Analog Multi-Finger Fitts' Law Experiments: Modifying Indices of Difficulty Based on Distance Variation for Improved Combined Model Fit.

by

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to obtain the degree of Master of Science
in Mechanical Engineering
Track Biomechanical Design
at the Delft University of Technology,
to be defended publicly on Tuesday April 15, 2025 at 14:00.

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***Abstract*—Effective Human-Machine Interaction (HMI) depends on accurately capturing and interpreting information from the human user. For systems relying on hand-based operation, understanding the limits of human cognitive-motor abilities is crucial to designing intuitive and efficient interfaces. This study presents an experimental setup involving four analog buttons with a minimally complex control, where human hand performance is assessed through simultaneous multi-finger Fitts' Law tasks. Initially, task difficulty was assumed to be computed by summing the individual indices of difficulty for each button, which resulted in peak throughput performance with two fingers. However, this approach did not align with Fitts' Law. By applying a weighted summation, with weights based on the variation of distances within a task, the difficulty measure better conformed to Fitts' Law, and the highest throughput was achieved with a single finger. These findings highlight the interdependence in multi-finger movement complexity and emphasize the importance of considering cognitive-motor limitations when designing HMI interfaces to optimize user performance.**

***Index Terms*—Human-Machine Interaction, multi-finger coordination, cognitive-motor performance, Fitts' law, throughput**

I. INTRODUCTION

The human hand plays a crucial role in performing activities of daily living (ADLs), enabling individuals to grasp objects, manipulate tools, and interact with their environment. Loss of hand function, whether due to amputation, neuromuscular impairment from injury or disease, or congenital conditions, can significantly affect a person's independence and quality of life [1]. Technological solutions, such as prosthetic hands and active hand-assistive devices, aim to restore or support hand function, thereby improving quality of life [2]. Additionally, the concept of human augmentation has emerged, where devices not only compensate for lost function but also extend a person's natural capabilities [3].

The success of such assistive and augmentative devices relies heavily on the quality of interaction between the user and the technology. This challenge is addressed within the field of Human-Machine Interaction (HMI). While both humans and machines are capable of executing complex actions independently, the effectiveness of HMI is determined by how well the two can work together. Poor interaction design often leads to limited usability, as demonstrated by the rejection of prosthetic devices [4]

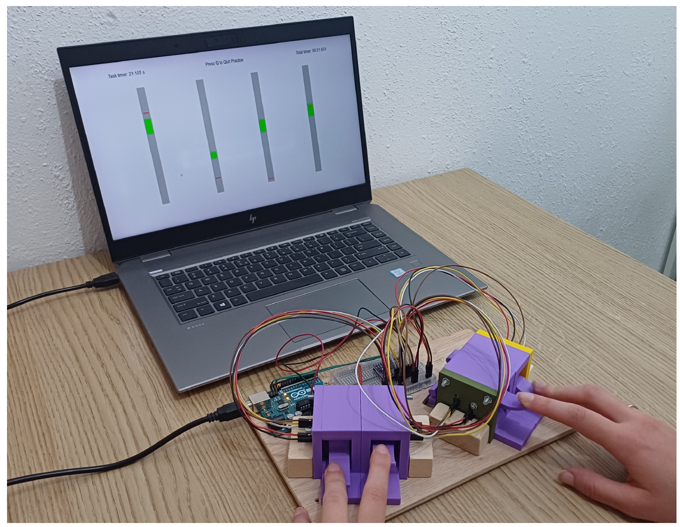

Fig. 1. Demonstration of the experiment using four fingers, showing both the physical setup and the display. The setup consists of four 3D-printed buttons, each operated by an individual finger, along with electronic circuitry for capturing sensor data. The system is connected to a computer, which provides power and translates the sensor data into cursor movements on the display.

A fundamental aspect of HMI is the ability to accurately extract and utilize information from the human user. This process involves two primary components: sensing the user's input signals, such as muscle activity, force, or motion, and applying appropriate control strategies to generate effective output responses for the machine.

Various interfaces exist to facilitate the exchange of information between the user and the machine. These include tangible interfaces, gesture-based interfaces, brain-computer interfaces (BCIs), and gaze-based interfaces [5]. In the domain of prosthetics, interface technology has evolved from body-powered mechanisms, relying on muscle-driven cable systems, to advanced myoelectric systems that detect muscle activity through surface or intramuscular electromyography (sEMG and iEMG) [6]. Similarly, active hand-assistive devices integrate a variety of sensors to capture user intention, including measurements of position, force, and bio-signals such as EMG [7].

Translating these input signals into meaningful commands for the machine requires robust control strategies. In transradial prostheses, for instance, myoelectric control methods include simple on-off control, which activates the device based on a threshold level of muscle contraction, and proportional control, where force, velocity, or position is scaled according to the amount of muscle contraction [8]. More recently, pattern recognition and deep learning techniques have emerged in HMI applications to enhance the extraction of information from EMG signals and classify user intent more accurately [9].

At its core, the performance of any HMI device depends on both the quality of the input signals and the effectiveness of the control system. Given the complexity of human hand movements, understanding how much information can be reliably obtained for control is crucial. This understanding is key to optimizing the functionality of devices that rely on hand input. Striking the right balance between user cognitive-motor capabilities and device interface complexity is essential for ensuring effective performance and usability.

Previous research by Nizamis et al. explored human control over finger movements using a setup with six digital buttons to assess multi-finger movement performance [10] [11]. In their experiment, inspired by the work of Klemmer et al. [12], participants were required to press the correct buttons in response to various visual stimuli. The study suggested that using three fingers resulted in optimal cognitive-motor performance. However, digital buttons provide only binary input (on/off states), which does not fully capture the nuances of human finger movement. In contrast, analog buttons allow for continuous input variations, potentially enabling a richer transfer of information and a more precise representation of human motor control.

Given the complexity of finger movement and the potential of analog buttons to provide more detailed motor control information, this study investigates multi-finger movement performance using an experimental setup with four analog buttons, each controlled by a separate finger. The goal is to explore how performance varies with different numbers of fingers responding to visual stimuli simultaneously, and whether the results align with the previous findings suggesting that cognitive-motor complexity becomes too high when using more than three fingers to improve performance. While Nizamis et al. relied on the Information Transfer Rate (ITR) to assess discrete inputs in bits per second, this metric does not apply to analog buttons due to their continuous nature [13]. Instead, this study employs Fitts' Law to quantify performance, as it is a well-established method for assessing human control capabilities in an analog setting, as detailed in Appendix A. A Fitts' Law experiment will be conducted for each finger individually, and the difficulty measures for each finger will be combined to assess the overall difficulty of performing multi-finger movements. Fitts' throughput will then be used to measure performance in bits per second, aiming to enhance the understanding of cognitive-motor limitations. The focus will be on healthy participants to establish baseline measurements. Ultimately, these insights may inform the design of more effective and customized HMI interfaces.

II. Materials and Methods

In this chapter, the experimental setup and methodology used to quantify multi-finger coordination are described. Participants performed multiple trials using one to four analog buttons on the setup. In each trial, Fitts' Law tasks were assigned to each active finger, and participants were required to complete them simultaneously. Task difficulty levels and movement times were recorded, and key performance metrics, such as the average throughput, were calculated for each trial. These calculations aim to provide insights into how multi-finger performance varies as the number of fingers used increases.

A. Participants

The experiment was conducted with 12 healthy adults (6 male, 6 female). All participants were right-handed and had no hand-related impairments. Right-handed participants were preferred due to the specific order in which the fingers were recruited (see section II-C). Participants' ages ranged from 22 to 25 years, with a mean age of 24.08 years ($SD = 0.86$). None of the participants had prior experience with the experimental setup, so a familiarization period was provided (see section II-D). The study was approved by the Human Research Ethics Committee of the TU Delft, and informed consent was obtained from each participant before the experiment. Participation was voluntary and uncompensated.

B. Experimental setup

The experimental setup (shown in Fig. 1) consisted of four custom 3D-printed analog buttons, which participants operated using their index and middle fingers. For both stability and portability, the buttons were mounted on a wooden surface. The two buttons on the left were assigned to the left index and middle fingers, and the two on the right to the right index and middle fingers. To ensure a comfortable wrist position during the experiment, the buttons were positioned at a slight angle on the board.

Each button featured a rotating lever with an integrated ball bearing to facilitate smooth movement. Pressing the levers was primarily achieved through the flexion of the metacarpophalangeal (MCP) joints in the hand. A small rubber band located at the back of the lever acted as a spring mechanism, returning the lever to its original position upon release. Participants controlled the buttons by relying on both position and force information. Position information was provided by proprioception, allowing participants to be aware of their finger positions based on feedback from the muscles, tendons, and joints. Force information was derived from tactile feedback, where participants perceived the resistance exerted by the rubber band when pressing the button. A light press required minimal force, whereas a stronger press required overcoming greater resistance from the rubber band, providing a clear distinction in tactile feedback.

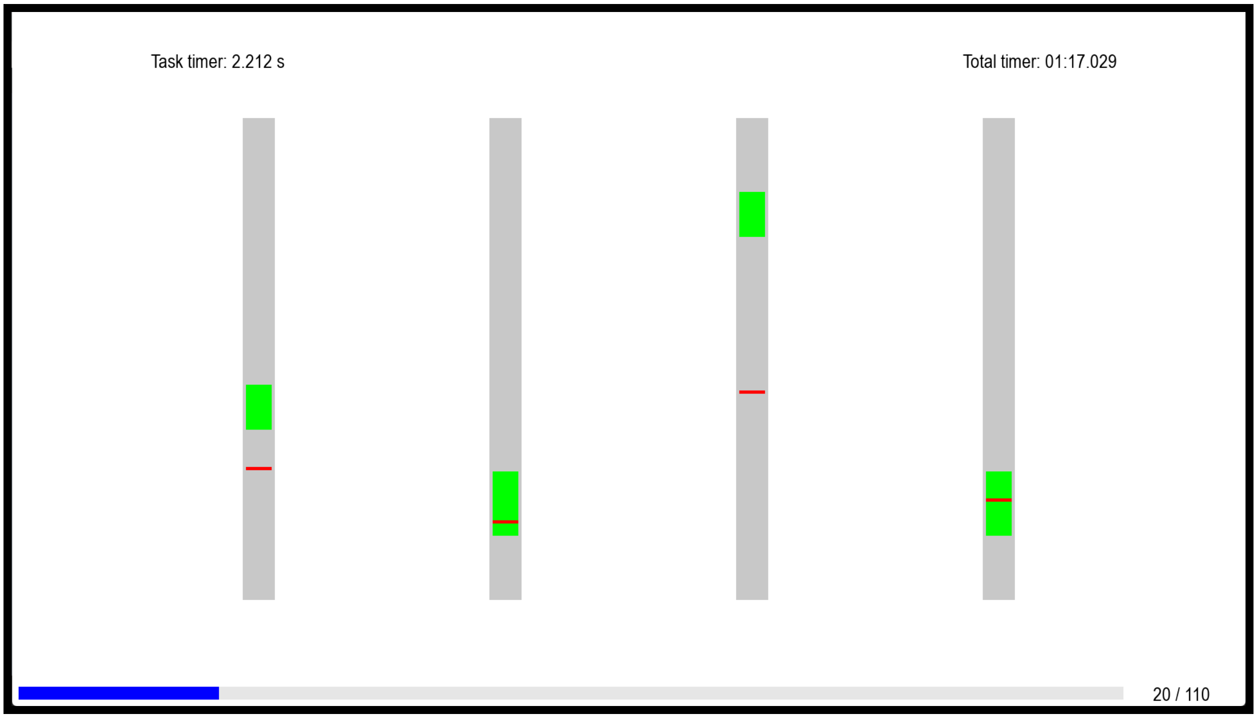

Fig. 2. Display of a trial involving four fingers. The goal is to move the red cursors to the green targets simultaneously and as quickly as possible. During the experiment, only the subscreens corresponding to the fingers used in the trial are shown. Additionally, timers and a progress bar are displayed.

To measure button rotation, a diametrically magnetized magnet ($6\,\mathrm{mm}$ in diameter) was embedded in the lever along its rotating axis, and its angular displacement was measured by an AS5600 12-bit magnetic encoder sensor. For further details, an exploded view of the button assembly is provided in Appendix B.

All sensors were connected to an Arduino Uno via the I2C bus. Since all sensors shared the same I2C address, an I2C multiplexer (PCA9548A) was used to facilitate communication between the sensors and the Arduino. The system was programmed in the Arduino IDE, utilizing libraries for the AS5600 magnetic encoder and PCA9548A I2C multiplexer [14]. The electronic circuit, operating at $3.3\,\mathrm{V}$, is depicted in Appendix C.

The Arduino was connected to a computer for both power supply and data transmission via a serial connection. Sensor data was sampled at an intended rate of $1\,\mathrm{kHz}$, transmitting the angular positions of all four sensors every millisecond. However, the actual sampling rate was found to be lower after the experiment (see section IV-C). The received sensor data was then used to move cursors on the computer monitor for the Fitts' Law experiment.

C. Experiment and display

During the experiment, participants completed multiple trials, each involving a different number of buttons from the setup. In the single-button trial, only the right index finger was used. When two buttons were involved, the right middle finger was added. Similarly, in the three-button trial, the left index finger was incorporated, and in the four-button trial, the left middle finger was also engaged.

This specific order of finger recruitment, starting with fingers on one hand and then including the other hand, was chosen to align more with the design of most hand-based interface systems, which are often operated primarily with a single hand. Since all participants were right-handed, their dominant hand was used for the simpler trials involving one and two fingers. This approach allowed for a better assessment of the limits of human finger control when task complexity was low. Introducing the non-dominant hand for trials with three or four buttons reflected the added difficulty and coordination demands of bimanual tasks and provided insights into how increased complexity affects motor control and task performance.

During each trial, participants were presented with a series of tasks displayed on a 1920×1080 pixel computer monitor. An example of the display during a four-finger trial is shown in Fig. 2. The tasks were programmed in Python using the Pygame library. For each active finger, a 750-pixel-high subscreen was shown, containing a red cursor that moved vertically in response to pressing the corresponding button. A target was also displayed within each subscreen. In addition to the subscreens, a timer in the upper-left corner displayed the duration of the current task, while another timer in the upper-right corner indicated the total elapsed time for the trial. A progress bar at the bottom of the screen visualized the number of completed tasks relative to the total number of tasks.

To accurately map the analog button input to the cursor movements, the physical displacement range of each button was first determined and scaled to match the subscreen height. Due to minor lateral slack in the 3D-printed buttons, small unintended cursor movements occurred, occasionally preventing them from fully returning to the starting position after release. To compensate for this, a 25-pixel margin was applied at both ends of the sensor range before mapping it to the cursor movement. This adjustment ensured that releasing the buttons consistently returned the cursors to the bottom of their respective subscreens.

Participants were instructed to simultaneously move all active cursors to their respective targets as quickly as possible by pressing the analog buttons. Each task presented a new target configuration, and to complete a task, all cursors had to reach their respective targets and remain within them for $500\,\mathrm{ms}$, known as the dwell time [15]. At the start of each task, the targets turned green, signaling the participant to move their cursors. Upon successful task completion, the targets disappeared, indicating that the participant should release the buttons and return the cursors to their starting positions. During this time, new targets for the next task also appeared in red, allowing participants to anticipate where the targets would be before the task started. After another $500\,\mathrm{ms}$ at the starting position, the new targets turned green again, initiating the next task. This sequence was repeated for all tasks within each trial until the trial was completed. The step-by-step process for a single subscreen is illustrated in Fig. 3.

For each task, targets could appear at one of three possible distances from the bottom of the subscreens (150, 300, or 600 pixels) and with one of two possible widths (70 or 100 pixels). This resulted in six unique target conditions. These distances and widths were chosen to evenly distribute the values for the index of difficulty (ID), calculated according to Fitt's Law (see Appendix A), resulting in a range from 1.32 to 3.26 bits. The easiest condition (lowest ID) corresponded to the largest, closest target (100 pixels wide at 150 pixels distance), while the most difficult condition (highest ID) was represented by the smallest, farthest target (70 pixels wide at 600 pixels distance).

For trials involving more than one finger, multiple targets appeared simultaneously within a single task, resulting in various possible combinations of the six target conditions. To ensure a comprehensive set of task variations, target conditions could be repeated within a task. However, since finger-specific performance was not analyzed, targets were randomly assigned to fingers, making the order of targets across fingers irrelevant.

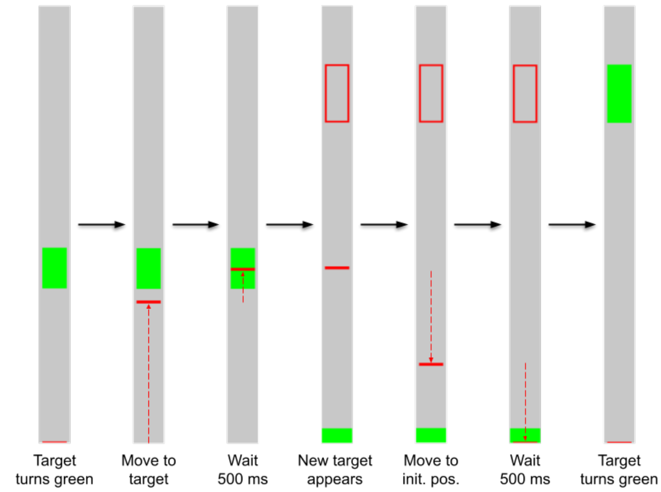

Fig. 3. Step-by-step process for a task for a single subscreen. This sequence repeats until all tasks in the trial are completed. Faster completion results in higher performance.

Consequently, the total number of unique task configurations per trial, denoted as $T(n,k)$, is given by the binomial coefficient:

$$T(n,k) = \binom{n+k-1}{k} \tag{1}$$

where $n = 6$ represents the number of possible target conditions, and k denotes the number of fingers used in the trial.

However, as the number of fingers increases, the total number of unique tasks grows rapidly (see Table I). Moreover, to minimize variability and improve accuracy, it is recommended to repeat each ID condition multiple times within a trial [16]. As a result, the number of tasks per trial (particularly in the four-finger trial) becomes excessive, making it impractical to test all possible task configurations.

To address this, a subset of task combinations was selected to reduce the total number of tasks. This selection was based on the combined index of difficulty for each task (see section II-E), ensuring that the chosen tasks were evenly distributed across the difficulty range. To further limit the total number of tasks, tasks were repeated only five times in the three- and four-finger trials, compared to ten times in the one- and two-finger trials. This approach helped maintain a manageable number of tasks and kept trial durations reasonable.

Since participants were expected to require some time to adjust to the number of fingers at the start of each trial, five dummy tasks were presented first. These dummy tasks

TABLE I
OVERVIEW OF THE NUMBER OF TASKS DURING THE DIFFERENT TRIALS.

Number of fingers	**Number of unique tasks**	**Number of tasks in the subset**	**Repetitions per task**	**Added dummy tasks**	**Total number of tasks**
1	6	6	10	5	65
2	21	11	10	5	115
3	56	16	5	5	85
4	126	21	5	5	110

were excluded from data analysis but allowed participants to refamiliarize themselves with the setup and task demands.

Taking all factors into account, the total number of tasks presented in one-, two-, three-, and four-finger trials were 65, 115, 85, and 110, respectively. These values are summarized in Table I.

D. Experimental procedure

Upon arrival, participants were seated in front of the experimental setup and computer monitor. The protocol was explained to them, and they were asked to sign the consent form. Fresh rubber bands were placed on the buttons to prevent breakage during the experiment. To begin, participants calibrated the sensor range by moving all four buttons through their full range of motion for five seconds.

Following calibration, participants were given ten minutes to familiarize themselves with the experiment and practice using different numbers of fingers on the setup. This familiarization period consisted of one minute of training with one finger, followed by two minutes with two fingers, three minutes with three fingers, and four minutes with four fingers. Participants were instructed to place only the fingers involved in the trial on the buttons while keeping the remaining fingers in a relaxed position. Additionally, they were informed that it was important to move their fingers simultaneously during the multi-finger trials.

During the familiarization phase, targets appeared in the subscreens at random distances from the starting position (ranging from 150 to 600 pixels) and with randomized widths (between 35 and 125 pixels). This variability was introduced to prevent participants from memorizing the finger positions and the force required to reach the six fixed target conditions used in the actual experiment. After the familiarization period, participants were given a five-minute break.

Participants then completed the four trials, each with a different number of fingers. To mitigate potential learning and fatigue-related effects, participants were divided into four groups, with each group starting with a different trial. As a result, each group consisted of three participants. Between trials, a rest period equal in duration to the preceding trial was provided, under the assumption that longer trials would require longer recovery. A timeline of the full experiment is shown in Fig. 4.

Before each trial, participants were reminded to move their fingers simultaneously and reach the targets as quickly as possible. They were also informed about the number of tasks to be completed and the expected trial duration. Additionally, they were encouraged to stay focused, as concentration was emphasized as an important factor influencing performance.

E. Data analysis

During the experiment, data were collected for each task presented to the participants. Specifically, this included the target characteristics (distances and widths) and the movement time. Movement time was defined as the duration taken by a participant to move all visible cursors in a task to their respective targets, excluding both dwell time and reaction time [16]. Dwell time was omitted by stopping the timer as soon as the cursors entered the targets, provided they remained within them for the required $500\,\mathrm{ms}$ dwell period. Reaction time was minimized by displaying the upcoming targets in red before the task began, allowing participants to anticipate the required movements in advance.

Since each unique task was repeated multiple times, the mean and standard deviation of the movement time were calculated per task for each participant. Movement times exceeding three standard deviations from the mean were considered outliers and removed from the data, following the recommendations of [16].

For each task, the Index of Difficulty (ID) was calculated. This was achieved by first computing the individual ID for each target using the Shannon formulation [17], based on Fitts' Law (see Appendix A):

$$ID_{i,j} = \log_2\left(\frac{D_{i,j}}{W_{i,j}} + 1\right) \quad \text{[bits]} \tag{2}$$

where $D_{i,j}$ denotes the distance to target j in task i, and $W_{i,j}$ is the corresponding target width.

The combined index of difficulty for task i was then defined as the sum of the individual ID values for all k targets (i.e., active fingers) involved in that task:

$$ID_i = \sum_{j=1}^{k} ID_{i,j} \tag{3}$$

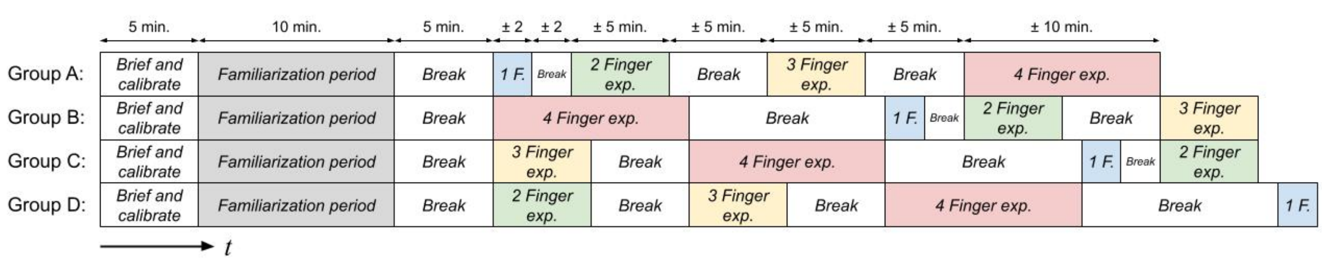

Fig. 4. Timeline of the experiment for each participant group. Trial durations are estimates, as they vary between participants depending on their performance.

The Throughput (TP) for each task was calculated by dividing the combined index of difficulty by the corresponding Movement Time (MT):

$$TP_i = \frac{ID_i}{MT_i} \quad \text{[bits/s]} \tag{4}$$

To enable comparison across trials involving different numbers of fingers, the mean throughput for each trial was computed as:

$$\overline{TP} = \frac{1}{N_k} \sum_{i=1}^{N_k} TP_i \tag{5}$$

where N_k is the total number of tasks in a trial with k fingers.

Similarly, the mean movement time for each trial was calculated as:

$$\overline{MT} = \frac{1}{N_k} \sum_{i=1}^{N_k} MT_i \tag{6}$$

These calculations were performed individually for each participant. The resulting mean throughput and movement time were then averaged across all participants to identify performance trends and assess the impact of increasing the number of fingers.

III. Results

In this chapter, the experimental results are presented. First, the effect of using multiple fingers on both average movement time and throughput is analyzed. Next, the relationship between movement time and the task index of difficulty is examined to test whether Fitts' Law holds, as it predicts a linear relationship between these variables.

A. Average Movement Time vs Number of Fingers

In Fig. 5, the relationship between the number of fingers used in the experiment and the average movement time ($\overline{MT}$) in seconds is illustrated. Boxplots show the distribution of average movement times across all participants for each finger configuration, while the gray lines represent the individual trends for each participant across trials.

The general trend indicates that the average movement time increases as the number of fingers used grows. The upward trend in each participant's individual line further suggests that using more fingers results in longer movement times. Additionally, variability in movement time also increases, especially in the four-finger configuration, which exhibits the widest spread.

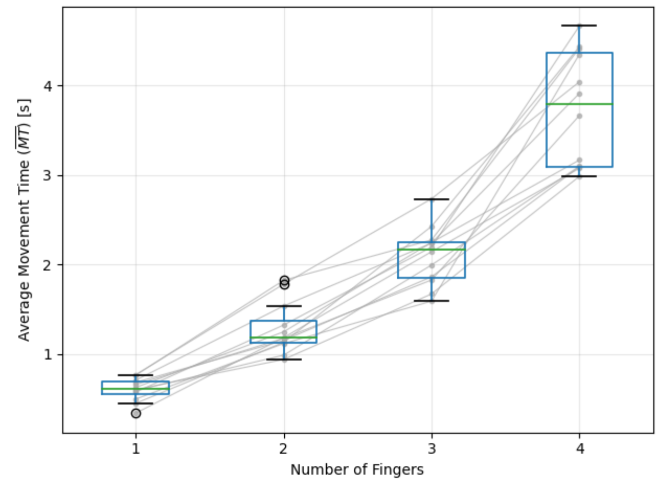

Fig. 5. Average movement times of all participants across different numbers of fingers.

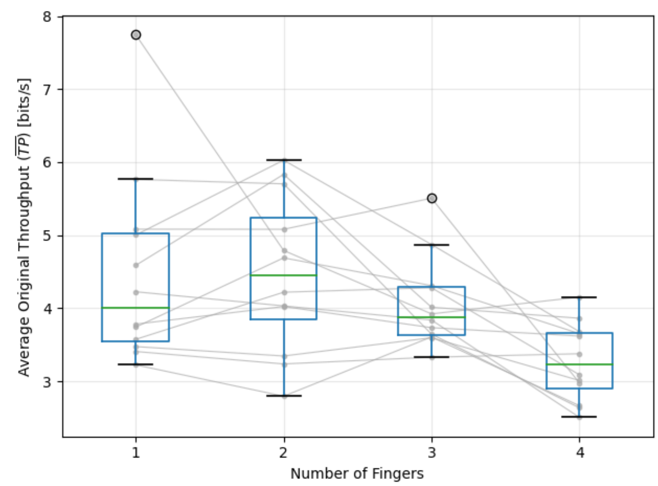

Fig. 6. Average original throughputs of all participants across different numbers of fingers.

B. Average Throughput vs Number of Fingers

Fig. 6 presents the average throughput ($\overline{TP}$) in bits per second in relation to the number of fingers used in the experiment. The boxplots illustrate the distribution of the average throughput values, while the gray lines represent individual participant trends.

The results indicate that the average throughput increases with the addition of a second finger but decreases with three and four fingers. This suggests that peak performance is achieved with two fingers. For higher numbers of fingers, the increase in index of difficulty was not sufficient to compensate for the increase in movement time, resulting in a decline in throughput.

However, not all individual participant trends align with this pattern. For instance, one participant achieved remarkably high throughput in the one-finger configuration due to an exceptionally low average movement time. Randomizing the trial order across participants was, therefore, an appropriate decision, as it helped account for such variations and minimized the impact of potential learning and fatigue-related effects on the overall results. As a result, the overall trend suggests that two fingers yield the highest throughput on average, despite the individual differences.

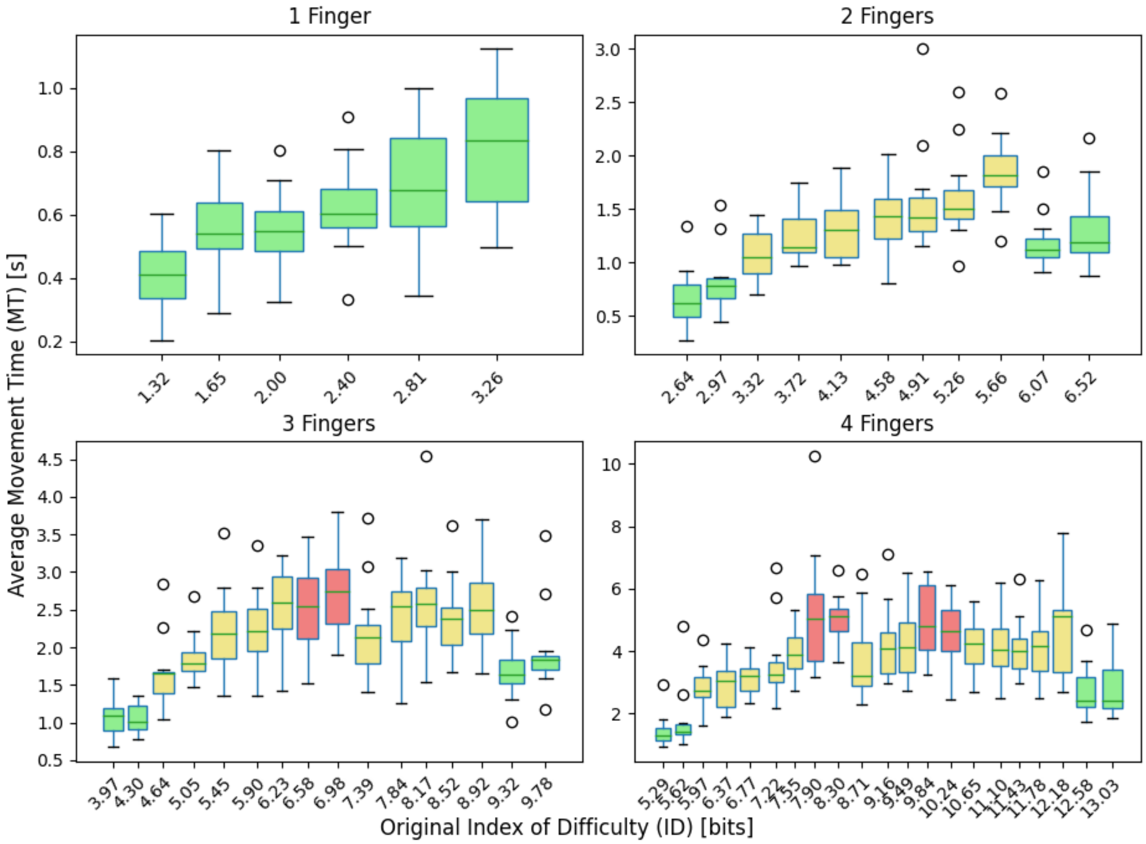

Fig. 7. Average movement times across different index of difficulty conditions for each finger configuration. The colors represent the number of unique distances involved in the task: green for a single distance, yellow for two distances, and red for three distances.

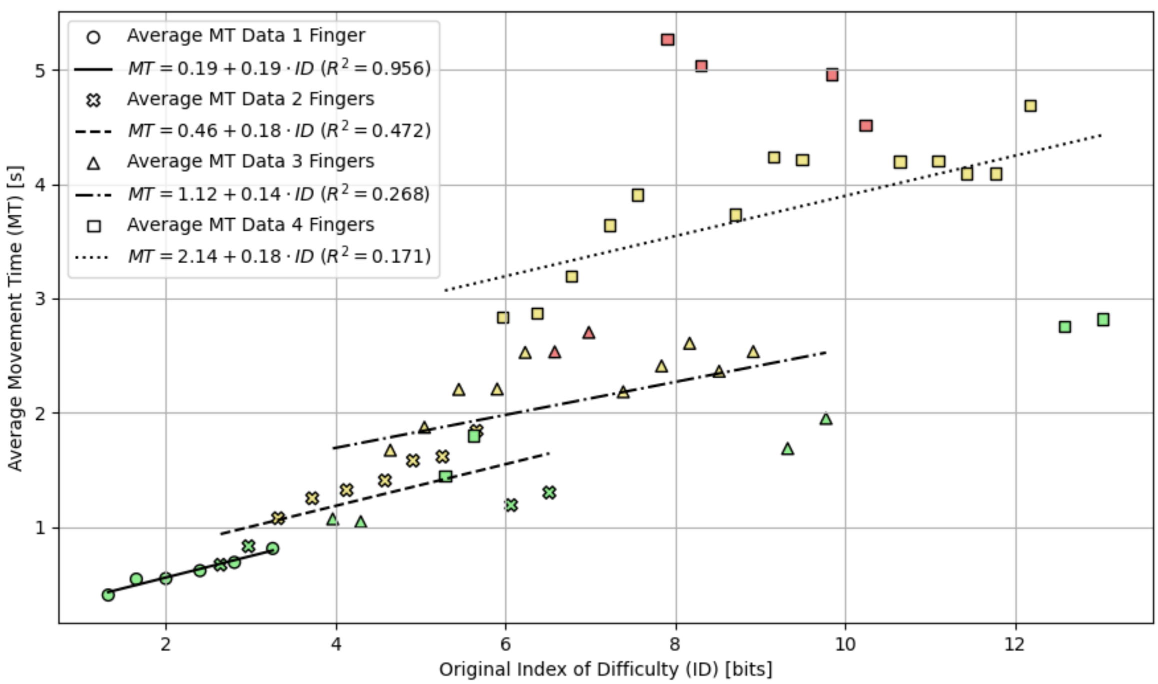

Fig. 8. Linear regression fits for average movement times across different index of difficulty conditions for each finger configuration. The colors represent the number of unique distances involved in the task: green for a single distance, yellow for two distances, and red for three distances.

C. Average Movement Time vs Task Index of Difficulty

Fitts' Law, as discussed in Appendix A, suggests a linear relationship between Movement Time (MT) and the Index of Difficulty (ID), expressed by the equation:

$$MT = a + b \cdot ID \tag{7}$$

To evaluate this relationship, the average movement times were analyzed across different ID conditions for each number of fingers used. The results are presented in Fig. 7, where boxplots illustrate the distribution of movement times for each ID condition.

In the one-finger configuration, a clear linear relationship between MT and ID is observed. However, in the multi-finger trials, MT decreases at certain increased ID values, making the relationship nonlinear. This deviation from linearity becomes more evident when a linear regression is applied to MT as a function of ID, as shown in Fig. 8. While the regression provides a strong fit for the one-finger configuration ($R^2 = 0.956$), the quality of the fit diminishes for the multi-finger configurations.

A closer examination suggests that the drop in MT occurs primarily in tasks with fewer unique target distances. In the figures, tasks where all targets share the same distance are marked in green, those with two distinct distances are in yellow, and those with three different distances are in red. Tasks involving multiple targets at the same distance appear easier than expected, likely because the fingers move more synchronously. This indicates that the original approach of summing the individual ID values for each finger, as in equation 3, does not accurately reflect the combined ID of a task. Instead, a refined method is required for multi-finger tasks to better represent the combined task difficulty and improve the fit to Fitts' Law.

D. Weighted Index of Difficulty

Fig. 7 and Fig. 8 suggest that the original index of difficulty for tasks with targets at equal distances may be overestimated. To obtain a more accurate representation of the combined task difficulty, a weighted sum of the individual ID values is considered:

$$ID_{i,weighted} = \sum_{j=1}^{k} w_{i,j} ID_{i,j} \tag{8}$$

This weighted sum aims to ensure a more linear relationship between MT and ID. The most intuitive choice for the weight function $w_{i,j}$ is to reduce the difficulty of an individual target when other targets share the same distance. For example, this can be achieved by:

$$w_{i,j}(D_{i,j}) = \frac{1}{c_{i,j}(D_{i,j})} \tag{9}$$

Here, $c_{i,j}$ represents the number of times distance $D_{i,j}$ appears in task i. This means that adding an extra target at a distance

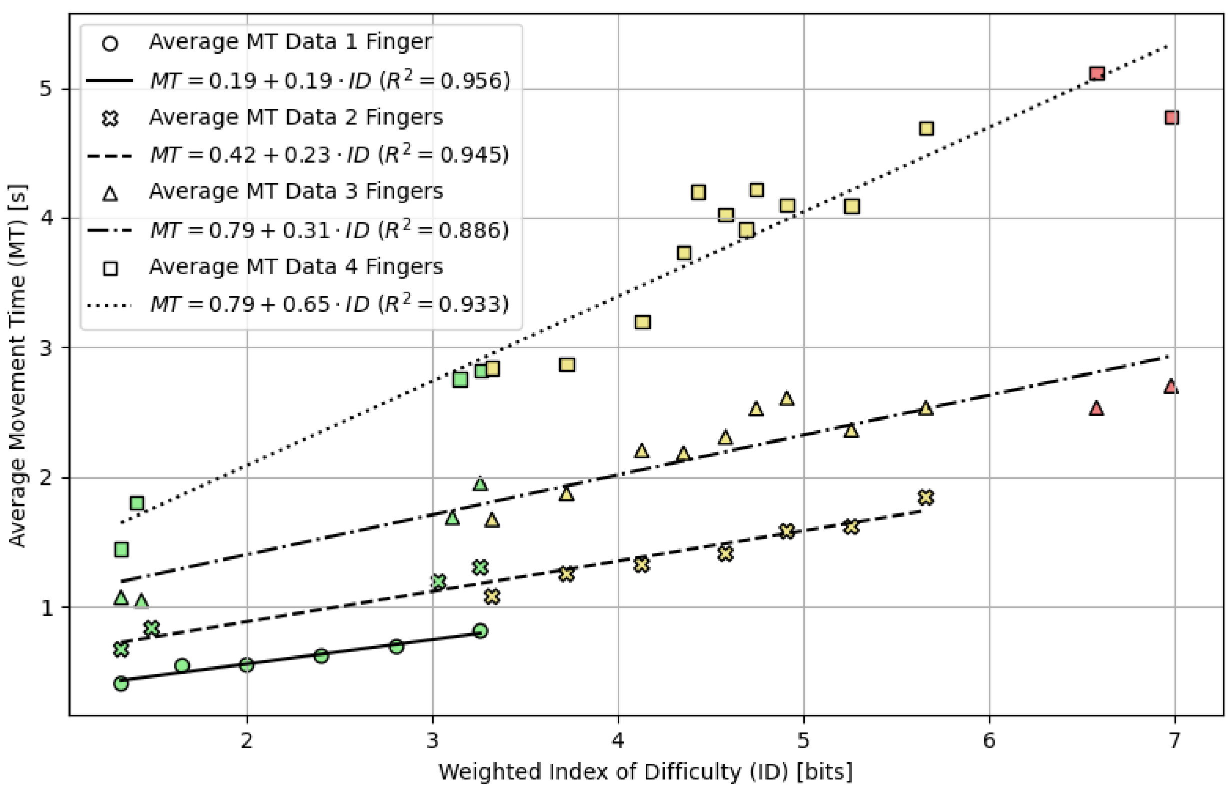

Fig. 9. Linear regression fits for average movement times across different weighted index of difficulty conditions for each finger configuration. The colors represent the number of unique distances involved in the task: green for a single distance, yellow for two distances, and red for three distances.

already present in the task does not significantly increase the overall task difficulty. In other words, moving one finger to a target with a particular ID is as difficult as moving multiple fingers to targets with that same ID.

By using this weighted approach, the ID values are no longer evenly distributed, but the linear relationship between MT and ID is improved, as seen in Fig. 9.

This adjustment also affects the average throughput ($\overline{TP}$), as throughput is directly related to ID. The average throughput with different numbers of fingers used, employing the new weighted index of difficulty, is shown in Fig. 10. The figure demonstrates peak performance for one finger, followed by a decline in $\overline{TP}$ as the number of fingers increases.

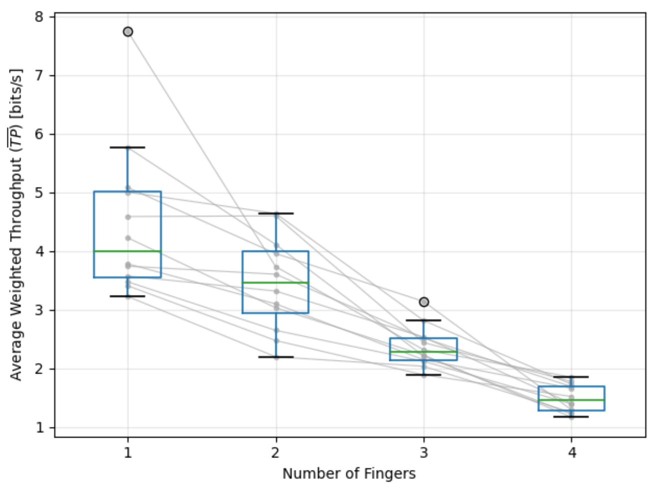

Fig. 10. Average weighted throughputs of all participants across different number of fingers.

IV. Discussion

A. Fitts' Law analysis

Over the years, Fitts' Law has been widely used in research to evaluate human performance across various input devices, such as computer mouses [16], touchscreens [18], and eye trackers [19] [20]. However, comparing results across different Fitts' Law studies is challenging [21]. For example, Soukoreff and MacKenzie observed significant variations in throughput values across studies even when the same type of input device, i.e., a computer mouse, was used [16]. They attributed these discrepancies to inconsistencies in experimental design, particularly in the formulation of the index of difficulty (ID) and the range of ID values used. To address these issues, they proposed a set of recommendations aimed at improving consistency and comparability across studies. This study has followed most of these recommendations, although a few deviations were made.

One significant deviation concerns the lack of using the adjustment for accuracy, as described in Appendix A, which aims to better align with actual participant movements. However, applying this adjustment did not seem applicable to this experiment, as no selection errors could occur due to the use of dwell-based selection. In this setup, selection was triggered only when the cursors were inside the targets, resulting in a zero error rate. While introducing a time-out mechanism, as used in [20], could have allowed for errors to occur, determining an appropriate time-out threshold would have been arbitrary. Moreover, in the multi-finger configurations, this would require longer time-out durations to give participants enough time to complete the tasks, which would have introduced additional complexity to the experiment.

Another deviation concerns the range of ID values. Soukoreff and MacKenzie recommend using a broad range, typically between 2 and 8 bits. In this study's one-finger experiment, however, the ID range was relatively narrow, from 1.32 to 3.26 bits. This limited range was intentionally chosen to prevent excessively large ID values when combining multiple fingers, based on the original formulation of combined difficulty. However, with the proposed weighted formulation of ID, this concern became less of a problem, and future experiments could consider a broader range of ID values.

Although direct comparisons between the results of this study and those adhering strictly to the full set of recommendations may not be entirely valid, the one-finger experiment closely resembles a conventional 1D Fitts' Law task, allowing for some level of comparison. The throughput value obtained in this experiment falls within the typical range reported for mouse-based pointing, between 3.7 and 4.9 bits per second [16]. The observed throughput even exceeds the values recorded for touchpad and isometric joystick inputs. Similarly, the setup used in this study outperforms common game controller inputs, achieving a higher throughput than the gyrosensor, thumbstick, and touchpad found on controllers [22]. All of these, including the device used in this study, are considered indirect pointing devices, where input actions occur on a separate device, and output responses are displayed on the screen via a cursor.

In contrast, direct input devices, such as touchscreens, allow users to interact with on-screen targets directly, eliminating the need for a cursor. This typically results in higher throughput, as seen with finger-based input on touchscreens, which tends to outperform typical mouse-based input [23]. When comparing the throughput of this study, which used the dominant index finger on an indirect input device, with that from a study using the same finger on a mobile touchscreen, the touchscreen throughput indeed exceeds the throughput from the current setup [24]. That study also found that the dominant index finger achieved the highest throughput compared to the dominant thumb, nondominant index finger, and nondominant thumb. It would be interesting to investigate whether similar performance differences between fingers emerge when using an indirect input device, such as the one from this study.

It is important to remember that Fitts' Law remains a theoretical framework, and interpreting throughput measurements in the context of interface design can be challenging. Priya and Joshi attempted to bridge this gap by performing 1D and 2D tapping experiments on a smartphone, where they compared Fitts' throughput with an empirical throughput defined based on their realistic interface [25]. In the 1D condition, Fitts' throughput was higher, but in the 2D experiment, the empirical throughput surpassed Fitts' throughput. These findings highlight the complexity of translating theoretical throughput measurements into practical insights for the design of hand-operated devices.

B. Multi-finger performance

To the best of the author's knowledge, no prior studies have conducted multiple Fitts Law experiments simultaneously or applied its principles to assess combined task complexity in multi-finger movements. A fundamental assumption of Fitts' Law is that it models rapid, aimed movement. However, in the multi-finger trials of this study, the movement times spanned several seconds, raising the question of whether the model still applies. Despite this concern, a strong fit was achieved for the multi-finger configurations by employing a relatively straightforward weighted summation approach to calculate combined task difficulty. This leads to the belief that Fitts' Law can indeed apply in this context.

A closer examination of the average movement time across trials with different numbers of fingers reveals an increase in movement time as more fingers are used. This is expected, as coordinating multiple fingers inherently increases task complexity and demands greater motor control. Additionally, variability across participants grows with the number of fingers, emphasizing how individual differences in dexterity and coordination abilities become more pronounced under more complex configurations.

An important aspect of this research was evaluating how to define a combined index of difficulty for multi-finger tasks. Using the original definition of the combined ID, which sums the individual indices of difficulty, a peak performance was observed with two fingers. This pattern aligns with the studies by Nizamis et al. [10] [11], who reported the highest information transfer rate with three fingers. These results suggest that increasing the amount of information in a task improves performance up to a certain point. Beyond this threshold, the cognitive-motor load may exceed what can be effectively managed, highlighting the limitations of human motor control and the importance of designing HMI interfaces that remain within manageable levels of complexity.

However, when movement time was compared against the original index of difficulty, the data did not follow the linearity predicted by Fitts' Law in the multi-finger trials. This suggests that the complexity introduced by each finger movement is not independent and cannot simply be summed to calculate the overall task complexity.

To address this, an alternative version of task difficulty was introduced, using a weighted summation. In this approach, each target's ID was weighted based on how frequently its distance occurred throughout the task. This method provided an intuitive way to handle the drop in movement time for certain indices of difficulty and resulted in a strong linear fit across all finger configurations. However, this method may oversimplify the actual task difficulty, as it assumes that a task with multiple identical targets is as difficult as one with only a single occurrence of that target. In reality, coordinating multiple fingers requires managing additional control signals and dividing attention between multiple targets, which likely increases the actual difficulty. A more refined model might include a weighting factor that also accounts for the number of active targets or fingers. Additionally, the effect of variability in target width could provide further insights. If significant, this factor could also be incorporated into the model.

When examining the average throughput ($\overline{TP}$) under the weighted summation method, the previously observed pattern with the original ID no longer held. Instead of peak performance with two fingers, the highest throughput was observed with one finger, and performance declined as more fingers were added. This outcome is expected, as the weighted summation approach reduces the index of difficulty for multi-finger tasks, while the movement time remains unchanged.

It is important to note that applying the weighted sum causes the selected subset of target combinations to become unevenly distributed across the range of ID values. This imbalance directly affects the calculation of $\overline{TP}$ and could skew the result, as certain difficulty ranges become over- or underrepresented. This issue is especially problematic if the regression lines cross, as this would imply that for certain parts of the range, one line would show the highest throughput, while for other parts, a different line would dominate. Fortunately, an analysis of the fitted regression lines reveals that both the slope and intercept increase with the number of fingers used. As a result, the lines do not cross for positive ID values, indicating that throughput consistently decreases with more fingers, provided the ID conditions are roughly distributed across the range. Therefore, the effects of this imbalance are limited and do not undermine the observed trend.

C. Setup limitations

Several improvements could be made to the experimental setup. First, the mechanical design introduced some lateral slack in the levers, primarily due to the use of only a single ball bearing for rotation. This slack allowed the magnet to deviate from the central axis, which affected the accuracy of the angle measurements. To ensure the cursor could reliably reach the top of the subscreen and return fully to the initial position, a margin was applied at both ends of the sensor range. While this approach prevented issues at the extremes of the sensor range, it did not eliminate cursor positioning errors caused by small lateral finger movements during button presses. To mitigate this issue, the buttons could be reinforced, and an additional ball bearing could be incorporated to stabilize the lever and minimize slack.

Second, the sampling frequency of sensor data transmission to the computer was lower than expected. Although the intended rate was $1\,\text{kHz}$, the actual sampling frequency was closer to $50\,\text{Hz}$. This discrepancy was likely due to the use of a multiplexer, which needed to switch between sensors sharing the same I2C address for every data reading. However, given that movement times in the experiment ranged from hundreds of milliseconds to several seconds, this lower sampling frequency is unlikely to have significantly impacted the accuracy of the measurements.

Lastly, the rubber bands used to return the buttons to their initial position introduced unintended difficulty. Since they applied force opposite to the direction of pressing, participants' fingers could gradually drift away from their intended positions. This effect was particularly noticeable during multi-finger trials. While participants focused on aligning one target, their other fingers, which were already correctly positioned, slowly shifted away. As a result, movement time increased for certain tasks. A potential solution would be to modify the setup so that the fingers are fixed to the buttons, thereby preventing this drift.

D. Experimental and display limitations

In designing the experiment, it was decided that each trial would consist of a series of discrete tasks [16], requiring participants to return to the starting position after completing each task. To exclude reaction time from the movement time measurements, the targets for the next task were displayed in red while participants returned to the starting position. Additionally, since the wait time for the targets to turn green was always $500\,\mathrm{ms}$, participants could develop a sense of this timing, allowing them to anticipate when and where to move. However, this method may not fully eliminate reaction time, as participants could feel compelled to wait until they see the targets turning green before reacting. Moreover, participants occasionally moved too early, attempting to complete the task while the targets were still red, leading to frustration when they realized their mistake. To reduce this issue, only the borders of the targets were shown, which helped to decrease the frequency of these errors, although they still occurred occasionally for each participant.

A potential solution to these limitations would be to use serial tasks instead [16], where participants tap back-and-forth between targets. This design would naturally exclude reaction time from the movement time, as participants would already be aware of the next target's location and would not need to wait. Additionally, this method could reduce trial duration since participants would not have to return to the starting position after each task.

To limit the number of tasks in the trials, only a subset of all possible target combinations was used. This subset was selected to generate a set of evenly distributed ID values based on the original definition of task difficulty. However, it may be more validated to choose the subset for each number of fingers such that the ID values become evenly distributed after applying the weight function. Furthermore, the number of repetitions was limited to 5 or 10 per target combination, whereas 15-25 repetitions are typically recommended [16]. This could have reduced the accuracy of the results. However, given the sufficient number of participants tested, the results are still expected to be reliable.

Due to the already lengthy duration of the experiment, participants were given limited training time with the setup. However, as the number of fingers increases, more training would likely be necessary. The lower performance observed with multiple fingers could potentially be attributed to insufficient practice. One-finger performance may already be near the human maximum, while performance with two or more fingers may still have room for improvement. With additional practice, multi-finger throughput could then potentially exceed that of single-finger use. This suggests that the impact of training should be considered in future studies exploring multi-finger interaction.

V. Conclusion

This paper investigated human cognitive-motor performance in finger movements during the simultaneous completion of multiple Fitts' Law tasks. A series of finger movement tasks were conducted using a multi-button setup. The results reveal that the combined difficulty of multi-finger movements does not align with Fitts' Law when approximated by simply summing the individual finger difficulties of each finger. Instead, a weighted sum of the individual target difficulties is proposed, with weights determined by the frequency of target distance repetition. This adjustment provides a more accurate representation of task difficulty, aligning more closely with Fitts' Law. Future work could build upon these findings by conducting more validated Fitts' Law multi-finger experiments.

While directly translating throughput in bits per second to real information transfer through hand-operated devices remains complex, comparing the performance across different finger configurations is feasible. The results underscore the importance of minimizing interface complexity in HMI device design, as peak cognitive-motor performance is achieved when fewer fingers are engaged. However, it should be noted that training effects were not considered in this study. Future research should explore this factor to capture a more accurate representation of real cognitive-motor limits.

Acknowledgment

The author would like to thank Arno H. Stienen for his supervision and valuable input throughout this thesis. Special thanks are also extended to the participants in the experiment, whose voluntary and uncompensated involvement was essential to this study. Additionally, the author appreciates the student group under Arno's supervision for their constructive feedback and contributions during the biweekly sessions.

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APPENDIX A
FITTS' LAW

Fitts' Law is a predictive model of human motor behavior introduced by Paul Fitts in 1954 [26]. It describes the time required to move rapidly to a target as a linear function of the task's difficulty, expressed by the equation:

$$MT = a + b \cdot ID \tag{10}$$

where MT is the movement time, a and b are empirically determined constants, and ID represents the Index of Difficulty, which quantifies the difficulty of the movement task. The index of difficulty depends on the spatial characteristics of the task, specifically the distance to the target and the size of the target.

Fitts originally defined the index of difficulty (ID) as:

$$ID = \log_2\left(\frac{2D}{W}\right) \tag{11}$$

where D is the distance to the center of the target, and W is the target width. This formulation was inspired by Shannon's information theory [27], interpreting motor movements as information transmissions, with task difficulty measured in bits. To achieve a higher empirical fit and to better align with the theorem Fitts' index of difficulty was based on, MacKenzie proposed a refined version, often referred to as the Shannon formulation [17]:

$$ID = \log_2\left(\frac{D}{W} + 1\right) \tag{12}$$

This version ensures that ID remains positive and has since become standard in experimental research, particularly in human-computer interaction [16].

In addition to modeling movement time, Fitts introduced the idea of an Index of Performance (IP) to quantify the rate at which the human motor system can process and execute aimed movements. This metric is now commonly referred to as Throughput (TP):

$$TP = \frac{ID}{MT} \tag{13}$$

Throughput is expressed in bits per second (bps) and provides a useful metric for comparing performance across different tasks, users, or input devices. However, this definition of throughput does not account for the accuracy of the movement. A user may produce fast movements that frequently miss the target, resulting in high throughput but low actual performance.

To incorporate accuracy into the analysis, an adjustment is made to the nominal target width W by considering the actual distribution of movement endpoints. The effective target width W_e is defined as the width that encompasses 96% of the movement endpoints, assuming that the variability in endpoints follows a normal distribution. This leads to the following equation:

$$W_e = \sqrt{2\pi e} \cdot \sigma = 4.133 \cdot \sigma \tag{14}$$

where e is Euler's number, and σ represents the standard deviation of the position error, measured as the deviation between the final cursor coordinates and the target coordinates across all successful trials.

Similarly, the distance parameter D can also be adjusted for accuracy. The effective distance D_e is then defined as the distance to the mean of the endpoints.

Using these adjustments, the effective index of difficulty (ID_e) is computed as:

$$ID_e = \log_2\left(\frac{D_e}{W_e} + 1\right) \tag{15}$$

and the effective throughput (TP_e) is:

$$TP_e = \frac{ID_e}{MT} \tag{16}$$

This method ensures that both speed and accuracy are integrated into the throughput, providing a more realistic assessment of user behavior in pointing tasks.

Appendix B
3D-printed Buttons

The buttons in the experimental setup were custom-designed using Autodesk Fusion and 3D-printed. The design consists of three components that are bolted together. The lever is connected to the base via a ball bearing, allowing for smooth rotation. A diametrically magnetized magnet is placed on the rotating axis of the lever. The third component houses the AS5600 sensor, which detects the rotation of the magnet. An exploded view of the components is shown in Fig. 11, and Fig. 12. Additionally, a back view of the setup can be seen in Fig. 13, which shows the rubber bands used to return the buttons to their original position.

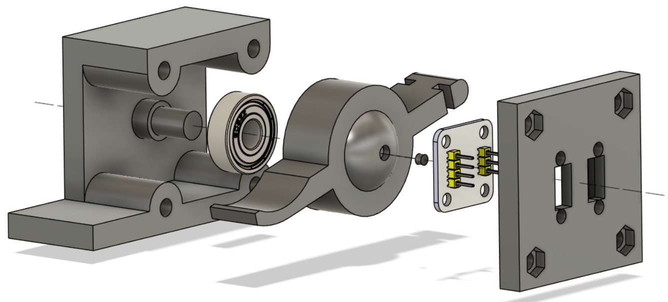

Fig. 11. Exploded view of the 3D-printed buttons from the front.

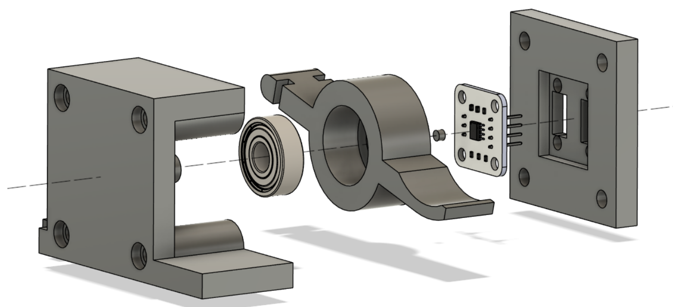

Fig. 12. Exploded view of the 3D-printed buttons from the back.

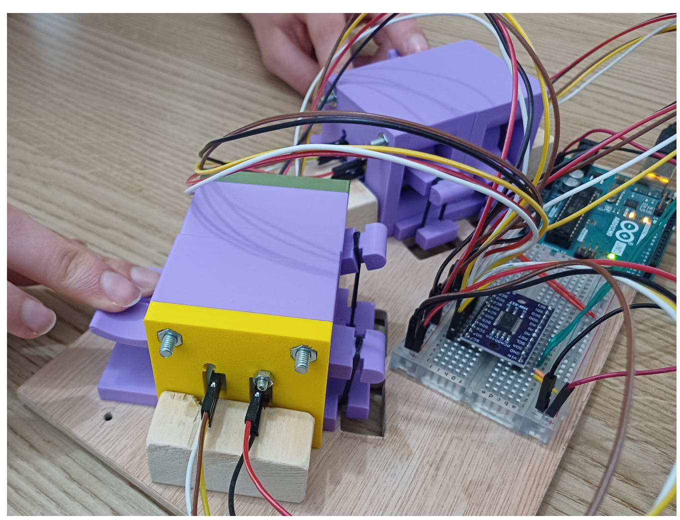

Fig. 13. Back view of the experimental setup, showing the rubber bands that return the buttons to their original position after release.

APPENDIX C
ELECTRONIC CIRCUIT

The electronic circuit of the experimental setup consist of four AS5600 magnetic rotary sensors connected to an Arduino Uno via the I2C communication bus. Since all AS5600 sensors share the same I2C address, a PCA9548A I2C multiplexer is used to enable communication with each sensor individually. The DIR pin of each AS5600 is connected to ground, setting the sensors to hardware clockwise mode. To accommodate different button orientation, the rotation direction for two of the buttons is reversed using the AS5600 software library. A full overview of the circuit is shown in Fig. 14. Finally, the Arduino Uno collects the sensor readings and transmits it to the computer for further processing.

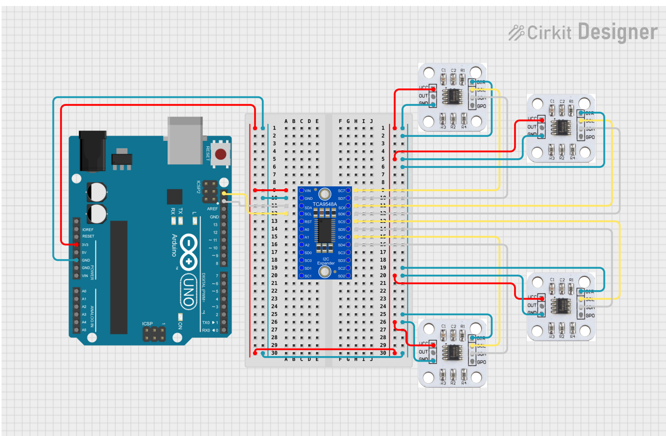

Fig. 14. Electronic circuit design for the interaction device, created using Cirkit Designer.