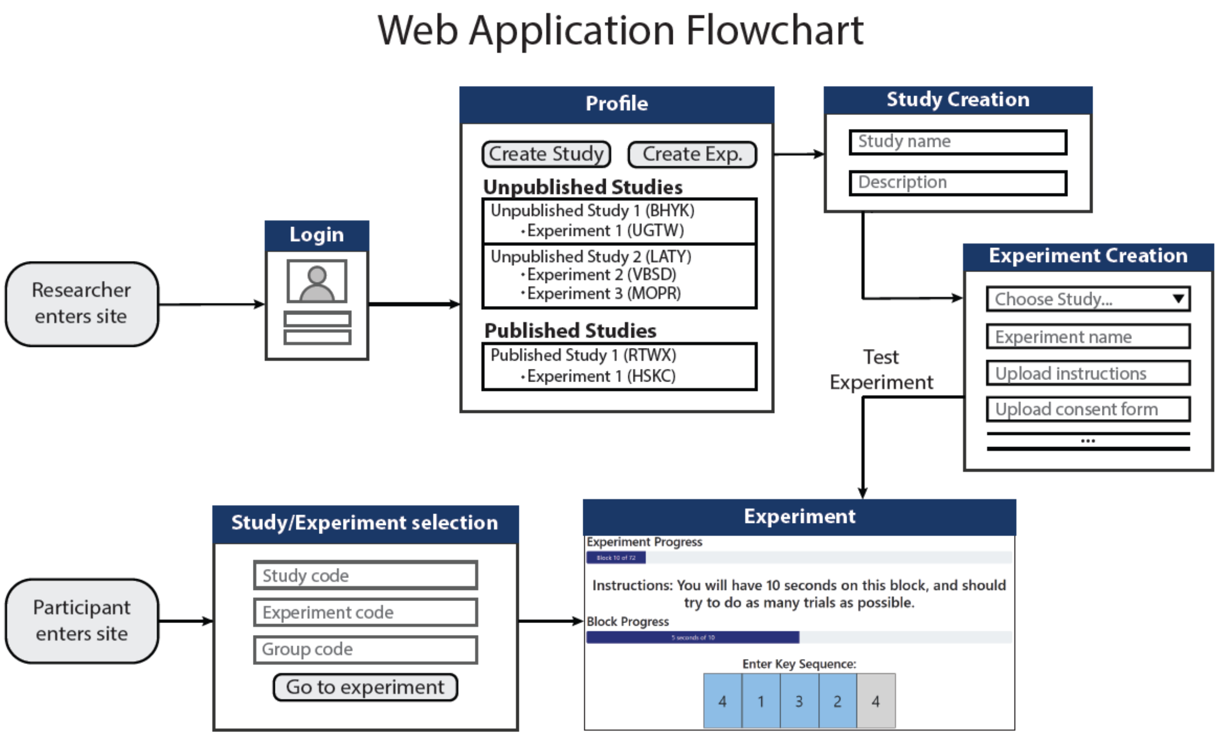

Figure 1 – Web application flowchart: A schematic of the webpage flow as seen by the two types of users: researchers (top) and participants (bottom). Researchers log in to the platform and are then presented with a profile page. There, they can create either a study or an experiment, manage unpublished and published studies, and test experiments (mock examples shown). Participants enter the study, experiment, and group codes given to them by the researchers, and then are redirected to the corresponding experiment.

When creating a new study or editing an unpublished study, the investigator's user interface allows the investigator full control of the study parameters. Within a study, the investigator can select the number of groups that will be included in the study and define the experiments that each group will do. For example, an investigator could create a simple interlimb transfer study with one group that performs two experiments: one experiment with their right hand and then a second experiment (e.g., a duplicate of the first) with their left. Each experiment is divided into blocks, the number of which is specified by the investigator, and each block is defined by a fixed time interval or a fixed number of key-pressing sequences. Each key pressing sequence is referenced as a "trial" in the platform and all trials in a block have the same sequence. This key sequence can be either manually defined or randomly generated by the program. Through the user interface, the investigator can also control the participant's access to performance feedback during the experiment (both correctness of the most recently pressed key and improvement across blocks) and the rest time (both between blocks and between trials within each block). The platform can also facilitate study execution by allowing the investigator to include instructional videos for the participants and the informed consent document so that participants can view and sign it online.

In the participant interface, the user is first shown a text box, in which they type a study code provided by the investigator. Once the participant submits the code, they are shown the study inclusion/exclusion criteria and the informed consent document, which they are asked to agree to. After consenting to the study, they are shown a short instructional video detailing the experiment instructions, and then redirected to the start of the experiment. While participating in the experiment, the key sequence is presented on the screen and the participant is instructed to begin typing the sequence as instructed (e.g., "type as quickly and as accurately as possible"—these instructions can be customized based on the researcher's need and experimental protocol). Behind each character in the sequence is a grey box. The program offers feedback on the number of keys pressed in the current sequence by changing the color of the grey box behind the current character in the sequence when a key is pressed. If the investigator enables feedback regarding the correctness of the keypresses, the box will turn blue when the pressed key is correct or orange when incorrect.

If this feedback is disabled, the box will turn blue when a key is pressed, regardless of correctness. Once the background color behind a character has been changed, the new color is held until the end of the sequence, after which it resets to the default grey. If the investigator enables feedback on performance for each block, the participant will see a bar graph below the sequence with the number of correct and incorrect trials in the current block. Additionally, regardless of the experiment configurations, the participant will see their progress in the current experiment and their progress in the current block, as well as a short instruction passage to help remind participants what their objective is and what hand they should use for the current block (again, these instructions can be removed from display if needed). When the participants get to the end of the experiment, they are shown a short voluntary survey to fill out. There, the researcher can have the participant fill out some non-identifiable demographic information about themselves, such as age or gender.

Once the investigator is satisfied with the number of responses in a certain experiment, they can proceed to download the participants' data. Three different comma-separated-values (CSV) files can be downloaded, each with different information about the experiment. First, the survey data file provides responses of each of the participants to the survey questions, as well as the time when they started the experiment. Second, the raw data file provides the timestamp and value for each key that the participant pressed, as well as if it was correct in the context of the respective trial. Finally, the processed data file provides the data aggregated in trials, showing correctness and mean/average tapping speed for each trial and participant.

Feasibility study

A feasibility study was conducted to compare supervised and unsupervised learning (i.e., participants learning the task in their daily living environment) and to showcase the possibilities of the presented platform to conduct other similar motor learning studies. A total of 43 naïve adult participants (25 males, 18 females, age 30.46 ± 9.8) participated in this feasibility study. All participants were right-hand dominant with no history of significant neurological or orthopedic disorders. The study was reviewed and determined to be Exempt by the University of Michigan Human Subjects Institutional Review Board. All participants agreed to participate in the study with an online consent form before starting the experiment.

Participants were separated into two groups: a "supervised" group and an "unsupervised" group. Participants in the "supervised" group (18 participants, 10 males, 8 females, age 30.1 ± 10.9 years) performed the experiment in a controlled, laboratory environment while under the supervision of a study team member. Participants in the "unsupervised" group (25 participants, 15 males, 10 females, age 30.8 ± 9.2 years) performed the experiment outside of the laboratory (typically in their homes) via the internet, without supervision. Participants in the supervised group were mostly recruited from the university pool and had relatively similar background (college students), whereas participants in the unsupervised group were more diverse and were mostly outside the university pool to ensure that they represented a more heterogenous sample that are typically observed in the "wild" (i.e., ecologically valid settings). Except for the differing levels of supervision, all experimental protocols were identical between the groups.

The experiment consisted of two parts with one minute of rest between them. In the first part of the experiment, participants were instructed to accurately type the sequence '41324' as fast as possible with their non-dominant (left) hand [Figure 2A left]. While a shorter sequence like this may seem simple, it is important to note that the primary purpose of this study was to evaluate how the speed at which the participants accurately typed the sequence improved with practice, not in accuracy itself. Moreover, using a simpler sequence allowed participants to focus on motor performance improvements rather than other features of learning, such as sequence acquisition (Ghilardi et al., 2009). More importantly, this first part of the experiment was a replication of a previous study (Bonstrup et al., 2019) to directly compare the proposed platform's results with previous research without the confounding factor of a new experimental design. Each participant received 36 blocks of training with each block consisting of 10 seconds of practice and 10 seconds of rest. During practice, the participants were instructed to accurately type as many sequences as possible. Whenever a key was pressed, the platform informed the participant of the total number of keys pressed in each sequence, but not whether they were correct or not. Participants were instructed to look at their computer screens (not at their hands) throughout the experiment. In the second part of the experiment, participants typed the sequence '70897' as fast and as accurately as possible with their right hand [Figure 2A right]. Other than the sequence and the hand used for training, the second part of the experiment was identical to the first. The addition of the second part of the experiment enabled using the platform to examine the interlimb transfer of learning from the first part of the experiment. The sequence was chosen to be the mirrored version of the first sequence, as previous research has shown that interlimb transfer is present when the second sequence is mirrored from the first (Grafton et al., 2002). Note that the objective of the second part of the experiment was to demonstrate the feasibility of the platform's ability to quickly and easily conduct other forms of motor learning studies and answer a variety of motor learning research questions.

Data Analysis

All outcome metrics were computed from each participant's tapping speed in a trial. A description of all these variables, along with the mathematical notations to compute them, can be found in the supplementary material document. A trial's tapping speed was found using Equation (1) (Bonstrup et al., 2019), and it quantified the rate at which the participant was pressing keys:

$$Trial\ tapping\ speed\ = \frac{1}{\frac{1}{4}\sum_{i=1}^{4} interval_i}$$

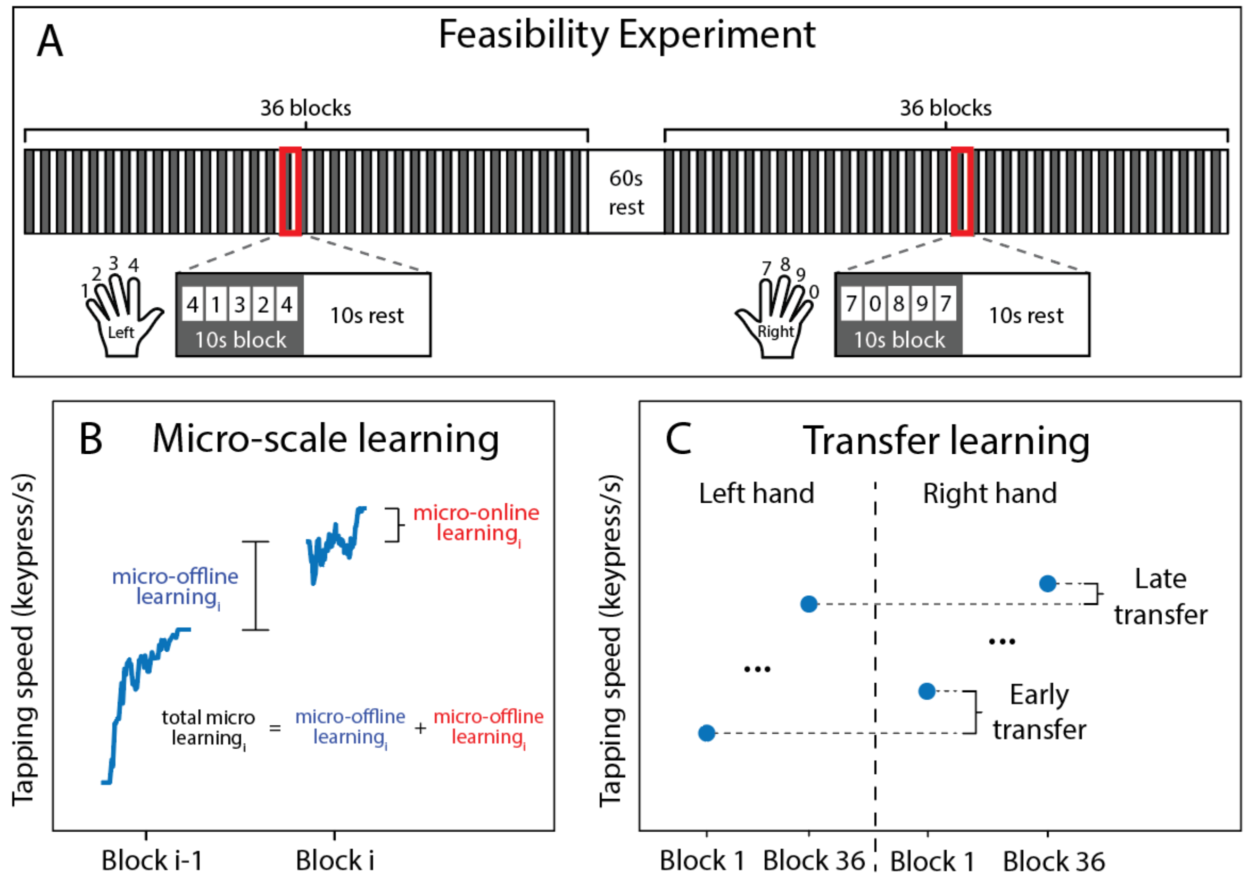

Figure 2 – Schematic of experimental protocol and data processing: (A) A schematic of the experimental protocol. Participants practiced a finger tapping task where they first learned to type the sequence '41324' as fast and as accurately as possible with their non-dominant, left hand. After a one-minute rest following the completion of the task with their left hand, they then learned to type the sequence '70897' as fast and as accurately as possible with their right hand. Participants received 36 blocks of training for each hand with each block consisting of 10 seconds of practice and 10 seconds of rest. **(B)** A schematic for the computation of micro-scale learning (micro-offline and micro-online learning). Micro-offline learning quantified the learning that occurred during short periods of rest, and micro-online learning quantified the learning that occurred during short periods of practice. For block i, micro-offline learning is defined as the difference in tapping speed (keypresses/second) between the first trial of block i and the last trial of block i-1. Micro-online learning is defined as the difference between the last and first trials of block i. Total micro-learning at that block is the sum of both quantities. **(C)** A schematic of the interlimb transfer of motor skill learning metrics. Early transfer is calculated as the difference in the mean trial tapping speed between the first block of the right and left hand. Late transfer is calculated as the difference in mean trial tapping speed between the last block of the right and left hand.

where $interval_i$ represents the time interval between keypresses i and $i + 1$ in a given trial. Tapping speed was only calculated when the trial was correct (i.e., all keys of the sequence were pressed in the correct order and within the time frame) (Bonstrup et al., 2020; Bonstrup et al., 2019).

The tapping speed was used to compute the following learning metrics: early micro-online learning, early micro-offline learning, early total micro-learning, and total learning across all trials. These metrics were computed for both the right and left hands, generating eight learning metrics. The first 11 blocks of training for the hand under consideration were used for studying early learning (Bonstrup et al., 2019). Micro-offline learning was defined as the difference in tapping speed (keypresses/second) between the first trial of a practice block and the last tria l of the previous block (Figure 2B, (Bonstrup et al., 2019)) and quantified learning that occurred during short periods of rest. Early micro-offline learning was computed as the sum of the micro-offline learning for the first 11 blocks. Micro-online learning was defined as the difference in tapping speed between the last and the first trial of a practice block (Figure 2B, (Bonstrup et al., 2019)) and quantified learning that occurred during short periods of practice. Early micro-online learning was computed as the sum of the micro-online learning for the first 11 blocks. Total micro-learning was defined as the sum of the micro-offline and micro-online learning and quantified the learning between blocks (i.e., from the beginning of one block to the beginning of the next block). Early total micro-learning was calculated as the sum of total micro-learning in the first 11 blocks and represented all changes in tapping speed during early learning (Bonstrup et al., 2019). Total learning over all trials was calculated as the difference between the mean trial tapping speed of the first and the last block of practice.

To quantify if performance improvements transferred from one limb to the other (i.e., interlimb transfer), two transfer metrics were calculated: early transfer and late transfer (Figure 2C). Early transfer was calculated as the difference between the mean trial tapping speed of the left and right hands on the first block of practice. Late transfer was calculated as the difference between the mean trial tapping speed of the left and right hands on the last block of practice.

Data Management and Analyses

Data from two participants were excluded from the analysis. One participant from the unsupervised group was excluded because they did not understand the experimental instructions and performed only one trial per block. A participant from the supervised group was excluded because they had a very high mean tapping speed and was identified as an outlier based on Tukey's fences (Tukey, 1977).

An inclusive statistical approach that involved classical (p-value) and Bayesian analyses (Bayes Factor) was used when comparing the results of supervised and unsupervised learning. Learning and interlimb transfer data were compared between the supervised and unsupervised groups using two-tailed two-sample t-tests and two-tailed Bayesian two-sample t-tests. The Bayes factor (BF_{01}) for the likelihood of the null hypothesis (groups are equal) over the alternative hypothesis (groups are different) was used to interpret the results from two-tailed Bayesian two-sample t-tests. P-values were adjusted for multiple comparisons using the Benjamini-Hochberg procedure (BHP) to control for false discovery rate (FDR) (Benjamini & Hochberg, 1995; Glickman, Rao, & Schultz, 2014; Korthauer et al., 2019). If no significant differences were observed between the groups across all metrics, the data from all participants were collapsed for each of these metrics and a two-tailed one-sample t-test was run to test for practice effects on learning and interlimb transfer. Again, the Benjamini-Hochberg procedure was used to control for FDR due to multiple comparisons. A significance level of $\alpha = 0.05$ was used for all statistical analyses.

Additionally, a linear discriminant analysis (LDA) model was trained to classify the group for each participant, using the ten learning and interlimb transfer metrics described above as features of the LDA model. The output from the LDA classifier was compared to that from a random classifier (a random classifier simply 'guesses' between the two groups) to determine whether the features contained enough information to discriminate between the two groups. The comparison between the two classifiers was performed using Dietterich's 5x2-fold cross-validation (CV) test (i.e., 5 iterations of twofold cross-validation), which is more powerful and less prone to type I errors than paired t-tests when comparing classifiers (Dietterich, 1998). This process was iterated 1000 times to get a distribution of the accuracy of the classifiers and the p-values. Note that if the null hypothesis is true (no difference in accuracy between LDA and random classifiers), then the p-values should follow a uniform distribution.

Results

All the data for the supervised (code = 5P6U) and unsupervised (code = C6XN) groups are available here: https://osf.io/k43qw/. Participants in the supervised group had similar learning curves across both hands to those in the unsupervised group (Figures 3A and 3B).

Both groups improved in tapping speeds in the early trials and then tended to stabilize towards the end. The initial tapping speed was generally higher on the right hand when compared with the left hand in both groups. No significant difference between the groups in any of the ten metrics described above were found (all BHP adjusted p-values ≥ 0.65, Table 1 and Supplemental Figures 1 and 2). The observed effect sizes were also small, and the BF_{01} values were generally favoring the null hypothesis (Table 1). The two classifiers (LDA and random) did not show a significant difference (52 ± 5% vs. 50 ± 3% (mean ± S.D.); mean p=0.55) when predicting the group of participants (Figure 4). The p-values from the Dietterich's test followed a uniform distribution with a mean p = 0.55 with p-values exceeding the significance level ($\alpha = 0.05$) for 97.2% of the time.

Table 1: Descriptive data for the ten learning metrics in the supervised and unsupervised groups.

Variable	Unsupervised (Mean ± S.D.)	Supervised (Mean ± S.D.)	Effect Size Cohen's d	Bayes Factor (BF_{01})
Left early total micro-learning	1.21 ± 1.70	2.08 ± 1.24	−0.602	0.80
Left early micro-offline learning	4.81 ± 4.89	3.75 ± 4.27	0.234	2.60
Left early micro-online learning	−4.10 ± 5.36	−2.10 ± 5.09	−0.384	1.81
Right early total micro-learning	1.12 ± 1.19	1.41 ± 1.88	−0.174	2.87
Right early micro-offline learning	2.75 ± 5.13	3.31 ± 5.58	−0.104	3.10
Right early micro-online learning	−2.08 ± 6.22	−2.33 ± 6.80	0.038	3.21
Total left learning	2.20 ± 1.81	2.24 ± 1.23	−0.022	3.23
Total right learning	1.02 ± 1.13	1.23 ± 1.54	−0.146	2.97
Early transfer	1.23 ± 1.57	1.21 ± 1.37	0.013	3.23
Late transfer	0.05 ± 0.81	0.20 ± 1.01	−0.162	2.91

S.D. = standard deviation. Note that two-sample t-tests with false discovery rate (FDR) corrections for multiple comparisons using the Benjamini-Hochberg procedure (BHP) indicated that none of the variables were significantly different between the groups (all BHP adjusted p-values > 0.65).

After collapsing data from both groups, all metrics except *late transfer* were significant (Table 2). On the left hand, micro-offline learning was positive for all early blocks of training, while micro-online learning was positive only in the first block and near-zero or negative for the remainder of early training (Figure 5A). The decomposition of early learning into micro-offline and micro-online learning showed that early learning was initially driven by positive gains in micro-offline learning but eventually plateaued as gains in micro-offline learning were offset by a loss in micro-online learning (Figures 5C and 6 left). On the right hand, early learning plateaued earlier, with most learning appearing on the first two blocks (Figure 5 B and D, and 6 right). The micro-offline and micro-online learning followed a similar pattern as the left hand, except that the extent of micro-offline gains was smaller.

Table 2: Descriptive data for the ten learning metrics collapsed between groups

Variable	**All participants (Mean ± S.D.)**	**Effect Size Cohen's d**
Left early total micro-learning	$1.72 \pm 1.49^{\dagger}$	1.155
Left early micro-offline learning	$4.19 \pm 4.51^{\dagger}$	0.930
Left early micro-online learning	$-2.93 \pm 5.23^{\dagger}$	−0.560
Right early total micro-learning	$1.29 \pm 1.62^{\dagger}$	0.797
Right early micro-offline learning	$3.08 \pm 5.34^{\dagger}$	0.577
Right early micro-online learning	$-2.23 \pm 6.49^{\dagger}$	−0.343
Total left learning	$2.22 \pm 1.48^{\dagger}$	1.503
Total right learning	$1.14 \pm 1.37^{\#}$	0.831
Early transfer	$1.22 \pm 1.43^{*}$	0.849

Late transfer	0.13 ± 0.93	0.146

S.D. = standard deviation. Note that one-sample t-tests with false discovery rate (FDR) corrections for multiple comparisons using the Benjamini-Hochberg procedure (BHP) indicated that all of the variables, except late transfer, were significantly different from 0. Daggers (†) denote $p<0.001$, hashes (#) denote $p<0.01$, and asterisks (*) denote $p<0.05$.

Early transfer (*i.e.,* the difference between tapping speed in the left and right hands in the first block of training) was significantly different from zero (1.22 ± 1.43 keypresses/s, Mean ± S.D., BHP adjusted p = 0.038), but late transfer (*i.e.,* the difference between tapping speed in the left and right hands in the last block of training) was not significantly different from zero (0.13 ± 0.93 keypresses/s, Mean ± S.D., BHP adjusted p = 0.356).

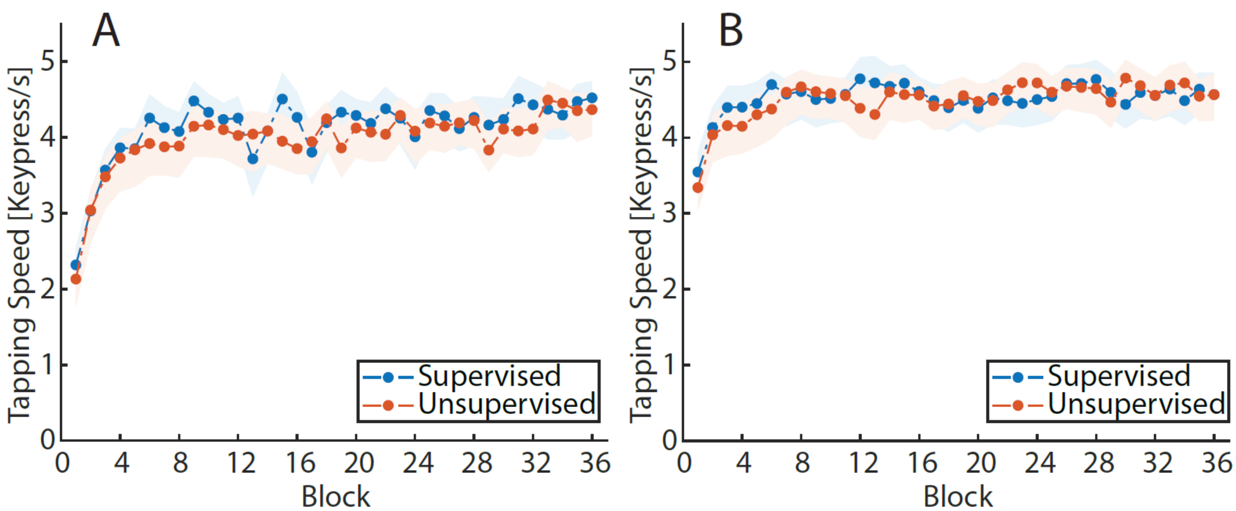

Figure 3 – Tapping speed performance: A scatterplot showing the mean tapping speed (keypresses/second) of the supervised and unsupervised groups in each block of practice for the **(A)** left and **(B)** right hand of the participants. The shaded region indicates the standard error of the mean (SEM). Note that the performance on the finger tapping task was similar between the supervised and unsupervised groups for both hands. Also, note that the tapping speed on the initial block of the right (i.e., transfer) hand was higher than the left (i.e., training) hand, indicating the presence of interlimb transfer of procedural skill learning.

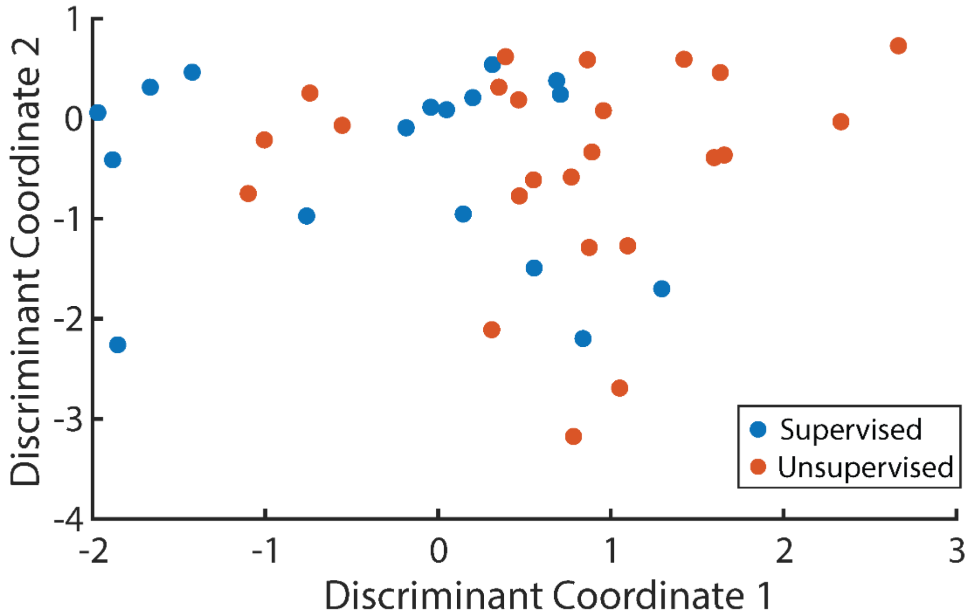

Figure 4 – Classification using Linear Discriminant Analysis (LDA) model: Scatterplot showing the projection of the ten features described in Tables 1 and 2 to the first two discriminant coordinates of a linear discriminant analysis (LDA) model. Each marker represents a single participant, and the color represents the group they belong to. No clear separation can be observed between the two groups, and no significant difference in classification accuracy was found between the LDA classifier and a random classifier (mean p = 0.55). Note that for visualization purposes only the first two discriminant coordinates have been plotted.

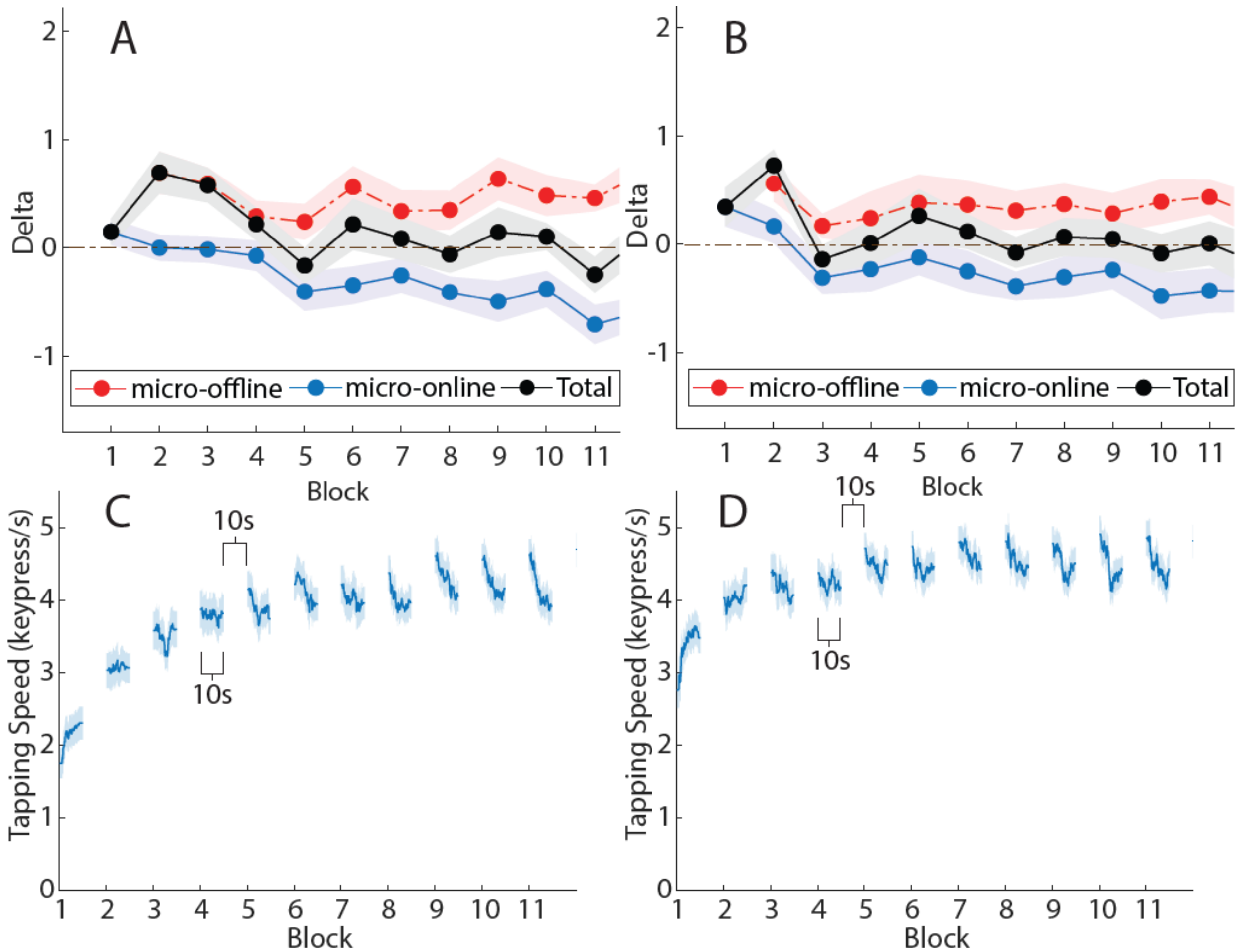

Figure 5 – Micro-scale learning: A scatterplot showing the mean micro-scale (micro-offline, micro-online, and total) early learning (first 11 blocks) for the **(A)** left and the **(B)** right hand across all participants. Micro-offline learning was defined as the difference in tapping speed (keypresses/second) between the first trial of a practice block and the last trial of the previous block and quantified learning that occurred during short periods of rest. Early micro-offline learning was computed as the sum of the micro-offline learning for the first 11 blocks. Micro-online learning was defined as the difference in tapping speed between the last and the first trial of a practice block and quantified learning that occurred during short periods of practice. Early micro-online learning was computed as the sum of the micro-online learning for the first 11 blocks. Total micro-learning was defined as the sum of the micro-offline and micro-online learning and quantified the learning between blocks. Early total micro-learning was calculated as the sum of total micro-learning in the first 11 blocks and represented all changes in tapping speed during early learning. The shaded region represents the standard error of the mean (SEM). The horizontal dashed line shows the zero value. Note that micro-online learning was negative for most of the blocks, indicating that participants had higher tapping speeds at the beginning than at the end of each block. Traces showing the mean tapping speed for the **(C)** left and **(D)** right hand across all participants for the ten

seconds in each block during early learning. The shaded region represents the SEM. Note that this plot was created only for visualization purposes and the details for creating this plot are provided in the supplementary material.

Discussion

This paper introduces a novel open-source web-based application that allows researchers with no coding experience to create and conduct their own motor sequence learning experiments from anywhere in the world. The feasibility of the application was also established by showing that (1) the results from unsupervised online experiments were comparable to those of supervised in-person experiments and (2) the results were qualitatively in close correspondence with previous studies (Bonstrup et al., 2020; Bonstrup et al., 2019). Finally, the flexibility of the platform was demonstrated by performing an interlimb transfer study to quantify the extent of motor skill transfer between the left and right hand. These findings demonstrate that the presented web-based platform could serve as a viable tool to conduct online procedural skill learning experiments that involve sequential finger tapping.

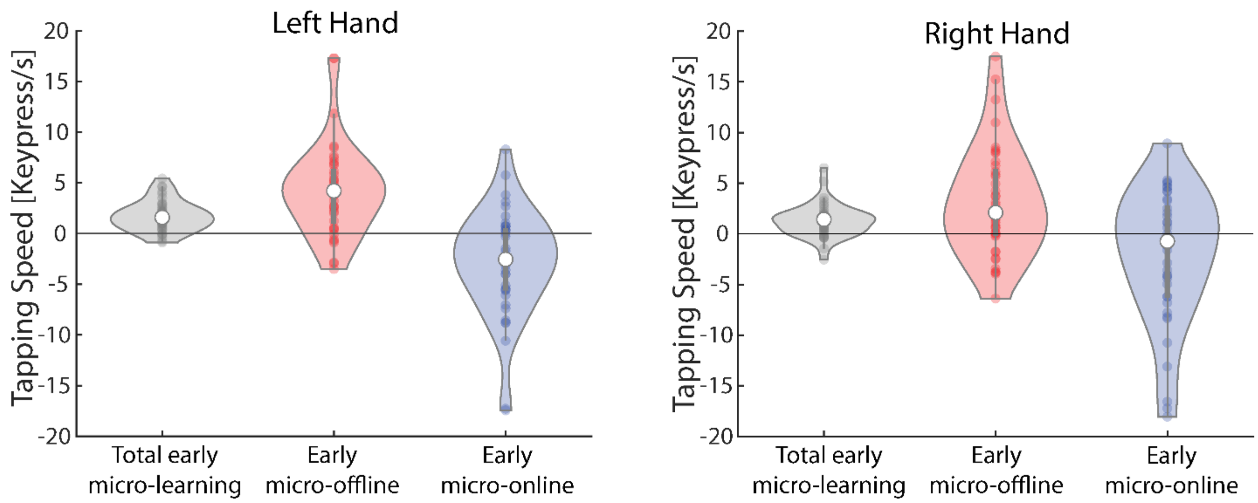

Figure 6 – Distribution of micro-scale learning: Violin plots showing the distributions of early micro-offline learning, early micro-online learning, and early total micro-learning for the **(left)** left and **(right)** right hand across all participants. Early micro-learning (micro-offline, micro-online, and total) was computed as the sum of the values observed in the first 11 blocks. Note that the white circles indicate the median values, the filled circles indicate individual data points, and the width of the shaded region represents the approximate frequency of data points in each region.

Previous studies have evaluated the feasibility of conducting online behavioral experiments ranging from reaction time measurements (Semmelmann & Weigelt, 2017) to motor learning studies involving sequential finger tapping task (Bonstrup et al., 2020) and visuomotor adaptations (Tsay et al., 2021). These studies have found that online experiments yield similar results to those performed in-person in the lab and can be a suitable alternative to laboratory experiments (Bonstrup et al., 2020; Casler, Bickel, & Hackett, 2013). The results presented here are consistent with these studies, as no meaningful differences were found in any of the measured parameters between the supervised and the unsupervised groups despite differences in background and ethnicity. This finding and those of others indicate that a highly structured laboratory environment may not always be necessary to conduct certain types of motor learning experiments, particularly when no special instrumentation other than a personal computer is needed for the experiment. Furthermore, conducting experiments online is helpful for researchers, as it allows them to collect data more efficiently from a broader subject pool that would otherwise be impossible due to financial or geographical constraints (Paolacci & Chandler, 2014). Recruiting from previously inaccessible subject pools makes study results more generalizable. Running experiments online also usually decreases the data collection time (Bonstrup et al., 2020), as subjects can participate simultaneously and at any time, without laboratory space or work hours constraints.

Participants showed a steep increase in tapping speed in the early blocks, followed by a rapid stabilization in the later blocks. When decomposing the early learning into micro-online and micro-offline learning, the results showed that the initial improvements mostly happened at rest rather than during practice. This finding is consistent with Bonstrup et al. (Bonstrup et al., 2019), who reported a rapid offline consolidation that contributed to early skill learning. While the exact mechanism for this phenomenon is unclear, some have argued that the emergence of offline improvements could be due to the loss of inhibitory drive or dissipation of fatigue during the short rest intervals (Robertson, 2019). Further studies are necessary to understand the mechanisms underlying these results.

The mean tapping speed on the initial block of the right hand was significantly higher than the left hand, indicating a significant interlimb transfer of motor skill learning. Other studies have shown similar inter-limb transfer in both adaptation (Lefumat et al., 2015; Jinsung Wang & Robert L Sainburg, 2004) and skill learning (Grafton et al., 2002; Japikse et al., 2003; Parlow & Kinsbourne, 1989; Perez et al., 2007) tasks. Previous studies on sequential motor learning tasks have shown that inter-limb transfer is present when the sequence for the second hand (i.e., transfer hand) is either the same or a mirrored sequence of the first hand (i.e., training hand) (Grafton et al., 2002). Thus, the observed interlimb transfer in this study may be due to the use of a mirrored sequence between the non-dominant and dominant hand, as opposed to some other random sequence. However, because of the study design, it is unclear whether the increase in tapping speed on the right hand was due to interlimb transfer or due to the advantage of the dominant hand. It is to be noted that no pre-test evaluations were performed to establish the baseline performance of the dominant, right hand because the use of pre-tests in motor learning has been criticized for yielding unreliable scores and providing practice of the task, thereby confounding the results of the intervention (Ranganathan, Lee, & Krishnan, 2022; Schmidt, Lee, Winstein, Wulf, & Zelaznik, 2011). However, when looking at the learning curves (Figure 3), it appears that this observation was primarily due to the transfer of the learned skill from the left hand, as this was only observed during the initial blocks of training. Further research may be needed to determine whether the transfer of learning occurs to the same extent when performing the task first with the dominant and then with the non-dominant hand, albeit, recognizing that this study design may also have limitations due to the presence of asymmetric transfer of learning between hands/hemispheres (Lavrysen et al., 2003; J. Wang & R. L. Sainburg, 2004).

Researchers interested in studying sequential motor learning with a finger tapping task will find the introduced software valuable because of its unique advantages over previously developed platforms. Specifically, the proposed platform has four innovative features. First, the platform requires no coding experience to create and manage sequential finger-tapping experiments online. Second, it is low cost and requires no specialized equipment or resources, including the need for web hosting. Third, it makes the experimental process highly time-efficient, as the set-up process is made easier by pre-hosting the platform on the google cloud platform and the data management process is made easier by pre-processing the data to extract key variables. Finally, the platform is highly flexible to run other forms of sequential finger tapping tasks (e.g., interlimb transfer) without the need for writing new scripts or codes to make this feasible.

Other software, such as PsychoPy (Peirce, 2007), PsyToolkit (Stoet, 2017), Gorilla (Anwyl-Irvine et al., 2020), and lab.js (Henninger et al., 2022), provide researchers with a common platform to create and/or distribute experiments. The four tools have great flexibility in the types of experiments that can be created and provide a way to either directly manage experiments or upload them to other management software, such as Pavlovia (https://pavlovia.org/). However, they have some limitations. PsychoPy requires the researchers to manually set up the necessary tools, which can be a challenge both in experiment creation and distribution. PsyToolkit, on the other hand, is a web-based platform; and thus, does not require any setup from the investigator. However, it requires learning the PsyToolkit scripting code to configure them, which could be a big challenge for most researchers. Gorilla overcomes the limitations of the previous tools, but its cost structure and closed-source nature could be a barrier and prevent the community from being able to actively participate in the development and prioritization of new bug fixes and features. Finally, lab.js is a recent open-source tool with great flexibility to create different types of motor learning experiments. However, it does not natively allow researchers to conduct online experiments and track participants' responses online, which makes it rely on other tools for that purpose. Furthermore, although finger tapping experiments can be created using their software, it requires researchers to have an intimate knowledge of the platform's documentation, experimental set-up process, and some amount of programming experience.

The software introduced here is an open-source web-based application that requires no setup and allows researchers to create sequential task motor learning experiments with a form-like graphical interface. Although it does not allow the creation of any type of motor learning or behavioral experiment, it greatly simplifies experiments involving finger tapping tasks by allowing the user to choose from an array of options for each possible configuration. Thus, it can facilitate online behavioral experiments for multiple research groups interested in procedural skill learning through sequential finger tapping tasks (Balas, Roitenberg, Giladi, & Karni, 2007; Bonstrup et al., 2020; Bonstrup et al., 2019; Friedman & Korman, 2016; Korzeczek et al., 2020; Van Der Werf et al., 2009; Witt et al., 2010) . The platform also simplifies the process of conducting experiments by providing a way of viewing the number of responses in real-time and allowing the researchers to enable or disable each experiment at any given time when satisfied with the number of responses.

The use of the web-based platform could potentially minimize the variation in tasks across studies, thereby reducing task fragmentation across motor learning studies. Scientists have argued that a high level of task fragmentation poses significant theoretical and methodological barriers to advancing the field (Ranganathan et al., 2021). The presented software addresses this issue by offering researchers a common task in the same platform to design and conduct their motor learning studies. This also allows for easier replication of motor learning studies. To ease this process further, a new feature will be eventually added to the platform that will allow users to export their experiment configurations as a file to be shared. Then, other users will be able to import that file and create a replica of the experiment created by the original researchers.

A limitation of the platform is that it can currently be used only to perform experiments involving sequential finger tapping tasks, making it less flexible than other similar coding-based platforms (Anwyl-Irvine et al., 2020; Henninger et al., 2022; Peirce, 2007; Stoet, 2017). It is to be noted, however, that there is a tradeoff between flexibility and usability. While other platforms are flexible to perform several cognitive and behavioral experiments, they only cater to the needs of researchers with programming/coding experience. Thus, the focus here was on the usability issue, where typical motor learning researchers (e.g., kinesiologists and rehabilitation scientists) find it difficult to use platforms that require coding experience. However, given the infrastructure developed for the platform, it would be relatively simple to expand the software to include other commonly used motor learning tasks with similar technical requirements. For instance, serial reaction-time tasks (Chambaron, Ginhac, & Perruchet, 2008; Robertson, 2007) could be easily integrated into the platform. In these tasks, stimuli must be shown at appropriate times, and the timing of the participant's responses must be recorded, both technical capabilities that the web application already possesses. Thus, extending the platform to those tasks would be a natural evolution. Furthermore, the platform is being released as open-source with a GNU GPL v3.0 license, allowing researchers to actively participate in the discussion and development of new features relating to online motor learning experiments. Another limitation is that there are no ready-made templates or a feature to export and import the experimental set-up. Given that it is straightforward to set up a new experiment in the platform quickly, there was no pressing need for this feature. However, this feature will be incorporated if future users of this platform request this ability.

Conclusion

In summary, this manuscript provides an open-source web-based platform for investigators in the motor learning field to easily create and conduct sequential finger tapping task studies. It allows researchers with no coding experience to design and manage their experiments completely online, with no setup requirements. The findings presented here establish the feasibility of obtaining valid results and pave the way to break the barriers to designing and conducting online motor learning experiments.

Availability of data and materials

All the data for the supervised (code = 5P6U) and unsupervised (code = C6XN) groups, including the supplementary material, are available here: https://osf.io/k43qw/. The full code for the platform is Open Source and can be found here: https://github.com/NeuRRoLab/motorlearningapp. All codes for post-processing the data and creating figures can be found here: https://github.com/NeuRRoLab/Online-Motor-Learning-Processing.

Conflict of Interest Statement

None of the authors have any conflict of interest.

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