From Pegs to Pixels: A Comparative Analysis of the Nine Hole Peg Test and a Digital Copy Drawing Test for Fine Motor Control Assessment

DOMINIK SCHÖN, Technical University of Darmstadt, Germany
THOMAS KOSCH, Humboldt-University Berlin, Germany
MARTIN SCHMITZ, Saarland University, Germany
SEBASTIAN GÜNTHER, Urban Software Institute, Germany
MAX MÜHLHÄUSER, Technical University of Darmstadt, Germany
FLORIAN MÜLLER, Technical University of Darmstadt, Germany

Fig. 1. In this work, we explore how the Fine Motor Control (FMC) assessed by the Nine Hole Peg Test (NHPT) (A) can be linked to metrics during drawing on a digital surface with a stylus (B) and touch (C).

User interaction with digital systems requires Fine Motor Control (FMC), especially if the interfaces are complex or require high fidelity and fine-grained interactions. Despite its importance, Fine Motor Control is often overlooked in interactive system design, partly because of its complex assessment. Measuring changes in fine motor abilities due to prolonged use or fatigue currently requires repeated manual testing. This paper analyzes the concept of using the digital mobile devices' input behavior to assess the user's Fine Motor Control. For this, we show that Fine Motor Control can be assessed for touch and stylus-based interaction with a digital mobile system. We conducted a user study, where participants performed a Nine Hole Peg Test and a predefined Copy Drawing Test before and after exercises that affect fine motor skills. Based on this data, we investigated how metrics such as pressure, velocity, and entropy for touch and stylus input can be used to predict Fine Motor Control.

CCS Concepts: • **Human-centered computing** → HCI theory, concepts and models; **Human computer interaction (HCI)**.

Authors' Contact Information: Dominik Schön, schoen@tk.tu-darmstadt.de, Technical University of Darmstadt, Darmstadt, Hesse, Germany; Thomas Kosch, thomas.kosch@hu-berlin.de, Humboldt-University Berlin, Berlin, Berlin, Germany; Martin Schmitz, mschmitz@cs.uni-saarland.de, Saarland University, Saarbrücken, Saarland, Germany; Sebastian Günther, research@sebastian-guenther.com, Urban Software Institute, Darmstadt, Hesse, Germany; Max Mühlhäuser, max@tk.tu-darmstadt.de, Technical University of Darmstadt, Darmstadt, Hesse, Germany; Florian Müller, florian.mueller@tu-darmstadt.de, Technical University of Darmstadt, Darmstadt, Hesse, Germany.

ACM 2573-0142/2025/9-ARTMHCI012
https://doi.org/10.1145/3743714

Additional Key Words and Phrases: Fine Motor Control, Nine Hole Peg Test

ACM Reference Format:
Dominik Schön, Thomas Kosch, Martin Schmitz, Sebastian Günther, Max Mühlhäuser, and Florian Müller. 2025. From Pegs to Pixels: A Comparative Analysis of the Nine Hole Peg Test and a Digital Copy Drawing Test for Fine Motor Control Assessment. *Proc. ACM Hum.-Comput. Interact.* 9, 5, Article MHCI012 (September 2025), 29 pages. https://doi.org/10.1145/3743714

1 Introduction

From tying shoelaces to using a smartphone, many everyday activities require precise finger movements, commonly known as Fine Motor Control (FMC). FMC therefore refers to the ability to coordinate muscles, bones, and nerves to perform precise, small-scale movements[1]. Fine-grained control over the limbs, particularly the hands and fingers, also significantly affects how effectively and accurately users interact with interactive systems. Almost all input mechanisms require a certain degree of finger and hand dexterity [57]. Whether using a desktop setup, where users rely on precise mouse and keyboard actions [96], a smartphone touchscreen [9, 63, 107] that demands accurate finger movements for tasks such as typing on small virtual keys, or Extended Reality (XR) environments, which require precise three-dimensional input and manipulation of holograms [86], FMC is essential to error-free and efficient interaction. When designing user input for digital mobile systems, designers often assume a fixed level of FMC by users. However, fine motor skills are significantly influenced by external factors such as diseases [15, 17, 20, 26, 26, 38, 46, 59, 75, 76, 108], physical exercise, or nutrition [31, 100], and variation between individuals. Consequently, depending on a user's general or situational fine motor abilities, the same interface might be seen as less effective.

This variability of FMC has significant implications: the design of interfaces may not be optimized for fine motor skills because their quantification has received limited attention in HCI and the outcomes of HCI experiments could be affected because fine motor skills are rarely measured, unlike other factors such as task load [37] or user experience [52]. While researchers often collect quantitative metrics such as error rates or task completion times, these measures are influenced by many factors, such as learning effects, fatigue, boredom, or distractions, and do not specifically isolate fine motor ability. As a result, changes in FMC over the course of an experiment may go unnoticed, misattributed or accounted to random noise. Our method enables the explicit observation of FMC and its fluctuations, offering a more targeted understanding of user input behavior and capabilities. It can also serve as a baseline measure in studies requiring precise input, helping to contextualize performance differences. For example, users with high FMC may complete complex and high-fidelity tasks more quickly and with less effort, while users with reduced FMC may struggle despite otherwise comparable cognitive or experiential factors. Recognizing and accounting for this variability is crucial for designing adaptive systems that respond effectively to individual motor capabilities. Given its relevant role in user input, interactive systems must accommodate their users' movement limits and capabilities, ideally adapting to the unique abilities of the individual in real time [57]. Achieving this level of dynamic adaptation requires the real-time recognition of FMC. To integrate FMC-aware adaptations, we first need to investigate the feasibility of detecting FMC directly on digital surfaces, such as tablets or smartphones.

Current approaches measuring FMC use special equipment, such as the widely used Nine Hole Peg Test (NHPT) [60]. Although the NHPT is a standard method for assessing fine motor control, it is also time-consuming [105] and requires specialized equipment and manual effort to conduct. To address these limitations, we propose to use copy drawing tasks on a mobile device, which leverage

[1] https://medlineplus.gov/ency/article/002364.htm, last visit: 22-01-2025

graphomotor skills, to predict NHPT completion time to gain insights in the FMC. Graphomotor skills, such as drawing, tracing, and writing, are considered specialized fine motor skills from a kinesiological perspective. These tasks involve coordinating visual and motor inputs, such as eye-hand coordination, to perform precise movements [6], rendering drawing a promising method for testing FMC. Copying drawing tasks could therefore be a practical and accessible substitute for traditional tests, like the NHPT.

This paper compares the established NHPT with a copy drawing test for assessing fine motor skills on a digital surface of a mobile device. In a user study, we observe different metrics, like velocity and pressure, while drawing using the touch or stylus pen as input. Using physical exercises, we endue a temporary change of FMC in individuals and observe the recovery using the NHPT and our Fine Motor Control Copy Drawing Tests. This allows us to observe the influence of the different levels of FMC on individuals' input behavior. Using this, we propose metrics that can be monitored to detect changes in FMC of the user.

2 Related Work

In this section, we summarize previous research in FMC, its relation to Physical Exercise (PE) and assessment, as well as previous handwriting and drawing analysis.

2.1 FMC in HCI

Fine Motor Control refers to the targeted coordination of small muscle movements, typically involving hands and fingers manipulating an object or system. It involves the complex interaction between the nervous system and small muscle groups to perform precise tasks, such as writing, buttoning clothes, or manipulating small objects [58]. Understanding and considering FMC is especially relevant in HCI as it enables humans to precisely manipulate input devices like keyboards, mice, touchscreens, and styluses, allowing for effective and efficient interaction with interactive systems [5, 57, 98, 107].

For instance, Smith et al. [96] investigated changes in the FMC in elderly people. Their finding indicated that older participants showed a decline in FMC, resulting in difficulty with controlling the mouse. Changes in the FMC result in changes in the performance of user input in interactive systems, highlighting the necessity to further investigate FMC in HCI for adaptation and prescreening of user study participants. Similarly, Kong et al. [49] proposed the Ability-Based Design Mobile Toolkit. The work showcases a toolkit for creating apps and being aware of the users' abilities. Combining detection and observation of human capabilities, like FMC or attention, enables the app to react to changes. Our work supports this approach by investigating in FMC quantification and detection of changes in such.

Another part of HCI research evolved around the accessibility of digital systems like touch screens [9, 63]. As previously mentioned, people with FMC impairment struggle with precise and fast input. For instance, Mott et al. [63] build a system called SmartTouch, to cope with non-regular touch input. Their work explored how people with impaired FMC interact with a digital surface and propose a way to allow relatively high precision input still.

Combining these works, we summarize that FMC plays a non-negligible role for user input. This underlines the necessity to put more effort into investigating ways to detect and quantify differences in FMC for future interactive systems, especially when talking about XR environments, which shows a correlation between FMC in the real and virtual world, and HCI user studies.

2.2 Assessments, Tests, and Changes of Fine Motor Control

Previous research has shown that FMC can be learned and trained, especially at a young age [6, 7, 43]. Previous research further showed a beneficial influence of physical exercise in children on fine motor control [6, 16, 77, 115], as well as in adults [45, 80, 101]. While there is considerable research highlighting the benefits for cognitive performance when doing Physical Exercise [14, 39, 92, 111], it also shows positive effects for motor performance [40] and motor learning [36, 41, 104]. Reasons for the improvement of FMC when doing regular Physical Exercise can be found in factors like an increased blood flow in the motor cortex [113], increased activity in the sensorimotor network [110], a larger basal ganglia volume [64, 66], increased the size of the hippocampus [4, 32, 67], and greater white matter volume [88]. All these systems are involved in forming the FMC of individuals.

To assess FMC, researchers came up with various approaches and tools. Most of them rely on manipulating small objects by the proband's hand. Example tests are the NHPT, the Purdue Pegboard Test (PPT), the Minnesota Manual Dexterity Test (MMDT) [94], or a pinch-test designed by Pradhan et al. [74]. Both tests rely on participants grabbing small objects and placing or stacking them in predefined places, like holes or pins. This work will use the NHPT by Mathiowetz et al. [60]. A standardized, quick, and widely used assessment tool to measure individuals' finger dexterity and fine motor skills. This task provides valuable data on hand function, coordination, and fine motor control. It is commonly used in clinical settings to evaluate patients with conditions such as stroke [15, 38], Alzheimer's [17, 26], Parkinson [20, 26, 75, 76], or Multiple Sclerosis [46]. The NHPT was also adopted in a Virtual Reality environment using a portable haptic device [21], enabling the collection of additional analysis metrics while conducting the test.

While these tests were proven to test the FMC, they require special hardware and manual assessment and can be,with completion times over a minute not including the setup time, very time-consuming to conduct [105]. With our work, we explore how interactive systems can assess and rank the users' FMC using data from the user input.

2.3 Handwriting and Drawing Analysis

Using Computers to analyze and extract information and properties about the writer using handwriting or drawing has been extensively researched in the past and is still relevant in today's context. The research not only explored methods to detect what the user has written using Optical Character Recognition (OCR) [22, 65, 102] and Handwritten Text Recognition (HTR) [3, 68], but also looked into techniques to reveal the writer's personality, psychological state, or behavior through graphology [70, 84], writer identification [23], and even detecting diseases.

Diseases and Disorders As an example, researchers found an influence of Alzheimer's disease on handwriting [10, 30]. They could detect the early stages of Alzheimer's using simple drawing and writing tasks. Recently, research also found a strong correlation between Attention Deficit Hyperactivity Disorder (ADHD) and the individual's handwriting [13, 51, 79]. Shin et al. present a way to detect Attention Deficit Hyperactivity Disorder (ADHD) in children using simple scribble and drawing tasks, designed to be accessible even to participants unable to write conventional words [61, 91].

Fatigue and Exertion Previous research not only investigated understanding the biomechanics of writing and the associated fatigue, pain, and exertion during writing [8, 50] but also used handwriting as a tool to observe exertion [28, 83, 87]. Garnacho-Castaño et al. observed the correlation of handwriting and drawing and fatigue responses of the body after physical activities [28]. They observed that the handwriting analysis showed noticeable differences in handwriting performance even after the muscles recovered from physical exertion, as indicated by lactate concentration. This work shows that drawing tasks can be used to investigate fatigue and exertion. Recently, Sesa-Nogueras et al. further investigated the connection between handwriting and fatigue [87]. Their work examines how physical fatigue affects the performance of signature and text-based biometric recognition methods. In the study, they found that fatigue negatively impacts signature-based recognition. However, it has little effect on text-based recognition if long sequences are used. While these studies provide valuable insights into fatigue-detection, our work focuses on a different but related construct of FMC. Unlike fatigue, which refers to the strain experienced from prolonged use, for example, FMC concerns the precision and coordination of small movements, such as accurately manipulating or moving. Although fatigue can influence FMC, the two are conceptually distinct and require independent investigation. By studying FMC in the context of smartphone-based tasks, we contribute new understanding of how to detect and quantify FMC on smartphones, which has direct implications for the design of accessible and adaptive mobile interfaces.

Fine Motor Control Cohen et al. [11, 12] explored using copy and tracing tasks to assess the development of Fine Motor Control in elementary school children. In a user study, children were tasked to copy and trace a circle using a graphic tablet. Their work shows the applicability of both tasks to evaluate FMC in a rapid, economical, and non-invasive way, aligning with previous work [29, 97, 103, 112]. While previous research has shown the value of drawing- and graphic tablet tasks, our method enables a more intuitive and natural interaction by allowing, for instance, free hand and arm placement [29] and does not require specialized hardware [97, 112] compared to previous work, making it well-suited for use in everyday environments. The advancements in technology allow us to use stock hardware compared to previous work having to use specialized tools and hardware to assess stylus data, like pen-tip pressure, required for the analysis [97, 112]. Especially circular patterns, like spirals, circles, or loops, were used to test FMC [53, 78]. These patterns test the individual through simple and repetitive movements [58]. They do not impose other strains on the subject, like a heavy cognitive load, because the drawings are simple, straightforward, and easy to memorize at a glance. However, they require good motor control in order to fulfill them[28].

2.4 Summary

Handwriting and drawing tasks have proven to be valuable tools for assessing various aspects like psychological states, health conditions, and FMC. These tasks are effective in testing FMC, as they require precise and controlled movements. This renders them a good candidate for evaluating fine motor skills. Simple patterns like spirals, circles, or loops demand minimal cognitive effort while still challenging motor abilities. Simple circular drawings make testing for FMC accessible and straightforward. To provoke changes in the FMC, we opted for Physical Exercise. PEs are effective in inducing both short- and long-term changes in FMC. This allows us to induce different states of FMC capabilities in individuals in our study. This approach allowed us to observe how variations in FMC affect participants' ways of drawing and NHPT completion time. Ultimately, we can observe changes in the subject's input behavior and interaction with a digital system.

3 Methodology

Based on the analysis approaches of handwriting and drawing in previous work, we formed the following hypothesis:

H: Drawing metrics can be used to predict Fine Motor Control assessed by the NHPT completion time

To check our hypothesis, we conducted a data gathering study to obtain data pairs of NHPT completion time and time series data of drawings. In addition to testing our hypothesis, we seek insight into which features contribute to the prediction. For this part of the experiment, We formulate the following research questions:

RQ1 What features or feature combinations that can be extracted from drawing with a pen on a digital surface best explain the FMC?
RQ2 What features or feature combinations that can be extracted from drawing with the finger on a touch surface best explain the FMC?
RQ3 How do the best stylus and finger models compare in terms of their accuracy in prediction?

3.1 Study Design and Task

We conducted a within-subjects data gathering study, where participants had to complete the NHPTand our copy drawing test, including drawing two shapes using touch and a stylus as input. Participants conducted the tests before and after physical activity, inducing a change in the FMC. Participants were asked to redo the two consecutive back-to-back tasks in swapped order for a total of four times with a 1-minute rest in between each set of test sequences. The 1-minute break was chosen based on related work [28] and facilitated time for the central nervous system and FMC to recover from the physical exercise exposure. The order of the copy drawing tests were randomized for all trials, shuffling input type (stylus or pen), and drawing (Archimedes Spiral or Loops). We opted for a counterbalanced approach for the NHPT and the copy drawing test to avoid carry-over effects, like testing fatigue, between the two tests. Switching the order grants no advantage for one test to be always carried out first.

Nine Hole Peg Test. The NHPT is an assessment tool to measure fine motor skills in individuals. We 3D printed a NHPT with the measures established by Mathiowetz et al. [60]. The board consists of nine evenly spread holes with 3.2cm center distance apart, 0.71cm diameter, and 1.3cm depth. The pegs have a diameter of 0.64cm and a length of 3.2cm. A peg tray was fitted on one side of the board to hold all nine pegs, see Figure 3. For further details on how to conduct the NHPT test, please see subsection 3.5.

Copy Drawing Test. We designed two copy drawing tests based on related work [25, 28, 117]. The user is tasked to copy a predefined shape using the touch screen and a stylus [23, 91]. Participants were asked to copy the displayed task template. We did not enforce a certain drawing style, as changes in speed and accuracy could be indicative for changes in the FMC. Therefore, participants were tasked to copy the template in a style they deemed necessary. Both tests required the performance of five repetitive movements. The Loops have five loops with leading and trailing ends, while the Archimedes Spiral has five circles with a trailing end, balancing the trade-off between required drawing space and repetition count. This information was communicated in the familiarization set. While the shapes seem simple, they involve repetitive patterns requiring accurate hand movement to draw them perfectly. We opted for the Archimedes Spiral and Loops, see Figure 2, to test our participant's FMC [28, 55]. The Archimedes Spiral task specifically challenges fine motor skills by requiring the participant to gradually increase the size of the circular movement to produce spirals without overlapping previously drawn lines. On the contrary, the Loops drawing task demands consistent rhythm and pattern throughout the drawing process. We further included a stylus in addition to touch input to reassemble a tool-based input and to gain insights about the user's exerted pressure on the digital surface.

3.2 Predictors

While related work proposes many metrics suitable for drawing- and writing tasks [28], we excluded metrics unsuitable for our study or not replicable. For instance, prior work proposes to measure the time in air. However, this metric is only suitable for figures and drawings that cannot be drawn using one continuous stroke, like our tasks, see Figure 2. For the analysis, we calculated key metrics for each time series data like *maximum*, *standard deviation*, and *entropy*, based on

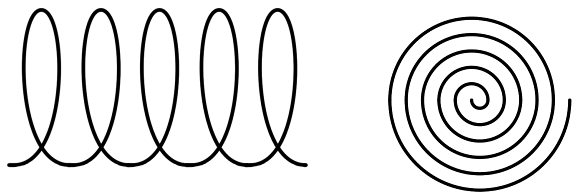

Fig. 2. The two drawing tasks from left to right: The two Fine Motor Control Tasks Loops, Archimedes Spiral.

related work [28]. Entropy is often used in signal processing [89] and is a measure of the signal's uncertainty, randomness, or complexity. It is defined as follows:

$$H(X) = -\sum_{i=1}^{n} p_i \log_2 p_i$$
$$\text{where } n = \text{number of bins},$$
$$p_i = \frac{\text{count of data points in bin } i}{\text{total number of data points}}$$

We recorded the following predictors:

Drawingtime Time elapsed between the first and last contact with the touchscreen using the finger or stylus, measured in *seconds*. We included Drawingtime as a predictor due to its property of being a task completion time. Because both our drawing test and the NHPT assess how long fine motor tasks take, drawing time is a natural predictor.

Speed The velocity of the fingertip or stylus-tip on the screen, measured in *pixels*/*milliseconds*. Further we calculated *Standard Deviation* (stdev_speed), *Maximum* (max_speed), and *Entropy* (entropy_speed). With these metrics, we can explore how fast and consistent the user moves the fingertip or stylus across the 2D digital surface. The key metrics help us to see fast and consistent the user moved. We suspect changes in the maximum speed and the overall consistency.

X Position Horizontal coordinate of the fingertip or stylus on the drawing pane, measured in *pixels*. We calculated the *Entropy* (entropy_x).

Y Position Vertical coordinate of the fingertip or stylus on the drawing pane, measured in *pixels*. We calculated the *Entropy* (entropy_y).

Delta X Movement-offset in horizontal direction since the last recording of the fingertip's or stylus' position, measured in *pixels*. Further we calculated *Standard Deviation* (stdev_dx), *Maximum* (max_dx), and *Entropy* (entropy_dx).

Delta Y Movement-offset in vertical direction since the last recording of the fingertip's or stylus' position, measured in *pixels*. Further we calculated *Standard Deviation* (stdev_dy), *Maximum* (max_dy), and *Entropy* (entropy_dy). *Delta X* and *Delta Y* allow us for a more in-depth analysis of the *Speed*. These two predictors split the velocity into two axis movements, vertical and horizontal. We suspect to find more information in *Delta Y* as the vertical based on the hypothesis that the vertical motion is less uniform than horizontal motion, as our participants share the same cultural horizontal left-to-right writing habits. This can lead to higher variability in vertical strokes, making it a sensitive indicator of fine motor performance.

Pressure (stylus only) Pressure detected at the stylus' tip. This predictor was only recorded for the stylus condition. Further we calculated *Standard Deviation* (stdev_pressure), *Maximum* (max_pressure), and *Entropy* (entropy_pressure). This metric directly reflects how controlled the

Fig. 3. The Copy Drawing Task on the left, with the template to copy at the top. Right shows the 3D printed NHPT.

user can move the stylus. Further, the key metrics quantify the unpredictability in how pressure is applied. This is a key indicator of unstable or imprecise control often linked to reduced FMC [58].

3.3 Outcome

NHPT Completion Time The time needed to complete the NHPT.

3.4 Study Setup and Apparatus

To test our participants, we 3D printed a NHPT pegboard [60] using polylactide (PLA) filament, see Figure 3, and developed a mobile app to guide the user through the copy drawing test. The 3D printed parts and source code files can be found on GitHub [2].

The copy drawing test was conducted using an iPad (7. generation running iPadOS 16.5) with an Apple Pencil (1. generation) as a stylus. The app, see Figure 3 for reference, was developed using Flutter (Version 3.22.3). After accounting for the space taken up by the app bar and the drawing template display, the app provides a drawable area of 810 x 788 pixels (28.58 x 27.8 cm of physical drawing space). The touch and stylus input was sampled roughly every 16 milliseconds.

3.5 Procedure

After welcoming the participants, we introduced them to the experiment. If no objections were raised against participation in the study, the subjects consented to participate by signing a formal agreement and recording their demographics. Before conducting the baseline test for the NHPT and our copy drawing test, participants could complete unrecorded trial runs to get used to the tools and task, see Figure 4.

The NHPT was presented and explained to the user, following the guidelines and manual provided by the National Multiple Sclerosis Society [3]. To conduct the NHPT, the user sits at a table with the pegboard in front of them. When given the start command, the user picks up the pegs, stored in a compartment on the board, one at a time and places them in the holes as quickly as possible. Users were instructed to move the pegs with their dominant hand while holding the board in place with the other hand [116]. Once all pegs are placed, the user immediately removes them and places them back in the compartment one at a time. If a peg falls on the table, the user is asked to pick it up and continue the task as usual. If a peg instead falls on the ground, the user is asked to continue the task while the study conductor collects the peg and places it at the last location. The test was

[2]https://github.com/Dominik-Schoen/FromPegsToPixels

[3]https://cdn.sanity.io/files/y936aps5/production/d52d1d7a55e52d10b09dcc39e47682ce2f735bb7.pdf?dl=, last visit 08-30-2024

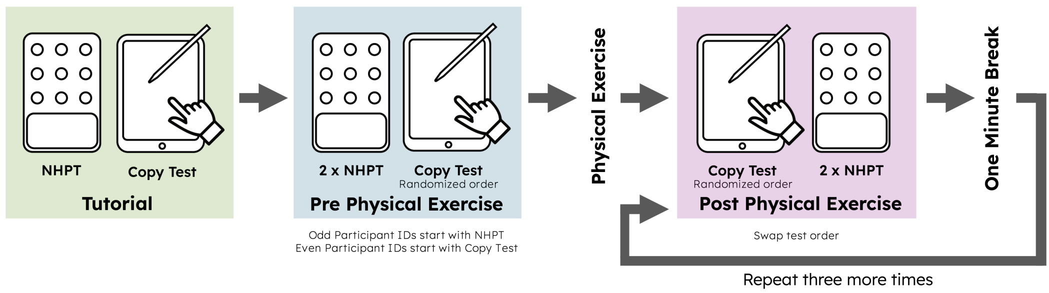

Fig. 4. Illustration of the experiment procedure. Participants started with a tutorial of both test to familiarize. Afterwards they conducted their pre phyiscle exercise tests, followed by the physical intervention. After reaching a predefined exertion, they conducted the tests again in swapped order with one minute break in between.

repeated two times, as proposed by prior work [116] and the National Multiple Sclerosis Society [4], and averaged. The total time taken to finish the task is recorded using a video to measure the time from the first and last contact of the peg.

When all questions about the NHPT were answered, we presented the copy drawing test, where participants could test drawing with their fingers and the stylus. Participants were instructed to copy the template shape displayed at the top of the screen in the lower part of the screen. Size, speed, and position on the drawing space could be freely chosen by the participant as they deemed necessary. When no questions remained regarding both tests, the experiment started with the pre physical exercise assessment. Depending on the Participant ID, they started with the NHPT or the copy drawing test. When conducting the copy drawing test, we first enter the participant ID, and present the participant the four tests. They were tasked to draw the Loops and Archimedes Spiral two times each. One time, they use the touch as input, and one time, they use the stylus. The order of these four tests were randomized for each trial.

After finishing both, the NHPT and the copy drawing test, participants were free to start their workout routine. Participants were recruited in a local functional fitness gym. Surpassing the threshold of seven on the Borg 10 scale, a subjective rating of exertion from 0 (no effort) to 10 (maximal effort), participants were asked to report to the study conductor. A value of seven indicates severe physical exhaustion, but not to the point of reaching or even exceeding the individual's maximum capacity and risking harm. This marked the period for the post physical exercise tests. Participants then redid the NHPT and the copy drawing test in swapped order. Completing the second task, the study conductor started the one-minute cooldown for the second retest. Participants redid this procedure a total of four times. Once the last two tests were conducted, we thanked the participants for participating in the user study and answered any further questions about the user study, if present.

3.6 Participants

We recruited eighteen participants (seven female, eight male, three preferred not to say) between 18 to 47 years ($\bar{x}$ = 32, s = 7.39) through peer network at a local gym. All participants confirmed the absence of musculoskeletal injuries or limitations of the arm and shoulder potentially influencing FMC measurement.

[4]https://www.nationalmssociety.org/for-professionals/for-researchers/researcher-resources/research-tools/clinical-study-measures/9-hpt, last visit 08-30-2024

Participants voluntarily agreed to take part in the study and were free to withdraw from the study at any time without a reason. The collected data can be viewed by the respective participant at any time and deleted at request. Recorded data includes drawings, input time series, and NHPT completion time. Videos used for measuring completion time were deleted after evaluation. No additional media was recorded during the study to protect user privacy. Besides snacks and drinks, no compensation was provided. Participants declared their willingness to participate in the user study by signing an informed consent form.

3.7 Analysis

To analyze the data gathered during the acquisition user study, we used *R* (version 4.3.2), the *lmerTest* package (version 3.1.3), and the MuMIn package (1.48.4) to fit Linear Mixed Effects Models.

4 The Impact of Physical Exercise on Fine Motor Control

As a prerequisite for fitting a model that can predict the NHPT time from the finger or stylus movements during the copy drawing test, we need data pairs that were recorded under different FMC levels. In the following section, we analyze whether our chosen approach of physical exercise was effective in provoking different FMC capabilities. For this, we conduct a Linear Mixed Effects Model to examine the effect of physical exercise on the NHPT completion time. The model includes the four assessment times *pre-PE*, *post-PE-1*, *post-PE-2*, *post-PE-3*, and *post-PE-4* as fixed effects, with random intercepts by *participant*, resulting in the formula $time\ assessment + (1|pid)$.

Model Fit and Variance Components The fit of the model was assessed using the REML criterion, which is *892.1* for convergence. The scaled residuals ranged from *-2.79* to *2.85*, with the median at *-0.08*, indicating a reasonable distribution of residuals around zero [85].

Random Effects The random effects, see Table 1, suggest variability in baseline NHPT completion time across participants.

Fixed Effects The fixed effects, see Table 2, suggest an affection of assessment time and the NHPT completion time. The NHPT completion time before the physical exercise (*pre-PE*) differs significantly from all post physical exercises (*post-PE-1*, *post-PE-2*, *post-PE-3*, and *post-PE-4*). The estimates reveal a decrease in the completion time after physical intervention. Interestingly, this trend continues throughout all *post-PE* assessments, see subsection 6.3.

Group	Effect	Variance	Std. Dev.
participant	Intercept	1.03	**1.01**
Residual	-	0.80	0.89

Table 1. Random Effects Summary for physical exercise intervention

Effect	Estimate	SE	df	t	p
pre-PE (Intercept)	17.46	0.30	19.79	63.10	< .001
post-PE-1	-0.92	0.16	300.00	-5.85	< .001
post-PE-2	-1.35	0.16	300.00	-8.54	< .001
post-PE-3	-1.49	0.16	300.00	-9.44	< .001
post-PE-4	-1.76	0.16	300.00	-11.17	< .001

Table 2. Fixed Effects Summary for *pre-PE*, *post-PE-1*, *post-PE-2*, *post-PE-3*, and *post-PE-4*. (PE = Physical Exercise)

Effect Sizes We observed the following $R^2_{marginal} = 0.17$, the proportion of variance explained by our fixed factor (*time assessment*), and $R^2_{conditional} = 0.64$, the proportion of variance explained by both the fixed and random factors (*Participant ID*).

Conclusion The analysis reveal a significant impact on the FMC induced by physical exercise. The intervention decreased the task completion time of the NHPT. Further, the high discrepancy between the $R^2_{marginal}$ and $R^2_{conditional}$ reveal a strong influence of the random factor *Participant*

ID, revealing a personal influence of individuals on the time as well. With this finding, we can confirm changes in the FMC after being exposed to physical exercise and explore the influence on the NHPT and drawing metrics in the following chapters. Please refer to subsection 6.3 for a more in-depth discussion and Appendix A for individual plots of the NHPT completion times of our participants.

5 Multiple Regression to Predict NHPT Completion Time

We conducted a multiple regression to reveal the correlation between the NHPT completion time and the different drawing metrics. We split the analysis for touch and stylus input, as different predictors are available. With this analysis, we aim to create a minimum set of predictors for the linear model. Adhering to Occam's razor, which favors simpler models with equivalent generalization error [18], we streamline the model using correlation-based feature selection [35] and by removing non-significant predictors. Reducing the feature set benefits machine learning by minimizing noise [27]. A good predictor subset includes features that are highly correlated with the prediction (e.g., NHPT Completion Time) but not with each other [35].

For the first simplification using correlation-based feature selection , we calculate a correlation table and eliminate predictors that correlate. With this approach, we get the first subset of predictors to create a base linear mixed effects model. For the second simplification using predictor elimination, we analyze the fixed effects and identify contributors with weak contribution-power. Ultimately, we compare both models to investigate the information loss after refinement.

5.1 Stylus Input

5.1.1 Stylus Base Model. We checked the predictors' correlation using a correlation Table 3. Strongly correlating predictors with $r > |0.700|$ were considered multicollinear and excluded. We identified *max_speed*, *entropy_speed*, *stdev_dx*, *max_dx*, *entropy_dx*, *max_dy*, and *entropy_dy* to be strongly correlated to *stdev_speed*. We, therefore, excluded those seven predictors. Further, *stdev_pressure* was found to be multicollinear to *max_pressure*, and *entropy_pressure*. Additionally, *max_pressure*, and *entropy_pressure* were strongly correlating aswell. We removed *stdev_pressure* and *max_pressure*, as *entropy_pressure* facilitates the highest correlation with the outcome, *NHPT Time*. Lastly, we identified a strong correlation between *entropy_x* and *entropy_y*. We removed *entropy_x*, as *entropy_y* has a stronger correlation to *NHPT Time*.

Beyond the multicollinearity check, our predictor selection was guided by FMC theory and related work [28]. *Drawingtime* was included as both our drawing task and the NHPT measure task completion time, making it a conceptually aligned predictor. *entropy_pressure* and *stdev_speed* reflect unpredictability and variability in pressure and movement across the digital surface, capturing imprecise motor control commonly linked to reduced FMC [58]. *entropy_y* and *stdev_dy* further refine this by specifically focusing on vertical movement. We hypothesis that vertical motion is less uniform than horizontal motion, as our participants share the same cultural horizontal left-to-right writing habits. This can lead to higher variability in vertical strokes, making it a sensitive indicator of fine motor performance. For further discussion of predictor relevance and interpretation, see subsection 6.1.

Based on the reduced set of predictors, we formulate the following linear mixed effects model: $time \sim drawingtime + entropy\_y + entropy\_pressure + stdev\_speed + stdev\_dy$. Since we observed a high personal effect in section 4, we included a random intercept for the participant id (pid), resulting in: $time \sim drawingtime + entropy\_y + entropy\_pressure + stdev\_speed + stdev\_dy + (1|pid)$.

			Speed			Pressure			DX			DY				
	time	drawingtime	stdev	max	entropy	stdev	max	entropy	stdev	max	entropy	stdev	max	entropy	entropy x	entropy y
time	1.000	0.221	0.101	0.067	0.135	0.057	0.026	0.105	0.103	0.076	0.137	0.038	0.006	0.051	0.106	0.119
drawingtime	0.221	1.000	0.330	0.281	0.280	0.029	0.053	0.003	0.263	0.314	0.238	0.468	0.343	0.455	0.575	0.493
stdev_speed	0.101	0.330	1.000	**0.743**	**0.920**	0.381	0.368	0.392	**0.948**	**0.932**	**0.878**	0.683	**0.773**	**0.720**	0.123	0.196
max_speed	0.067	0.281	**0.743**	1.000	0.486	0.042	0.070	0.053	0.525	0.674	0.449	0.466	0.462	0.448	0.149	0.016
entropy_speed	0.135	0.280	**0.920**	0.486	1.000	0.492	0.459	0.504	**0.971**	**0.867**	**0.983**	0.674	**0.788**	**0.772**	0.006	0.331
stdev_pressure	0.057	0.029	0.381	0.042	0.492	1.000	**0.948**	**0.950**	0.482	0.391	0.492	0.431	0.513	0.449	0.085	0.246
max_pressure	0.026	0.053	0.368	0.070	0.459	**0.948**	1.000	**0.895**	0.456	0.368	0.455	0.445	0.521	0.448	0.089	0.249
entropy_pressure	0.105	0.003	0.392	0.053	0.504	**0.950**	**0.895**	1.000	0.492	0.399	0.507	0.405	0.484	0.423	0.095	0.273
stdev_dx	0.103	0.263	**0.948**	0.525	**0.971**	0.482	0.456	0.492	1.000	**0.905**	**0.945**	0.668	**0.803**	**0.738**	0.004	0.327
max_dx	0.076	0.314	**0.932**	0.674	**0.867**	0.391	0.368	0.399	**0.905**	1.000	**0.827**	0.698	**0.769**	**0.731**	0.106	0.206
entropy_dx	0.137	0.238	**0.878**	0.449	**0.983**	0.492	0.455	0.507	**0.945**	**0.827**	1.000	0.624	**0.761**	**0.760**	0.067	0.404
stdev_dy	0.038	0.468	0.683	0.466	0.674	0.431	0.445	0.405	0.668	0.698	0.624	1.000	**0.899**	**0.917**	0.082	0.131
max_dy	0.006	0.343	**0.773**	0.462	**0.788**	0.513	0.521	0.484	**0.803**	**0.769**	**0.761**	**0.899**	1.000	**0.888**	0.015	0.301
entropy_dy	0.051	0.455	**0.720**	0.448	**0.772**	0.449	0.448	0.423	**0.738**	**0.731**	**0.760**	**0.917**	**0.888**	1.000	0.023	0.281
entropy_x	0.106	0.575	0.123	0.149	0.006	0.085	0.089	0.095	0.004	0.106	0.067	0.082	0.015	0.023	1.000	**0.811**
entropy_y	0.119	0.493	0.196	0.016	0.331	0.246	0.249	0.273	0.327	0.206	0.404	0.131	0.301	0.281	**0.811**	1.000

Table 3. Rounded correlation values between different predictors (values > 0.7 are bold) for stylus input

Model Fit and Variance Components The model fit was evaluated using the REML criterion, being *521.9* at convergence. The scaled residuals ranged from *-2.24* to *2.73*, with the median at *-0.17*, indicating a reasonable distribution of residuals around zero.

Random Effects The Random Effects, see Table 4, suggest variability in baseline NHPT completion time across participants. We further report the Unadjusted ICC = 0.415 and Adjusted ICC = 0.448. This highlights that about 44.8% of the variance is attributable to participant differences.

Fixed Effects The Fixed Effects, see Table 5, suggest the significance affection of *drawingtime* and the NHPT completion time. Further, *entropy_pressure* should also be highlighted, being close to significant. We, therefore, consider this variable to be kept in the model in further refinements and simplifications.

Group	Effect	Variance	Std. Dev.
participant	Intercept	0.95	**0.97**
Residual	-	1.17	1.08

Table 4. Random Effects Summary for Stylus Base Model.

Effect	Estimate	SE	df	t	p
(Intercept)	15.47	1.56	153.99	9.92	< .001
drawingtime	0.13	0.05	143.73	2.313	< .05
entropy_y	-0.14	0.28	154	-0.5	0.62
entropy_pressure	0.41	0.28	131.17	1.94	0.0544
stdev_speed	-0.47	0.38	154	-1.23	0.22
stdev_dy	0.03	0.03	153.5	0.94	0.35

Table 5. Fixed Effects Summary for Stylus Base Model.

Effect Sizes We observed the following $R^2_{marginal} = 0.07$ and $R^2_{conditional} = 0.49$.

Conclusion The proposed linear mixed effects model successfully identifies *drawingtime* as a significant predictor of NHPT completion time and accounts for subject-level variability, but it does not effectively utilize other predictors. Again, the effect sizes reveal a strong personal influence of individuals on the time as well.

5.1.2 Refined Stylus Base Model. Since the *Stylus Base Model*, see subsubsection 5.1.1, includes lots of predictors not significantly contributing to the prediction of the NHPT completion time, we further fitted a simplified model, just utilizing the *drawingtime* and *entropy_pressure* to compare this even more simplified model, resulting in: $time \sim drawingtime + entropy\_pressure + (1|pid)$.

Model Fit and Variance Components The model fit was evaluated using the REML criterion, being *518.3* at convergence. The scaled residuals ranged from *-2.34* to *2.63*, with the median at *-0.13*, indicating a reasonable distribution of residuals around zero.

Random Effects The Random Effects, see Table 6, suggest variability in baseline NHPT completion time across participants. We further report the Unadjusted ICC = 0.419 and Adjusted ICC = 0.443. This highlights that about 44.3% of the variance is attributable to participant differences.

Fixed Effects The Fixed Effects, see Table 7, suggest the significance affection of *drawingtime* and the NHPT completion time. However, *entropy_pressure* does not seem to significantly contribute to the model.

Group	Effect	Variance	Std. Dev.
participant	Intercept	0.93	**0.97**
Residual	-	1.17	1.08

Table 6. Random Effects Summary for Refined Stylus Base Model.

Effect	Estimate	SE	df	t	p
(Intercept)	14.94	0.65	97.49	22.81	< .001
drawingtime	0.10	0.04	155.92	2.56	< .05
entropy_pressure	0.32	0.19	127.74	1.63	0.11

Table 7. Fixed Effects Summary for Refined Stylus Base Model.

Effect Sizes We observed the following $R^2_{marginal} = 0.05$ and $R^2_{conditional} = 0.47$.

Conclusion The proposed linear mixed effects model again identifies *drawingtime* as a significant predictor of the NHPT completion time. However, *entropy_pressure* does not seem to improve the model in a significant way.

5.1.3 Comparing Stylus Base Model and Refined Stylus Base Model. We compared both models from above using an ANOVA, see Table 8. The results indicate that the more complex *Stylus Base Model* is not significantly better than the *Refined Stylus Base Model*. This can also be observed when comparing the model's prediction of the NHPT completion time with the actual measured one, see Figure 5. Please refer to subsection 6.1 for further discussion.

Model	AIC	BIC	logLik	deviance	Chisq	Df	p
Refined Stylus Base Model	521.30	536.67	-255.65	511.30			
Stylus Base Model	524.54	549.14	-254.27	508.54	2.7607	3	0.43

Table 8. ANOVA comparing Comparing Stylus Base Model and Refined Stylus Base Model

5.2 Touch Input

5.2.1 Touch Base Model. We followed the same process we used to analyze the stylus input for the touch input. To do so, we checked the predictors' correlation using a correlation Table 9. Strongly correlating predictors with $r > |0.700|$ were considered multicollinear and excluded. we identified *stdev_dx*, *max_dx*, *entropy_dx*, *max_dy*, *entropy_dy* to strongly correlate with *entropy_speed* and *stdev_speed*. We removed all five predictors because of their multicollinearity. Further, we removed *stdev_speed* because it strongly correlates with *entropy_speed* but has a worse correlation with *NHPT time* compared to *entropy_speed*. Finally, we removed *entropy_x* because of the correlation with *entropy_y*. *Entropy_x* had a higher correlation with *NHPT Time* rendering it a better predictor.

Similar to the *Stylus Base Model* we performed a multicollinearity check and the FMC theory to find the most relevant predictors. Again, we included the *Drawingtime* as a predictor, as well as key metrics of *speed* and vertical screen movement (y). For further discussion of predictor relevance and interpretation, see subsection 6.1.

Based on the reduced set of predictors after the multicollinearity check, we formulate the following linear mixed effects model: $time \sim drawingtime + entropy\_y + entropy\_speed + stdev\_dy +$

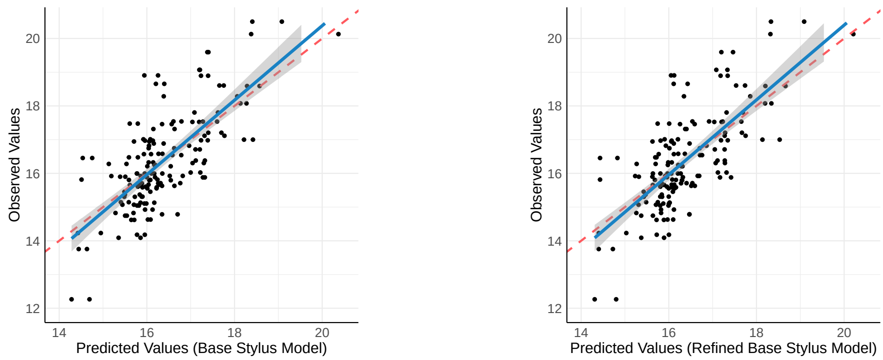

Fig. 5. Graphs comparing the predicted values to the observed values for the NHPT completion time. The red line shows the linear reference line, while the blue one shows a linear regression of the predictions, with the grey area depicting the confidence interval. Left graph shows the *Base Stylus Model*, the right one shows the *Refined Base Stylus Model*.

max_speed. Since we observed a high personal effect in section 4, we included the participant id (pid) as a random effect, resulting in: $time \sim drawingtime + entropy\_y + entropy\_speed + stdev\_dy + max\_speed + (1|pid)$.

			Speed			DX			DY				
	NHPT Time	drawing	stdev	max	entropy	stdev	max	entropy	stdev	max	entropy	entropy x	entropy y
NHPT Time	1.000	0.168	0.071	0.032	0.097	0.066	0.060	0.099	0.037	0.062	0.036	0.037	0.097
drawingtime	0.168	1.000	0.249	0.348	0.236	0.215	0.272	0.195	0.458	0.334	0.363	0.588	0.521
stdev_speed	0.071	0.249	1.000	**0.619**	**0.971**	**0.994**	**0.856**	**0.942**	**0.678**	**0.743**	**0.768**	0.033	0.241
max_speed	0.032	0.348	**0.619**	1.000	0.531	0.547	**0.872**	0.483	0.524	0.513	0.507	0.191	0.136
entropy_speed	0.097	0.236	**0.971**	0.531	1.000	**0.974**	**0.793**	**0.988**	**0.673**	**0.749**	**0.798**	0.080	0.314
stdev_dx	0.066	0.215	**0.994**	0.547	**0.974**	1.000	**0.815**	**0.953**	**0.655**	**0.730**	**0.759**	0.084	0.297
max_dx	0.060	0.272	**0.856**	**0.872**	**0.793**	**0.815**	1.000	**0.761**	0.606	**0.666**	**0.665**	0.027	0.094
entropy_dx	0.099	0.195	**0.942**	0.483	**0.988**	**0.953**	**0.761**	1.000	0.634	**0.722**	**0.787**	0.145	0.382
stdev_dy	0.037	0.458	**0.678**	0.524	**0.673**	**0.655**	0.606	0.634	1.000	**0.863**	**0.909**	0.184	0.006
max_dy	0.062	0.334	**0.743**	0.513	**0.749**	**0.730**	**0.666**	**0.722**	**0.863**	1.000	**0.877**	0.047	0.158
entropy_dy	0.036	0.363	**0.768**	0.507	**0.798**	**0.759**	**0.665**	**0.787**	**0.909**	**0.877**	1.000	0.005	0.215
entropy_x	0.037	0.588	0.033	0.191	0.080	0.084	0.027	0.145	0.184	0.047	0.005	1.000	**0.836**
entropy_y	0.097	0.521	0.241	0.136	0.314	0.297	0.094	0.382	0.006	0.158	0.215	**0.836**	1.000

Table 9. Rounded correlation values between different predictors (values > 0.6 are bold) for touch

Model Fit and Variance Components The model fit was evaluated using the REML criterion, being *530.6* at convergence. The scaled residuals ranged from *-2.29* to *2.68*, with the median at *-0.14*, indicating a reasonable distribution of residuals around zero.

Random Effects The Random Effects, see Table 10, suggest variability in baseline NHPT completion time across participants. We further report the Unadjusted ICC = 0.419 and Adjusted ICC = 0.437. This highlights that about 43.7% of the variance is attributable to participant differences.

Fixed Effects The Fixed Effects, see Table 11, suggest the significance affection of *drawingtime* and the NHPT completion time.

Effect Sizes We observed the following $R^2_{marginal} = 0.04$ and $R^2_{conditional} = 0.46$.

Conclusion The proposed linear mixed effects model identifies drawingtime as a significant predictor of NHPT completion time and accounts for subject-level variability. However, it does

Group	Effect	Variance	Std. Dev.
participant	Intercept	0.95	**0.97**
Residual	-	1.22	1.1

Table 10. Random Effects Summary for the Touch Base Model.

Effect	Estimate	SE	df	t	p
(Intercept)	15.93	1.88	153.2	8.5	< .001
drawingtime	0.13	0.06	145.53	2.16	< .05
entropy_y	0.03	0.33	152.76	0.1	0.92
entropy_speed	-0.25	0.26	153.95	*0.94	0.92
stdev_dy	0.01	0.03	153.78	0.34	0.73
max_speed	0.04	0.07	151.8	0.51	0.61

Table 11. Fixed Effects Summary for the Touch Base Model.

not effectively utilize other predictors. Again, the effect sizes reveal a strong personal influence of individuals on the time as well.

5.2.2 Refined Touch Base Model. Since the *Touch Base Model*, see subsubsection 5.2.1, includes lots of predictors not significantly contributing to the prediction of the NHPT completion time, we further fitted another more simplified model, just utilizing the *drawingtime* to create this more simplified model, resulting in: $time \sim drawingtime + (1|pid)$.

Model Fit and Variance Components The model fit was evaluated using the REML criterion, being *521.3* at convergence. The scaled residuals ranged from *-2.36* to *2.72*, with the median at *-0.16*, indicating a reasonable distribution of residuals around zero.

Random Effects The Random Effects, see Table 12, suggest variability in baseline NHPT completion time across participants. We further report the Unadjusted ICC = 0.426 and Adjusted ICC = 0.44. This highlights that about 44% of the variance is attributable to participant differences.

Fixed Effects The Fixed Effects, see Table 13, suggest the significance affection of *drawingtime* and the NHPT completion time.

Group	Effect	Variance	Std. Dev.
participant	Intercept	0.94	**0.97**
Residual	-	1.2	1.1

Table 12. Random Effects Summary for the Refined Touch Base Model.

Effect	Estimate	SE	df	t	p
(Intercept)	15.87	0.32	32.14	50.15	< .001
drawingtime	0.12	0.04	152.31	2.66	< .01

Table 13. Fixed Effects Summary for the Refined Touch Base Model.

Effect Sizes We observed the following $R^2_{marginal} = 0.03$ and $R^2_{conditional} = 0.457$.

Conclusion The proposed linear mixed effects model identifies drawingtime as a significant predictor of NHPT completion time and accounts for subject-level variability.

5.2.3 Comparing Touch Base Model and Refined Touch Base Model. We compared both models using an ANOVA, see Table 14. The results indicate that the more complex *Touch Base Model* is not significantly better than the *Refined Touch Base Model*.

This can also be observed when comparing the model's prediction of the NHPT completion time with the actually measured one, see Figure 6. Please refer to subsection 6.1 for further discussion.

5.3 Interpreting the Multiple Regression

In this chapter, we will briefly interpret the most relevant findings of the previous chapter and put them into perspective.

Model	AIC	BIC	logLik	deviance	Chisq	Df	p
Refined Touch Base Model	523.96	536.26	-257.98	515.96			
Touch Base Model	530.56	555.16	-257.28	514.56	1.396	4	0.84

Table 14. ANOVA comparing Comparing Touch Base Model and Refined Touch Base Model

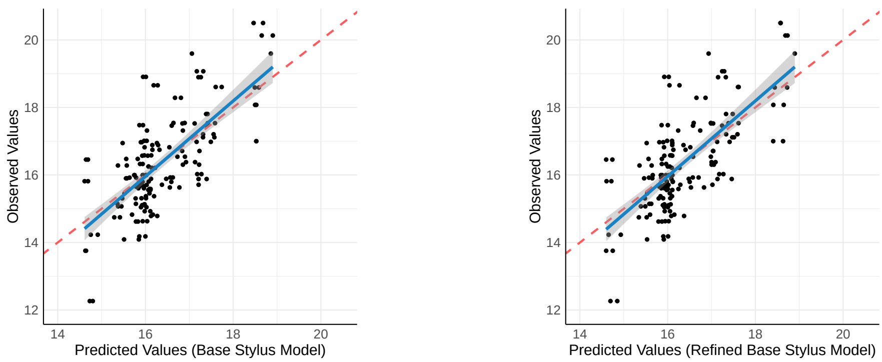

Fig. 6. Graphs comparing the predicted values to the observed values for the NHPT completion time. The red line shows the linear reference line, while the blue one shows a linear regression of the predictions, with the grey area depicting the confidence interval. Left graph shows the *Base Touch Model*, the right one shows the *Refined Base Touch Model*.

5.3.1 Performance of Individual Models. To interpret the performance and models, we first look at the variance components of our models. These values represent the distribution of the residuals. In other words, the distribution of the differences between the observed and predicted NHPT completion time. Ideally, these should be symmetrically distributed around zero, which they roughly are on all models we propose (Median scaled residual is between $M = -0.17$ and $M = -0.13$). This suggests the model is not grossly skewed or misspecified when predicting. The models do not constantly over- or underestimate the NHPT time.

Looking at the fixed effects of our models, we identified two predictors that strongly contribute to the model fit, namely *drawingtime* and *entropy pressure*. For both input methods, touch and stylus, the *drawingtime* had a significant influence. The estimates of *drawingtime* suggest for each additional second of *drawingtime* an increase of *0.1* to *0.13* seconds on the NHPT completion time. The longer users draw, the longer they need to finish the NHPT. For *entropy of pressure*, we found that an increase of *1* results in an estimated increase of *0.32* to *0.41* seconds in the NHPT.

We evaluate the quality of our models in predicting NHPT completion time by comparing predicted times to measured times. The median prediction error ranges from $M = 0.65$ to $M = 0.7$, indicating an offset of about *0.65* to *0.7* seconds. With a median NHPT completion time of $M = 16.12$ seconds, an offset below 0.7 seconds is deemed good. For interpretation, the influence of the physical exercise decreased the NHPT time by 0.92 to 1.76 seconds, see Table 2. Therefore, our models are fine enough to distinguish the changes induced by physical exercise on the participants. To visualize the prediction, we plotted each model's predicted and actual time in Figure 5 and Figure 6. The points represent each measurement, while the red line indicates the perfect prediction. Points residing on this line indicate a perfect prediction by the model. The blue line is the linear regression of all predictions of the respective model. The more similar these two lines, the better the overall prediction capabilities of the model.

5.3.2 Comparing Model Performances. To answer the question about the best model to predict the NHPT completion time, we can state that the refined base models work the best. For stylus input, a simple model using just *drawingtime* and *entropy pressure* works just as fine as the more complex base model with three additional predictors. We base this decision on the $R^2_{conditional}$ score (base model: *0.49*, refined base model: *0.47*) and median error of the prediction (base model: *0.697*, refined base model: *0.69*). For touch input, we observed the same behavior. The more simple refined base model using just *drawingtime* as a predictor works as well as the more complex base model with four additional predictors, based on $R^2_{conditional}$ score (base model: *0.46*, refined base model: *0.457*) and median error of the prediction (base model: *0.67*, refined base model: *0.65*). While these R^2 scores seem quite low at first, they are actually reasonable. Since this work focuses on human factors and the quantification of fine motor control, which in itself can not easily be measured, we expect quite some variance. Working with humans always introduces some uncertainty. For this reason, some research fields consider $R^2 > .1$ as good [69]. Since our study explores a challenging-to-observe phenomenon and represents a first attempt using this approach, we do not anticipate R^2 scores near one. In summary, our results indicate that understanding the user's FMC using only a few key metrics is feasible. The small set of predictors enables easy testing and integration in interactive systems without excessive complexity.

Finally, we can state that the pressure entropy adds relevant information to increase the prediction accuracy. To this end, the stylus model performs slightly better than the touch input and should be preferred.

5.3.3 Model Bias and Personalization. The random effects of our models indicate variability in the intercept, also called bias, across different participants. The model uses one common slope to predict the outcome but uses a personalized intercept, also called bias. In other words, it is hard to generalize a model for different people. The unadjusted ICC scores of around *0.41* to *0.43* confirm the differences between participants. The ICC explains how much of the variation in the NHPT time is due to differences between groups, here between participants, rather than just random noise. Even after adjusting to factors (adjusted ICC) like covariates, fixed effects, and participants, about 43.7% to 44.3% of the variance is still attributable to participant differences.

6 Discussion

We showed that our models can quantify the FMC by predicting the NHPT completion time using a copy drawing test on a digital surface using touch and stylus as input. This chapter will discuss our findings and how they relate to previous research.

6.1 Drawing Time and Entropy of the Pressure Predict the Fine Motor Control

Based on related work [28], we started with an extensive list of fifteen potential predictors. Through multicollinearity elimination, we ended up with only five predictors for each *base model*. This is somewhat expected, as the key metrics for time series data can especially easily correlate as they are based on the same source time series. For example, *Speed* and *Delta x* and *Delta y* are related. *Speed* adds a relation to time. Therefore, it is expected that not all of the three predictors will be required. Worth mentioning, however, is that *Drawingtime* is part of all models we created. When refining the base models and eliminating predictors not strongly contributing to the prediction, we end up with *Drawingtime* and for the stylus model, additionally with *Entropy Pressure*. The high prediction contribution of *Drawingtime* can be explained by the models predicting a FMC test's task completion time [60]. *Drawingtime* itself being a FMC test's task completion time [25, 28, 117]. Changes in the FMC should change both task completion times. We can observe this strong positive correlation when looking at the correlation table and fixed effects of our models. This renders the *Drawingtime* the best single predictor for NHPT completion time.

Further, we found *Entropy Pressure* to be a strong predictor. The entropy expresses the randomness, complexity, or unpredictability of a time series or signal. Therefore, *Entropy Pressure* reveals how randomly or unpredictably a person applies pressure on the stylus [1] and to the digital surface. Previous work linked this unsteadiness in pressure exertion to tremor under physical stress [1]. The higher the entropy, the more random a signal appears. Our user study found that the more random the signal, the longer the measured NHPT completion time and lowered FMC. People with lower FMC show more randomness in how they press the stylus on the screen. This suggests they have less control over steady muscle movements, leading to more unpredictable pressure. The definition of FMC helps explain why pressure randomness is a good predictor. FMC involves the coordination of the nervous system and small muscles to do precise tasks like writing, buttoning clothes, or handling small objects [58]. In the case of the stylus input, a reduced FMC results in a bad, imprecise pen manipulation. This phenomenon can not only be observed in the one-dimensional pressure but also in the manipulation on the 2D digital surface, namely the *speed*. Both base models, for stylus and touch input, include a key metric of *speed*. In the case of the stylus, the *entropy speed*, and in the case of the touch, the *standard deviation speed*. Combining pressure and speed reflects movement in a three-dimensional space on the digital surface. The *speed* expresses the horizontal and vertical movement, while the *pressure* completes the third dimension. Therefore, our drawing test and models can catch imprecision and fine changes in the movement of the hand, indicating a potential reduced FMC on the digital surface.

6.2 Personalization Needed

The random effects in our models show variability in the intercept (bias) across participants, indicating difficulty in generalizing the model. The ICC suggests that a significant portion of the variation in NHPT time is due to participant differences rather than random noise, even after adjusting for factors like covariates and fixed effects. The effect of differences between individuals can be explained by the general underlying different FMC capabilities of each person based on age [6, 7, 43], sex [60], or if and how often they do sports [93, 95]. Changes in the FMC, detected by changes in the NHPT completion time, can also be detected by our approach. When just interested in the changes of the FMC, you can use the proposed model out of the box. However, if you want to quantify the true NHPT competition time and not just changes between tests, the model requires an initial bias to offset the users' differences. Therefore, the user needs to complete the NHPT under normal circumstances, with no prior physical exercise for example. Once the bias is established, combining the bias with our model, we are able to predict the true NHPT completion time as a FMC assessment and not just changes of it.

Further, since the adjusted ICC is not close to *1*, a substantial amount of variability still occurs within each participant. In other words, there's still a lot of variation in the measurements within the same participant. While we understand what is considered to be FMC, the underlying mechanisms and systems contributing to and building the actual FMC are very complex. Performing FMC tasks requires the coordination of various muscles and nervous systems to plan, carry out, and adjust movements. For example, moving a peg in the NHPT involves the motor cortex [2, 71], cerebellum [19, 72], and basal ganglia [19, 34] to plan and execute the action. The spinal cord links the nervous system to the arm and hand muscles, enabling the peg's movement, while the peripheral nervous system sends sensory feedback to handle unexpected changes, like a peg slipping. Further many acute influences, like sleep [109], drugs [33, 82], or caffeine [42], also affect the FMC. Combined with the previous finding, interpersonal differences exist, and intrapersonal differences may occur based on the state and surroundings of the individual. The high variability within the participants can be explained by the sheer complexity of accessing FMC. Breaking the complex process down into just a handful of metrics extracted while interacting with a digital surface is insufficient to comprehend the FMC fully. But as we can see in Figure 6, Figure 5, and subsection 6.1, utilizing multiple predictions is sufficient to unveil changes in the FMC. Future research should consider different predictors or more complex models to improve the prediction further.

6.3 Increase in Fine Motor Skill After a Bout of Exercise

We included physical exercise in our study to induce short-term changes in FMC, as prior work suggests. While our primary objective was not primarily to study the relationship in depth, we observed contrary to expectations from related literature an increase of FMC instead of a decrease. Previous research suggested that exposure to physical exercise has an influence on the individual's FMC and requires longer to recover from the exposure than muscles and their built-up lactate [28]. Their work indicates a recovery of the muscles after three minutes, while the recovery timer for FMC remains indefinitely longer. With our testing procedure of four rounds of testing post-physical exercise and a one-minute break in between, we observed participants' recovery throughout a five to seven-minute time interval after the exposure to physical exercise. We expected the NHPT completion time to be slightly worse after the workout and drop back to or even deteriorate the baseline after recovering, as proposed by related work [28].

However, as seen in section 4, participants had constantly lower NHPT completion time after their exercise, indicating a higher FMC, compared to their baseline recording before working out. The fact that our participants immediately and constantly performed better in the NHPT after the physical intervention is surprising and unexpected. A possible explanation could be the neurochemical processes involved when exercising and specifically training fine motor skills. Regular exercises and fine motor skills exercises facilitate enhanced levels of hormones like dopamine, serotonin, and norepinephrine [93, 95], which in turn might facilitate improved neuroplasticity, enabling the brain to form new connections and help us acquire new skills [93]. However, neuroplasticity requires a long time to show effect. But research not only showed the long-term effects of physical exercise on fine motor control but also the influence of acute exposure on motor performance and learning were explored [81, 99, 106]. Roig et al. [81], for example, showed that acute training shortly before or after practicing fine motor skills significantly improved fine motor skills compared to a control group without training. The effect could be observed after 1 hour, 24 hours, and even 7 days after training.

While the observed improvement in FMC after physical exercise is noteworthy, we, as non-domain matter experts, avoid making definitive claims about the underlying cause, as current research offers conflicting explanations. In this work, our primary goal was to examine how interaction with digital surfaces relates to NHPT completion time across different FMC levels. We introduced a physical exercise intervention to induce a change in FMC. For our study, it is irrelevant whether it was a positive or negative change. As shown in section 4, this intervention successfully triggered measurable changes in participants' FMC. Our models were able to capture these changes and predict the corresponding NHPT completion times.

6.4 Using A FMC Mediator to Predict a FMC Mediator

As seen in our four predictor plots, Figure 5 and Figure 6, our models reach high accuracy, especially when using multiple measurements, supporting our overall hypothesis **H**. However, FMC is challenging to measure directly as no device or tool is available to quantify it directly on the human body. Instead, we rely on tests like the NHPT to get an estimate. However, these tests do not directly measure FMC. They rather act as indicators or mediators. The time it takes to complete these tests not only reflects a person's FMC but also includes other factors and can be affected quite heavily by small mistakes. For instance, if a peg drops while picking up another one and maybe even falls on the floor, the time spent retrieving and placing the peg counts towards the total assessment time. Such a mistake can penalize the score quite strongly, although it might not be caused by an equally strong failure of the FMC. Further, randomness can heavily influence the test results, as dropping a peg will leave the peg at a random position. If lucky, the peg is close to the test and does not have a huge impact. If not, the retrieval will add a huge penalty to the time. While you could exclude such trials, the NHPT's instruction set does not allow for such removals.

Our approach of using graphomotor skills can be seen as a FMC mediator, too. This test cannot directly measure and quantify FMC but instead quantifies the result of a FMC test. By predicting the NHPT completion time, we effectively predict a FMC mediator with a FMC mediator to check the validity of using a copy drawing test to gain insights into the FMC. This paper showed that our drawing test correlates with the NHPT, but we can not tell which of the tests quantifies the FMC the best. As mentioned, the NHPT can react quite sensitively to minor mistakes, like dropping one peg. Especially if this peg randomly falls on the ground. While such occurrences are rare in healthy individuals [60], they can happen, rendering the result indicative. Our proposed copy drawing test and detection on a digital surface do not suffer from such randomness factors, potentially rendering them more stable than the NHPT.

7 Use Cases and Applicability

This section presents use cases to illustrate the applicability and necessity of assessing FMC through digital surfaces for HCI.

7.1 Quantified Self and Personal Assessment

In recent years, self-tracking of health and fitness data, like heart rate, sleep or step count for example, has gained significant popularity [24, 56]. Traditional assessment methods for FMC such as the NHPT are unsuitable for this, as users would have to carry additional hardware with them. In contrast to this, our approach, which uses simple touchscreen-based drawing copy test to quickly evaluate FMC, aligns with this trend by offering an accessible, fast, and convenient method for FMC assessment. Our method can be easily integrated into omnipresent devices like smartphones or tablets.

7.2 HCI User Studies

We argue that assessing varying FMC levels in future HCI user studies is important since an individual's FMC can significantly influence how easily they interact with user interfaces and input methods. From simple pointing tasks [90] to complex tracing or steering tasks [44], FMC plays a crucial role to enable individuals fast and precise input. For one person, a system may feel intuitive and effortless, while for another, it could be challenging to use. Also, temporary changes in the FMC, through factors like hypoglycemia [31, 100] or acute exhaustion, can render a system hard to control for individuals with a usually high FMC. Such differences can directly affect the perception and evaluation of interactive systems. Our approach addresses this by enabling quick assessment of FMC (especially compared to cumbersome assessment with NHPT).

7.3 Continuous Tracking

While our current implementation of FMC assessment relies on predefined sketches that users replicate, the predictor of pressure entropy could potentially generalize to everyday touch and stylus input. More specifically, an automated computation of FMC provides great potential for continuously assessing repetitive inputs (e.g., lock screen patterns or swipe gestures on touch-based keyboards) in the background. Such an approach would allow for monitoring changes throughout the day or a prolonged time by collecting regular data samples without requiring users to allocate time for specific tests. Such background tracking could support applications like disease recovery and rehabilitation (e.g., for stroke patients) and adaptive systems that could use this data to adjust interfaces dynamically (e.g., by increasing the size of hidden touch zones in digital keyboards [47] based on variations in FMC to increase typing accuracy).

8 Limitations and Future Work

We carried out a data-gathering experiment to investigate the correlation of different drawing metrics on the NHPT completion time to measure the FMC. However, it is essential to note that the outcomes found with a limited number of participants may not generalize to the entire population, especially considering the WEIRD [54] sample in our experiment. The proposed models reveal a difference between individuals, highlighting the interpersonal differences in FMC. Especially, recruiting participants in a local gym results in people being used to physical exercise and potentially having a better or more reactive FMC in general, compared to untrained people [40, 104]. Further, we did not control the physical exercise our participants performed. All participants partook in the same type of sport, functional fitness, but followed different workouts.

Besides these limitations, external factors, such as various physical characteristics, handedness, or age-related changes to the musculoskeletal and central nervous system influencing the FMC, need to be investigated.

Also, we have to acknowledge the need for sparse data sampling. We only recorded one pre physical exercise data pair of NHPT and copy drawing test. Further, based on related work, we did not expect the observed reaction of physical exercise on the participant's FMC. We recommend recording for longer after physical exercise exposure. Additionally, multiple days should be considered to sample, as the FMC show intraperson changes, see subsection 6.2.

Closely related to this, we only sampled two different drawings based on previous work. In future work, we want to further investigate more generalized input not requiring drawing predefined shapes.

Related to this, we only observed improvements in the FMC compared to the baseline. Future research should look into the deterioration of FMC, for instance, through alcohol intoxication [62].

Lastly, we acknowledge technical limitations in using the iPad for this study. iPadOS provides only preprocessed touch and stylus input, likely including smoothing and filtering, with no access to raw sensor data. This may introduce unmeasured jitter or latency. Nonetheless, our results show that FMC prediction is possible using this processed data, demonstrating the robustness of our approach. Importantly, our approach runs on unmodified, stock iPads—supporting its practicality and ease of deployment. Future work could explore validating input fidelity, input latency, and sensor noise more precisely on other platforms or devices where raw sensor access is available.

For future work, we investigate further into FMC assessment on digital surfaces. In this study, we only captured the pressure exerted by the stylus. Most of the current touchscreens cannot measure physical touch pressure [48]. They estimate it using touch area size. However, at the time of writing this paper, iPads do not allow the recording of this value. Finally, the current touchscreens also lack the resolution to capture small pressure changes potentially needed for predicting FMC.

9 Conclusion

In this paper, we compared the established NHPT to access FMC with a copy drawing test on a mobile device. In a data-gathering study, we collected data pairs of NHPT completion times and time series data of touch and stylus input while drawing on a digital surface. We fitted linear mixed effects models for both input modalities and refined the model using correlation and fixed effects analysis. We found robust prediction rates, highlighting the feasibility of using drawing as an alternative to assess FMC by predicting NHPT completion times. This enables FMC assessment using just a mobile device, specifically a stock iPad without the need for dedicated hardware or system modifications, and facilitates exciting opportunities for HCI by personalizing user interfaces and input of digital systems based on the individual's FMC. Further, it enables the exploration of influences of different FMC capabilities - and, the other way around, the impact of systems on the FMC - in HCI user studies. Additionally, following the use cases of the NHPT to detect diseases like stroke [15, 38], Alzheimer's [17, 26], or Parkinson [20, 26, 75, 76], Multiple Sclerosis [46], or observe the development of children while growing up [73, 114], enable assessment of them using commonly available hardware, like smartphones or tablets. Further explorations and investigations could even promote this technique to be used live, as most observed metrics can be assessed during an interaction and do not require performing and completing a predefined test.

Remarks

For the purpose of editing, we used GPT-4o, DeepL, and Grammarly.

Acknowledgments

This work is supported by the German Research Foundation (DFG), CRC 1404: "FONDA: Foundations of Workflows for Large-Scale Scientific Data Analysis" (Project-ID 414984028). This work has been co-funded by the LOEWE initiative (Hesse, Germany) within the emergenCITY center [LOEWE/1/12/519/03/05.001(0016)/72].

References

[1] [n. d.]. The Influence of Tremor on Handwriting Performance under Conditions of Low and Intermediate Physical Stress. ([n. d.]).

[2] 1994. Motor Areas of the Cerebral Cortex. *Journal of Clinical Neurophysiology* 11, 4 (July 1994), 392.

[3] May Mowaffaq Al-Taee, Sonia Ben Hassen Neji, and Mondher Frikha. 2020. Handwritten Recognition: A Survey. In *2020 IEEE 4th International Conference on Image Processing, Applications and Systems (IPAS)*. 199–205. https://doi.org/10.1109/IPAS50080.2020.9334936

[4] Geneviève Albouy, Virginie Sterpenich, Evelyne Balteau, Gilles Vandewalle, Martin Desseilles, Thanh Dang-Vu, Annabelle Darsaud, Perrine Ruby, Pierre-Hervé Luppi, Christian Degueldre, Philippe Peigneux, André Luxen, and Pierre Maquet. 2008. Both the Hippocampus and Striatum Are Involved in Consolidation of Motor Sequence Memory. *Neuron* 58, 2 (April 2008), 261–272. https://doi.org/10.1016/j.neuron.2008.02.008

[5] Caitlin Axford, Annette V. Joosten, and Courtenay Harris. 2018. iPad Applications That Required a Range of Motor Skills Promoted Motor Coordination in Children Commencing Primary School. *Australian Occupational Therapy Journal* 65, 2 (April 2018), 146–155. https://doi.org/10.1111/1440-1630.12450

[6] Danilo Bondi, Claudio Robazza, Christiane Lange-Küttner, and Tiziana Pietrangelo. 2022. Fine Motor Skills and Motor Control Networking in Developmental Age. *American Journal of Human Biology* 34, 8 (Aug. 2022), e23758. https://doi.org/10.1002/ajhb.23758

[7] Carol G. Brown. 2010. Improving Fine Motor Skills in Young Children: An Intervention Study. *Educational Psychology in Practice* 26, 3 (Sept. 2010), 269–278. https://doi.org/10.1080/02667363.2010.495213

[8] Shao-Hsia Chang, Chien-Liang Chen, and Nan-Ying Yu. 2015. Biomechanical Analyses of Prolonged Handwriting in Subjects with and without Perceived Discomfort. *Human Movement Science* 43 (Oct. 2015), 1–8. https://doi.org/10.1016/j.humov.2015.06.008

[9] Karen B. Chen, Anne B. Savage, Amrish O. Chourasia, Douglas A. Wiegmann, and Mary E. Sesto. 2013. Touch Screen Performance by Individuals with and without Motor Control Disabilities. *Applied Ergonomics* 44, 2 (March 2013), 297–302. https://doi.org/10.1016/j.apergo.2012.08.004

[10] Nicole D. Cilia, Giuseppe De Gregorio, Claudio De Stefano, Francesco Fontanella, Angelo Marcelli, and Antonio Parziale. 2022. Diagnosing Alzheimer's Disease from on-Line Handwriting: A Novel Dataset and Performance Benchmarking. *Engineering Applications of Artificial Intelligence* 111 (May 2022), 104822. https://doi.org/10.1016/j.engappai.2022.104822

[11] Erez James Cohen, Riccardo Bravi, Maria Angela Bagni, and Diego Minciacchi. 2018. Precision in Drawing and Tracing Tasks: Different Measures for Different Aspects of Fine Motor Control. *Human Movement Science* 61 (Oct. 2018), 177–188. https://doi.org/10.1016/j.humov.2018.08.004

[12] Erez J. Cohen, Riccardo Bravi, and Diego Minciacchi. 2021. Assessing the Development of Fine Motor Control in Elementary School Children Using Drawing and Tracing Tasks. *Perceptual and Motor Skills* 128, 2 (April 2021), 605–624. https://doi.org/10.1177/0031512521990358

[13] Rony Cohen, Batia Cohen-Kroitoru, Ayelet Halevy, Sharon Aharoni, Irena Aizenberg, and Avinoam Shuper. 2019. Handwriting in Children with Attention Deficient Hyperactive Disorder: Role of Graphology. *BMC Pediatrics* 19, 1 (Dec. 2019), 484. https://doi.org/10.1186/s12887-019-1854-3

[14] Stanley Colcombe and Arthur F. Kramer. 2003. Fitness Effects on the Cognitive Function of Older Adults: A Meta-Analytic Study. *Psychological Science* 14, 2 (March 2003), 125–130. https://doi.org/10.1111/1467-9280.t01-1-01430

[15] Earllaine Croarkin, Jerome Danoff, and Candice Barnes. 2004. Evidence-Based Rating of Upper-Extremity Motor Function Tests Used for People Following a Stroke. *Physical Therapy* 84, 1 (Jan. 2004), 62–74. https://doi.org/10.1093/ptj/84.1.62

[16] Laura C. Dapp, Venera Gashaj, and Claudia M. Roebers. 2021. Physical Activity and Motor Skills in Children: A Differentiated Approach. *Psychology of Sport and Exercise* 54 (May 2021), 101916. https://doi.org/10.1016/j.psychsport.2021.101916

[17] Jonas J. de Paula, Maicon R. Albuquerque, Guilherme M. Lage, Maria A. Bicalho, Marco A. Romano-Silva, and Leandro F. Malloy-Diniz. 2016. Impairment of Fine Motor Dexterity in Mild Cognitive Impairment and Alzheimer's Disease Dementia: Association with Activities of Daily Living. *Brazilian Journal of Psychiatry* 38 (April 2016), 235–238. https://doi.org/10.1590/1516-4446-2015-1874

[18] Pedro Domingos. 1999. The Role of Occam's Razor in Knowledge Discovery. *Data mining and knowledge discovery* 3 (1999), 409–425.

[19] Kenji Doya. 2000. Complementary Roles of Basal Ganglia and Cerebellum in Learning and Motor Control. *Current Opinion in Neurobiology* 10, 6 (Dec. 2000), 732–739. https://doi.org/10.1016/S0959-4388(00)00153-7

[20] Gammon M. Earhart, Jim T. Cavanaugh, Terry Ellis, Matt P. Ford, K. Bo Foreman, and Lee Dibble. 2011. The 9-Hole Peg Test of Upper Extremity Function: Average Values, Test-Retest Reliability, and Factors Contributing to Performance in People With Parkinson Disease. *Journal of Neurologic Physical Therapy* 35, 4 (Dec. 2011), 157. https://doi.org/10.1097/NPT.0b013e318235da08

[21] Christophe Emery, Evren Samur, Olivier Lambercy, Hannes Bleuler, and Roger Gassert. 2010. Haptic/VR Assessment Tool for Fine Motor Control. In *Haptics: Generating and Perceiving Tangible Sensations*, Astrid M. L. Kappers, Jan B. F. Van Erp, Wouter M. Bergmann Tiest, and Frans C. T. Van Der Helm (Eds.). Vol. 6192. Springer Berlin Heidelberg, Berlin, Heidelberg, 186–193. https://doi.org/10.1007/978-3-642-14075-4_27

[22] Safiullah Faizullah, Muhammad Sohaib Ayub, Sajid Hussain, and Muhammad Asad Khan. 2023. A Survey of OCR in Arabic Language: Applications, Techniques, and Challenges. *Applied Sciences* 13, 7 (Jan. 2023), 4584. https://doi.org/10.3390/app13074584

[23] Marcos Faundez-Zanuy, Jiri Mekyska, and Donato Impedovo. 2021. Online Handwriting, Signature and Touch Dynamics: Tasks and Potential Applications in the Field of Security and Health. *Cognitive Computation* 13, 5 (Sept. 2021), 1406–1421. https://doi.org/10.1007/s12559-021-09938-2

[24] Shan Feng, Matti Mäntymäki, Amandeep Dhir, and Hannu Salmela. 2021. How Self-tracking and the Quantified Self Promote Health and Well-being: Systematic Review. *Journal of Medical Internet Research* 23, 9 (Sept. 2021), e25171. https://doi.org/10.2196/25171

[25] Marshal F. Folstein, Susan E. Folstein, and Paul R. McHugh. 1975. "Mini-mental State". *Journal of Psychiatric Research* 12, 3 (Nov. 1975), 189–198. https://doi.org/10.1016/0022-3956(75)90026-6

[26] Nora E. Fritz, Deborah A. Kegelmeyer, Anne D. Kloos, Shannon Linder, Ariane Park, Maria Kataki, Anahita Adeli, Punit Agrawal, Douglas W. Scharre, and Sandra K. Kostyk. 2016. Motor Performance Differentiates Individuals with Lewy Body Dementia, Parkinson's and Alzheimer's Disease. *Gait & Posture* 50 (Oct. 2016), 1–7. https://doi.org/10.1016/j.gaitpost.2016.08.009

[27] Dragan Gamberger and Nada Lavrač. 1997. Conditions for Occam's Razor Applicability and Noise Elimination. In *Machine Learning: ECML-97*, Maarten van Someren and Gerhard Widmer (Eds.). Springer, Berlin, Heidelberg, 108–123. https://doi.org/10.1007/3-540-62858-4_76

[28] Manuel-Vicente Garnacho-Castaño, Marcos Faundez-Zanuy, and Josep Lopez-Xarbau. 2020. On the Handwriting Tasks' Analysis to Detect Fatigue. *Applied Sciences* 10, 21 (Oct. 2020), 7630. https://doi.org/10.3390/app10217630

[29] Arthur Gatouillat, Antoine Dumortier, Subashan Perera, Youakim Badr, Claudine Gehin, and Ervin Sejdić. 2017. Analysis of the Pen Pressure and Grip Force Signal during Basic Drawing Tasks: The Timing and Speed Changes Impact Drawing Characteristics. *Computers in Biology and Medicine* 87 (Aug. 2017), 124–131. https://doi.org/10.1016/j.compbiomed.2017.05.020

[30] Vincenzo Gattulli, Donato Impedovo, Giuseppe Pirlo, and Gianfranco Semeraro. [n. d.]. Handwriting Task-Selection Based on the Analysis of Patterns in Classification Results on Alzheimer Dataset. ([n. d.]).

[31] J. Geddes, I. J. Deary, and B. M. Frier. 2008. Effects of Acute Insulin-Induced Hypoglycaemia on Psychomotor Function: People with Type 1 Diabetes Are Less Affected than Non-Diabetic Adults. *Diabetologia* 51, 10 (Oct. 2008), 1814–1821. https://doi.org/10.1007/s00125-008-1112-y

[32] Freja Gheysen, Filip Van Opstal, Chantal Roggeman, Hilde Van Waelvelde, and Wim Fias. 2010. Hippocampal Contribution to Early and Later Stages of Implicit Motor Sequence Learning. *Experimental Brain Research* 202, 4 (May 2010), 795–807. https://doi.org/10.1007/s00221-010-2186-6

[33] David J. Goode, Alexander A. Manning, John F. Middleton, and Barry Williams. 1981. Fine Motor Performance before and after Treatment in Schizophrenic and Schizoaffective Patients. *Psychiatry Research* 5, 3 (Dec. 1981), 247–255. https://doi.org/10.1016/0165-1781(81)90071-8

[34] Henk J. Groenewegen. 2003. The Basal Ganglia and Motor Control. *Neural Plasticity* 10, 1-2 (2003), 108384. https://doi.org/10.1155/NP.2003.107

[35] Mark A Hall. 1999. Correlation-Based Feature Selection for Machine Learning. (1999).

[36] Ulrike Halsband and Regine K. Lange. 2006. Motor Learning in Man: A Review of Functional and Clinical Studies. *Journal of Physiology-Paris* 99, 4 (June 2006), 414–424. https://doi.org/10.1016/j.jphysparis.2006.03.007

[37] Sandra G. Hart. 2006. Nasa-Task Load Index (NASA-TLX); 20 Years Later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 50, 9 (2006), 904–908. https://doi.org/10.1177/154193120605000909

[38] A. Heller, D. T. Wade, V. A. Wood, A. Sunderland, R. L. Hewer, and E. Ward. 1987. Arm Function after Stroke: Measurement and Recovery over the First Three Months. *Journal of Neurology, Neurosurgery & Psychiatry* 50, 6 (June 1987), 714–719. https://doi.org/10.1136/jnnp.50.6.714

[39] Charles H. Hillman, Kirk I. Erickson, and Arthur F. Kramer. 2008. Be Smart, Exercise Your Heart: Exercise Effects on Brain and Cognition. *Nature Reviews Neuroscience* 9, 1 (Jan. 2008), 58–65. https://doi.org/10.1038/nrn2298

[40] Benjamin Holfelder and Nadja Schott. 2014. Relationship of Fundamental Movement Skills and Physical Activity in Children and Adolescents: A Systematic Review. *Psychology of Sport and Exercise* 15, 4 (July 2014), 382–391. https://doi.org/10.1016/j.psychsport.2014.03.005

[41] Lena Hübner and Claudia Voelcker-Rehage. 2017. Does Physical Activity Benefit Motor Performance and Learning of Upper Extremity Tasks in Older Adults? – A Systematic Review. *European Review of Aging and Physical Activity* 14, 1 (Sept. 2017), 15. https://doi.org/10.1186/s11556-017-0181-7

[42] Bert H Jacobson, Krista Winter-Roberts, and Hugh A Gemmell. 1991. Influence of Caffeine on Selected Manual Manipulation Skills. *Perceptual and motor skills* 72, 3_suppl (1991), 1175–1181.

[43] Krisztián Józsa, Tun Zaw Oo, Diana Borbélyová, and Gabriella Zentai. 2023. Exploring the Growth and Predictors of Fine Motor Skills in Young Children Aged 4–8 Years. *Education Sciences* 13, 9 (Sept. 2023), 939. https://doi.org/10.3390/educsci13090939

[44] Nobuhito Kasahara, Yosuke Oba, Shota Yamanaka, Anil Ufuk Batmaz, Wolfgang Stuerzlinger, and Homei Miyashita. 2024. Better Definition and Calculation of Throughput and Effective Parameters for Steering to Account for Subjective Speed-accuracy Tradeoffs. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–18. https://doi.org/10.1145/3613904.3642084

[45] K B Kiekpaeva, V A Gromov, R Gh Shaikhetdinov, and E Terekhina. [n. d.]. Original Article Integration of Fine Motor Skills in the Physical Education Courses of Law Students. ([n. d.]).

[46] Marcus W. Koch, Jop P. Mostert, Jerry S. Wolinsky, Fred D. Lublin, Bernard Uitdehaag, and Gary R. Cutter. 2021. Comparison of the EDSS, Timed 25-Foot Walk, and the 9-Hole Peg Test as Clinical Trial Outcomes in Relapsing-Remitting Multiple Sclerosis. *Neurology* 97, 16 (Oct. 2021), e1560–e1570. https://doi.org/10.1212/WNL.0000000000012690

[47] Ken Kocienda. 2018. *Creative Selection: Inside Apple's Design Process during the Golden Age of Steve Jobs*. Pan Macmillan.

[48] Sarah Martina Kolly, Roger Wattenhofer, and Samuel Welten. 2012. A Personal Touch: Recognizing Users Based on Touch Screen Behavior. In *Proceedings of the Third International Workshop on Sensing Applications on Mobile Phones*. ACM, Toronto Ontario Canada, 1–5. https://doi.org/10.1145/2389148.2389149

[49] Junhan Kong, Mingyuan Zhong, James Fogarty, and Jacob O. Wobbrock. 2024. The Ability-Based Design Mobile Toolkit (ABD-MT): Developer Support for Runtime Interface Adaptation Based on Users' Abilities. *Proceedings of the ACM on Human-Computer Interaction* 8, MHCI (Sept. 2024), 1–26. https://doi.org/10.1145/3676524

[50] Akisue Kuramoto, Kazuki Hiranai, and Akihiko Seo. 2021. Strategies of Pen Tip Path Estimation and of Workload Comparison for Handwriting Tasks. *IEEE Sensors Journal* 21, 3 (Feb. 2021), 3645–3652. https://doi.org/10.1109/JSEN.2020.3028605

[51] Rebecca A. Langmaid, Nicole Papadopoulos, Beth P. Johnson, James G. Phillips, and Nicole J. Rinehart. 2014. Handwriting in Children With ADHD. *Journal of Attention Disorders* 18, 6 (Aug. 2014), 504–510. https://doi.org/10.1177/1087054711434154

[52] Bettina Laugwitz, Theo Held, and Martin Schrepp. 2008. Construction and Evaluation of a User Experience Questionnaire. In *HCI and Usability for Education and Work*, Andreas Holzinger (Ed.). Springer Berlin Heidelberg, Berlin, Heidelberg, 63–76.

[53] Qiushi Lin, Jianfei Luo, Zhongcheng Wu, Fei Shen, and Zengwu Sun. 2015. Characterization of Fine Motor Development: Dynamic Analysis of Children's Drawing Movements. *Human Movement Science* 40 (April 2015), 163–175. https://doi.org/10.1016/j.humov.2014.12.010

[54] Sebastian Linxen, Christian Sturm, Florian Brühlmann, Vincent Cassau, Klaus Opwis, and Katharina Reinecke. 2021. How WEIRD Is CHI?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3411764.3445488

[55] M. G. Longstaff and R. A. Heath. 2006. Spiral Drawing Performance as an Indicator of Fine Motor Function in People with Multiple Sclerosis. *Human Movement Science* 25, 4 (Oct. 2006), 474–491. https://doi.org/10.1016/j.humov.2006.05.005

[56] Deborah Lupton. 2016. *The Quantified Self.* John Wiley & Sons.

[57] I Scott MacKenzie. 2003. Motor Behaviour Models for Human-Computer Interaction. (2003), 27–54.

[58] Philipp Martzog, Heidrun Stoeger, and Sebastian Suggate. 2019. Relations between Preschool Children's Fine Motor Skills and General Cognitive Abilities. *Journal of Cognition and Development* 20, 4 (Aug. 2019), 443–465. https://doi.org/10.1080/15248372.2019.1607862

[59] Philipp Martzog and Sebastian Paul Suggate. 2019. Fine motor skills and mental imagery: Is it all in the mind? *Journal of Experimental Child Psychology* 186 (2019), 59–72. https://doi.org/10.1016/j.jecp.2019.05.002

[60] Virgil Mathiowetz, Karen Weber, Nancy Kashman, and Gloria Volland. 1985. Adult Norms for the Nine Hole Peg Test of Finger Dexterity. *The Occupational Therapy Journal of Research* 5, 1 (1985), 24–38. https://doi.org/10.1177/153944928500500102

[61] Akiko Megumi, Akiko Suzuki, Jungpil Shin, and Akira Yasumura. 2022. Developmental Changes in Writing Dynamics and Its Relationship with ADHD and ASD Tendencies: A Preliminary Study. https://doi.org/10.21203/rs.3.rs-1616383/v1

[62] Fredrik Modig, Per-Anders Fransson, Måns Magnusson, and Mitesh Patel. 2012. Blood Alcohol Concentration at 0.06 and 0.10% Causes a Complex Multifaceted Deterioration of Body Movement Control. *Alcohol* 46, 1 (Feb. 2012), 75–88. https://doi.org/10.1016/j.alcohol.2011.06.001

[63] Martez E. Mott, Radu-Daniel Vatavu, Shaun K. Kane, and Jacob O. Wobbrock. 2016. Smart Touch: Improving Touch Accuracy for People with Motor Impairments with Template Matching. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, San Jose California USA, 1934–1946. https://doi.org/10.1145/2858036.2858390

[64] Lindsay S. Nagamatsu, Andrea M. Weinstein, Kirk I. Erickson, Jason Fanning, Elizabeth A. Awick, Arthur F. Kramer, and Edward McAuley. 2016. Exercise Mode Moderates the Relationship Between Mobility and Basal Ganglia Volume in Healthy Older Adults. *Journal of the American Geriatrics Society* 64, 1 (2016), 102–108. https://doi.org/10.1111/jgs.13882

[65] Thi Tuyet Hai Nguyen, Adam Jatowt, Mickael Coustaty, and Antoine Doucet. 2021. Survey of Post-OCR Processing Approaches. *ACM Comput. Surv.* 54, 6 (July 2021), 124:1–124:37. https://doi.org/10.1145/3453476

[66] C. Niemann, B. Godde, U. M. Staudinger, and C. Voelcker-Rehage. 2014. Exercise-Induced Changes in Basal Ganglia Volume and Cognition in Older Adults. *Neuroscience* 281 (Dec. 2014), 147–163. https://doi.org/10.1016/j.neuroscience.2014.09.033

[67] Claudia Niemann, Ben Godde, and Claudia Voelcker-Rehage. 2014. Not Only Cardiovascular, but Also Coordinative Exercise Increases Hippocampal Volume in Older Adults. *Frontiers in Aging Neuroscience* 6 (Aug. 2014). https://doi.org/10.3389/fnagi.2014.00170

[68] A Nikitha, J Geetha, and D.S JayaLakshmi. 2020. Handwritten Text Recognition Using Deep Learning. In *2020 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT)*. 388–392. https://doi.org/10.1109/RTEICT49044.2020.9315679

[69] Peterson K Ozili. 2023. The Acceptable R-square in Empirical Modelling for Social Science Research. In *Social Research Methodology and Publishing Results: A Guide to Non-Native English Speakers*. IGI global, 134–143.

[70] Ranjitha P and Akshatha Prabhu. 2020. A Review on Challenges and Applications of Digital Graphology. In *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*. 368–374. https://doi.org/10.1109/ICESC48915.2020.9156013

[71] Andrew E. Papale and Bryan M. Hooks. 2018. Circuit Changes in Motor Cortex During Motor Skill Learning. *Neuroscience* 368 (Jan. 2018), 283–297. https://doi.org/10.1016/j.neuroscience.2017.09.010

[72] Michael G. Paulin. 2008. The Role of the Cerebellum in Motor Control and Perception. *Brain Behavior and Evolution* 41, 1 (Jan. 2008), 39–50. https://doi.org/10.1159/000113822

[73] Janet L. Poole, Patricia A. Burtner, Theresa A. Torres, Cheryl Kirk McMullen, Amy Markham, Michelle Lee Marcum, Jennifer Bradley Anderson, and Clifford Qualls. 2005. Measuring Dexterity in Children Using the Nine-hole Peg Test. *Journal of Hand Therapy* 18, 3 (July 2005), 348–351. https://doi.org/10.1197/j.jht.2005.04.003

[74] Sujata D. Pradhan, Bambi R. Brewer, George E. Carvell, Patrick J. Sparto, Anthony Delitto, and Yoky Matsuoka. 2010. Assessment of Fine Motor Control in Individuals with Parkinson's Disease Using Force Tracking with a

Secondary Cognitive Task. *Journal of Neurologic Physical Therapy* 34, 1 (March 2010), 32. https://doi.org/10.1097/NPT.0b013e3181d055a6

[75] Elizabeth Proud, Meg E. Morris, Belinda Bilney, Kimberly J. Miller, Maarten J. Nijkrake, Marten Munneke, and Jennifer L. McGinley. 2021. Hand Dexterity Assessment in Parkinson's Disease: Construct Validity of the 9-Hole Peg Test for the More Affected Hand. *Disability and Rehabilitation* 43, 26 (Dec. 2021), 3834–3838. https://doi.org/10.1080/09638288.2020.1754474

[76] Elizabeth L. Proud, Kimberly J. Miller, Belinda Bilney, Meg E. Morris, and Jennifer L. McGinley. 2020. Construct Validity of the 9-Hole Peg Test and Purdue Pegboard Test in People with Mild to Moderately Severe Parkinson's Disease. *Physiotherapy* 107 (June 2020), 202–208. https://doi.org/10.1016/j.physio.2019.12.002

[77] Yugang Qi, Sijie Tan, Mingyang Sui, and Jianxiong Wang. 2018-Jan-Feb. SUPERVISED PHYSICAL TRAINING IMPROVES FINE MOTOR SKILLS OF 5-YEAR-OLD CHILDREN. *Revista Brasileira de Medicina do Esporte* 24 (2018-Jan-Feb), 09–12. https://doi.org/10.1590/1517-869220182401177117

[78] Eros Quarta, Riccardo Bravi, Diego Minciacchi, and Erez James Cohen. 2021. Circle Drawing and Tracing Dataset for Evaluation of Fine Motor Control. *Data in Brief* 35 (April 2021), 106763. https://doi.org/10.1016/j.dib.2021.106763

[79] Marie Brossard Racine, Annette Majnemer, Michael Shevell, and Laurie Snider. 2008. Handwriting Performance in Children With Attention Deficit Hyperactivity Disorder (ADHD). *Journal of Child Neurology* 23, 4 (April 2008), 399–406. https://doi.org/10.1177/0883073807309244

[80] Louise Robin, Laure Fernandez, Maxime T. Robert, Eric Hermand, Axelle Gelineau, and Stéphane Mandigout. 2023. Influence of Daily Physical Activity on Fine Motor Skills of Adults around a Fitts Task. *Folia Medica* 65, 6 (Dec. 2023), 950–957. https://doi.org/10.3897/folmed.65.e103060

[81] Marc Roig, Kasper Skriver, Jesper Lundbye-Jensen, Bente Kiens, and Jens Bo Nielsen. 2012. A Single Bout of Exercise Improves Motor Memory. *PLOS ONE* 7, 9 (Sept. 2012), e44594. https://doi.org/10.1371/journal.pone.0044594

[82] Marina Roizenblatt, Thiago Marques Fidalgo, Murilo Polizelli, Natasha Ferreira Santos da Cruz, Arnaldo Roizenblatt, Kim Jiramongkolchai, Peter Louis Gehlbach, Michel Eid Farah, Rubens Belfort, and Mauricio Maia. 2021. Effect of Chronic Cocaine Use on Fine Motor Coordination Tested during Ophthalmic Vitreoretinal Simulated Performance. *Journal of Psychiatric Research* 132 (Jan. 2021), 7–12. https://doi.org/10.1016/j.jpsychires.2020.09.032

[83] MG Roulston. 1959. The Fatigue Factor: An Essay Dealing with the Effects of Physical Fatigue on Handwriting Habits. *An Unpublished Report of a Study Conducted by the RCMP Crime Detection Laboratories* (1959).

[84] Samsuryadi Samsuryadi, Rudi Kurniawan, and Fatma Susilawati Mohamad. 2021. Automated Handwriting Analysis Based on Pattern Recognition: A Survey. *Indonesian Journal of Electrical Engineering and Computer Science* 22, 1 (April 2021), 196. https://doi.org/10.11591/ijeecs.v22.i1.pp196-206

[85] Holger Schielzeth, Niels J. Dingemanse, Shinichi Nakagawa, David F. Westneat, Hassen Allegue, Céline Teplitsky, Denis Réale, Ned A. Dochtermann, László Zsolt Garamszegi, and Yimen G. Araya-Ajoy. 2020. Robustness of Linear Mixed-effects Models to Violations of Distributional Assumptions. *Methods in Ecology and Evolution* 11, 9 (Sept. 2020), 1141–1152. https://doi.org/10.1111/2041-210X.13434

[86] Dominik Schön, Thomas Kosch, Florian Müller, Martin Schmitz, Sebastian Günther, Lukas Bommhardt, and Max Mühlhäuser. 2023. Tailor Twist: Assessing Rotational Mid-Air Interactions for Augmented Reality. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. ACM, Hamburg Germany, 1–14. https://doi.org/10.1145/3544548.3581461

[87] Enric Sesa-Nogueras, Marcos Faundez-Zanuy, and Manuel-Vicente Garnacho-Castaño. 2021. The Effect of Fatigue on the Performance of Online Writer Recognition. *Cognitive Computation* 13, 5 (Sept. 2021), 1374–1388. https://doi.org/10.1007/s12559-021-09943-5

[88] Claire E. Sexton, Jill F. Betts, Naiara Demnitz, Helen Dawes, Klaus P. Ebmeier, and Heidi Johansen-Berg. 2016. A Systematic Review of MRI Studies Examining the Relationship between Physical Fitness and Activity and the White Matter of the Ageing Brain. *NeuroImage* 131 (May 2016), 81–90. https://doi.org/10.1016/j.neuroimage.2015.09.071

[89] C. E. Shannon. 1948. A Mathematical Theory of Communication. *The Bell System Technical Journal* 27, 3 (July 1948), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

[90] Ather Sharif, Victoria Pao, Katharina Reinecke, and Jacob O. Wobbrock. 2020. The Reliability of Fitts's Law as a Movement Model for People with and without Limited Fine Motor Function. In *Proceedings of the 22nd International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3373625.3416999

[91] Jungpil Shin, Md. Maniruzzaman, Yuta Uchida, Md. Al Mehedi Hasan, Akiko Megumi, and Akira Yasumura. 2023. Handwriting-Based ADHD Detection for Children Having ASD Using Machine Learning Approaches. *IEEE Access* 11 (2023), 84974–84984. https://doi.org/10.1109/ACCESS.2023.3302903

[92] Benjamin A. Sibley and Jennifer L. Etnier. 2003. The Relationship between Physical Activity and Cognition in Children: A Meta-Analysis. *Pediatric Exercise Science* 15, 3 (Aug. 2003), 243–256. https://doi.org/10.1123/pes.15.3.243

[93] Amaya M. Singh and W. Richard Staines. 2015. The Effects of Acute Aerobic Exercise on the Primary Motor Cortex. *Journal of Motor Behavior* 47, 4 (July 2015), 328–339. https://doi.org/10.1080/00222895.2014.983450

[94] Darrell K. Skinner and Sandra L. Curwin. 2007. Assessment of Fine Motor Control in Patients with Occupation-Related Lateral Epicondylitis. *Manual Therapy* 12, 3 (Aug. 2007), 249–255. https://doi.org/10.1016/j.math.2006.06.018

[95] Kasper Skriver, Marc Roig, Jesper Lundbye-Jensen, Jessica Pingel, Jørn Wulff Helge, Bente Kiens, and Jens Bo Nielsen. 2014. Acute Exercise Improves Motor Memory: Exploring Potential Biomarkers. *Neurobiology of Learning and Memory* 116 (Dec. 2014), 46–58. https://doi.org/10.1016/j.nlm.2014.08.004

[96] Michael W. Smith, Joseph Sharit, and Sara J. Czaja. 1999. Aging, Motor Control, and the Performance of Computer Mouse Tasks. *Human Factors* 41, 3 (Sept. 1999), 389–396. https://doi.org/10.1518/001872099779611102

[97] Esther J. Smits, Antti J. Tolonen, Luc Cluitmans, Mark van Gils, Rutger C. Zietsma, Marina A. J. Tijssen, and Natasha M. Maurits. 2018. Reproducibility of Standardized Fine Motor Control Tasks and Age Effects in Healthy Adults. *Measurement* 114 (Jan. 2018), 177–184. https://doi.org/10.1016/j.measurement.2017.09.011

[98] Pablo Hidelbrando S. Souto, Juliana Nunes Santos, Hércules Ribeiro Leite, Mijna Hadders-Algra, Sabrina Conceição Guedes, Juliana Nogueira Pontes Nobre, Lívia Rodrigues Santos, and Rosane Luzia de Souza Morais. 2020. Tablet Use in Young Children Is Associated with Advanced Fine Motor Skills. *Journal of Motor Behavior* 52, 2 (March 2020), 196–203. https://doi.org/10.1080/00222895.2019.1602505

[99] Matthew A Statton, Marysol Encarnacion, Pablo Celnik, and Amy J Bastian. 2015. A Single Bout of Moderate Aerobic Exercise Improves Motor Skill Acquisition. *PloS one* 10, 10 (2015), e0141393.

[100] Anthony B Stevens, William R McKane, Patrick M Bell, Paul Bell, David J King, and John R Hayes. 1989. Psychomotor Performance and Counterregulatory Responses During Mild Hypoglycemia in Healthy Volunteers. *Diabetes Care* 12, 1 (Jan. 1989), 12–17. https://doi.org/10.2337/diacare.12.1.12

[101] David F. Stodden, Jacqueline D. Goodway, Stephen J. Langendorfer, Mary Ann Roberton, Mary E. Rudisill, Clersida Garcia, and Luis E. Garcia. 2008. A Developmental Perspective on the Role of Motor Skill Competence in Physical Activity: An Emergent Relationship. *Quest* 60, 2 (May 2008), 290–306. https://doi.org/10.1080/00336297.2008.10483582

[102] Nishant Subramani, Alexandre Matton, Malcolm Greaves, and Adrian Lam. 2021. A Survey of Deep Learning Approaches for OCR and Document Understanding. https://doi.org/10.48550/arXiv.2011.13534 arXiv:2011.13534 [cs]

[103] Sandra Sülzenbrück, Mathias Hegele, Gerhard Rinkenauer, and Herbert Heuer. 2011. The Death of Handwriting: Secondary Effects of Frequent Computer Use on Basic Motor Skills. *Journal of Motor Behavior* 43, 3 (May 2011), 247–251. https://doi.org/10.1080/00222895.2011.571727

[104] Marco Taubert, Arno Villringer, and Nico Lehmann. 2015. Endurance Exercise as an "Endogenous" Neuro-enhancement Strategy to Facilitate Motor Learning. *Frontiers in Human Neuroscience* 9 (Dec. 2015). https://doi.org/10.3389/fnhum.2015.00692

[105] Luigi Tesio, Anna Simone, Giuliano Zebellin, Viviana Rota, Calogero Malfitano, and Laura Perucca. 2016. Bimanual Dexterity Assessment: Validation of a Revised Form of the Turning Subtest from the Minnesota Dexterity Test. *International Journal of Rehabilitation Research. Internationale Zeitschrift Fur Rehabilitationsforschung. Revue Internationale De Recherches De Readaptation* 39, 1 (March 2016), 57–62. https://doi.org/10.1097/MRR.0000000000000145

[106] Jonathan S. Thacker, Laura E. Middleton, William E. McIlroy, and W. Richard Staines. 2014. The Influence of an Acute Bout of Aerobic Exercise on Cortical Contributions to Motor Preparation and Execution. *Physiological Reports* 2, 10 (2014), e12178. https://doi.org/10.14814/phy2.12178

[107] Feng Tian, Xiangmin Fan, Junjun Fan, Yicheng Zhu, Jing Gao, Dakuo Wang, Xiaojun Bi, and Hongan Wang. 2019. What Can Gestures Tell?: Detecting Motor Impairment in Early Parkinson's from Common Touch Gestural Interactions. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, Glasgow Scotland Uk, 1–14. https://doi.org/10.1145/3290605.3300313

[108] Arend Willem Alexander Van Gemmert. 1997. *The effects of mental load and stress on the dynamics of fine motor tasks*. Nijmegen: NICI, Nijmeegs Instituut voor Cognitie en Informatie.

[109] Y. L. Venevtseva, A. Kh Melnikov, and S. A. Nesterova. 2024. Sleep and fine motor skills: the influence of sex and level of physical activity. *Zhurnal nevrologii i psikhiatrii imeni S.S. Korsakova* 124, 5. Vyp. 2 (2024), 33–38. https://doi.org/10.17116/jnevro202412405233

[110] Claudia Voelcker-Rehage, Ben Godde, and Ursula M. Staudinger. 2011. Cardiovascular and Coordination Training Differentially Improve Cognitive Performance and Neural Processing in Older Adults. *Frontiers in Human Neuroscience* 5 (March 2011). https://doi.org/10.3389/fnhum.2011.00026

[111] Claudia Voelcker-Rehage and Claudia Niemann. 2013. Structural and Functional Brain Changes Related to Different Types of Physical Activity across the Life Span. *Neuroscience & Biobehavioral Reviews* 37, 9, Part B (Nov. 2013), 2268–2295. https://doi.org/10.1016/j.neubiorev.2013.01.028

[112] Stéphanie Vuillermot, Aniña Pescatore, Lisa Holper, Daniel C. Kiper, and Kynan Eng. 2009. An Extended Drawing Test for the Assessment of Arm and Hand Function with a Performance Invariant for Healthy Subjects. *Journal of Neuroscience Methods* 177, 2 (March 2009), 452–460. https://doi.org/10.1016/j.jneumeth.2008.10.018

[113] Gerd Wagner, Marco Herbsleb, Feliberto de la Cruz, Andy Schumann, Stefanie Köhler, Christian Puta, Holger W. Gabriel, Jürgen R. Reichenbach, and Karl-Jürgen Bär. 2017. Changes in fMRI Activation in Anterior Hippocampus and Motor Cortex during Memory Retrieval after an Intense Exercise Intervention. *Biological Psychology* 124 (March 2017), 65–78. https://doi.org/10.1016/j.biopsycho.2017.01.003

[114] Ying-Chih Wang, Richard W. Bohannon, Jay Kapellusch, Arun Garg, and Richard C. Gershon. 2015. Dexterity as Measured with the 9-Hole Peg Test (9-HPT) across the Age Span. *Journal of Hand Therapy* 28, 1 (Jan. 2015), 53–60. https://doi.org/10.1016/j.jht.2014.09.002

[115] W. Wijianto and Kartika Saktiyarini. 2022. RELATIONSHIP OF PHYSICAL ACTIVITY WITH FINE MOTOR SKILLS IN 3-4 YEARS OLD CHILDREN. *Gaster* 20, 2 (Aug. 2022), 207–215. https://doi.org/10.30787/gaster.v20i2.856

[116] Guido A Zäch and Hans Georg Koch. 2006. *Paraplegie: Ganzheitliche Rehabilitation.* Karger Medical and Scientific Publishers.

[117] Sergei Zarembo, Sven Nõmm, Kadri Medijainen, Pille Taba, and Aaro Toomela. 2021. CNN Based Analysis of the Luria's Alternating Series Test for Parkinson's Disease Diagnostics. In *Recent Challenges in Intelligent Information and Database Systems*, Tzung-Pei Hong, Krystian Wojtkiewicz, Rathachai Chawuthai, and Pawel Sitek (Eds.). Vol. 1371. Springer Singapore, Singapore, 3–13. https://doi.org/10.1007/978-981-16-1685-3_1

A Participation's NHPT Completion Time

Figure 7 shows our participant's NHPT completion times during the experiment. The graphs show on the x-axis the five trials *pre-PE*, *post-PE-1*, *post-PE-2*, *post-PE-3*, and *post-PE-4*. *pre-PE* marks the sample prior to Physical Exercise exposure, while the *post-PE-** shows the completion time after exposure with rest between sampling. NHPT times of the introduction to the test scenario were not recorded and are not presented here.

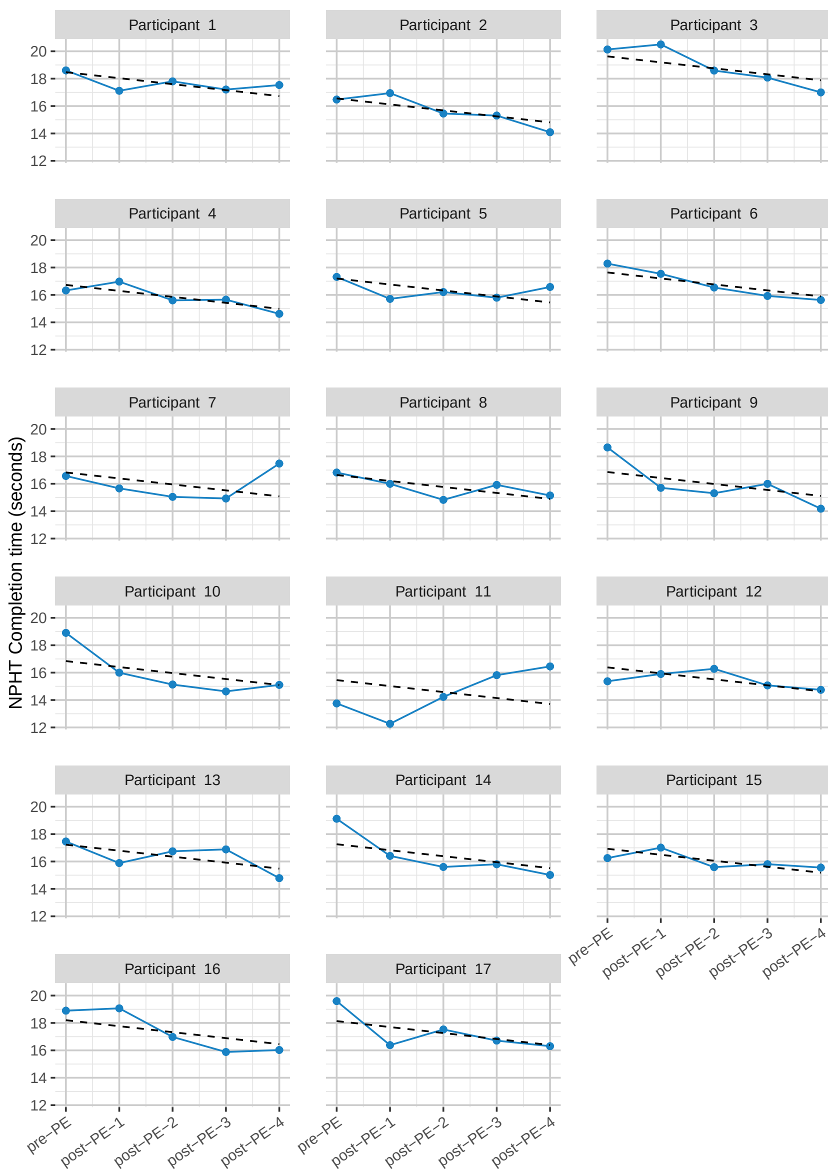

Fig. 7. Participants NHPT Completion times with the respective trend in decrease of the completion time. Participant 18 is not displayed to conform the request to not publish their respective raw data.