

The first four pages will be
sent to you by our secretary.
Please update the PDF
“titelseiten.pdf” accordingly.

English Title

Bachelor’s Thesis/Master’s Thesis

by

Name

Department of Informatics

Responsible Supervisor: Prof. Dr. Michael Beigl

Supervising Staff:

Project Period:

The first four pages will be
sent to you by our secretary.
Please update the PDF
“titelseiten.pdf” accordingly.

The first four pages will be
sent to you by our secretary.
Please update the PDF
“titelseiten.pdf” accordingly.

Erklärung

Hiermit erkläre ich, dass ich die vorliegende Bachelor/Masterarbeit selbstständig verfasst und keine anderen als die angegebenen Hilfsmittel und Quellen benutzt habe, die wörtlich oder inhaltlich übernommenen Stellen als solche kenntlich gemacht und weiterhin die Richtlinien des KIT zur Sicherung guter wissenschaftlicher Praxis beachtet habe.

Karlsruhe, den

The first four pages will be
sent to you by our secretary.
Please update the PDF
“titelseiten.pdf” accordingly.

Contents

1	Introduction	3
2	Background & Related Work	5
2.1	Passive learning	5
2.2	Braille Learning	14
2.3	Related Works	17
2.3.1	Piano Learning	17
2.3.2	Typing Skills	20
2.3.3	Braille Learning	21
2.3.4	Morse Code	22
2.3.5	Multi-limb Rhythm Learning	23
2.3.6	Skin Reading	24
2.3.7	Effects of PHL Practice in Rehabilitation	24
2.3.8	Stenography Learning	25
3	Implementation and Design	27
3.1	Implementation	27
3.1.1	Hardware	27
3.1.1.1	Actuator Design	27
3.1.1.2	Glove Design and Design Iterations	29
3.1.2	Software	32
3.1.2.1	Website	32
3.1.2.2	Communication between the gloves	34
3.1.3	Encoding Scheme	34
3.1.3.1	Encoding Chords	35
3.1.3.2	Audio-Chord Offset	36
3.1.3.3	Isogram Selection and Carry-Over Effect Minimisation	36
3.2	Study Design	38
4	Analysis	41
4.0.1	First Study	41
4.0.2	Second Study	53
5	Evaluation	65
5.0.1	First Study	65
5.0.2	Second Study	68
5.0.3	Threats to validity	70
5.1	Threats to Validity	70
5.1.1	Internal Validity	70

5.1.2	External and Construct Validity	70
6	Conclusion and Future Work	73
7	Summary	75
	Bibliography	77

List of Figures

2.1	Glove variants and designs used in previous works [15, 23, 21, 34, 35, 44, 48, 53, 69, 70, 68, 74, 85].	10
2.2	Actuator placement on the hand in previous works [44, 23, 21, 22, 19, 15, 33, 90, 70, 68, 69, 74, 35, 85, 38, 53, 34].	11
2.3	Chord encoding schemes used in previous literature [47, 48, 49, 50]. . .	11
2.4	Depiction of the human skin [46].	13
2.5	Braille finger mapping [69].	15
2.6	English Braille alphabet (Grade One) [63, 81].	15
3.1	3D model, and the implementation on a users finger of one element of the vibration system from [23]	28
3.2	3D models for the case and hammer-shaped contactor, and the implementation on a user's finger of one element of the tapping system from [23]	28
3.3	3D models for the case and the contactor, and the implementation on a users finger of one element of the stroking system from [23].	28
3.4	Final Glove- Case Design on a squared Din A5 paper for size reference.	29
3.5	Final Glove Design opened on a squared Din A5 paper for size reference.	29
3.6	Final Glove Design on a squared Din A5 paper for size reference.	30
3.7	Old design of the circuit.	31
3.8	Glove Circuit Diagram.	31
3.9	Website Design in a Mobile Phone.	33
3.10	Testing Site for the Writing Test.	33
3.11	Communication Architecture.	34
3.12	Audio vibration offset.	36
3.13	Encoding of the character D as an example for hand encodings.	36
3.14	Sentence used in the pre-study and its braille part.	38
3.15	Study design.	38

4.1	Participant Click-differences.	42
4.2	Raw Nasa TLX scores for the different Stimuli grouped by the Nasa TLX dimensions. Each dot represents one participant.	43
4.3	Self-assessment Results of the different Stimuli grouped by the self-assessment categories. 4 is the best score and 0 the worst score. Each dot represents one participant.	44
4.4	Results of the direct comparison between the different stimuli.	46
4.5	Jaccard coefficient results grouped by the Braille character during learning for the different stimuli. Each dot represents one participant.	47
4.6	Jaccard Word-Test results grouped by the results for the Braille test-words “THE”, “OLD” and “PUB” for different stimuli.	49
4.7	Jaccard Score comparison for the different Stimuli grouped by the Braille test-word characters.	50
4.8	FN (Missed) and FP (Surplus) key(s) for each stimuli.	52
4.9	FN (Missed) Character in blue and FP (Surplus) keys in red in percent for each Braille character grouped by stimulus.	52
4.10	Cosine Similariy for each of the Stimuli. Plotted using a Principal component analysis (PCA) dimensionality reduction.	54
4.11	Participant Click-differences.	55
4.12	Raw Nasa TLX scores of the different Encodings grouped by the Nasa TLX dimensions.	56
4.13	Self-assessment Results of the different Stimuli grouped by the self-assessment categories.	57
4.14	Results of the direct comparison between the different encodings.	58
4.15	Jaccard coefficient results grouped by the Braille characters during learning for the different Encodings.	59
4.16	Jaccard Word-Test results grouped by the Braille test-words for the different stimuli.	60
4.17	Jaccard Score comparison for the different Encodings grouped by Braille character.	61
4.18	FN (Missed) and FP (Surplus) Key(s) for each Braille Character by Encoding.	63
4.19	FN (Missed) and FP (Surplus) Key(s) in percent for each Braille character grouped by Encoding.	63
4.20	Cosine Similariy for each Encoding. Plotted using a PCA dimensionality reduction.	64
5.1	Threats to validity	71

List of Tables

2.1	Distraction tasks leveraged in previous literature.	6
2.2	Overview of the devices in previous literature.	10
3.1	Comparison of Wi-Fi, Bluetooth and Esp-Now [18]. EE stands for Energy Efficiency, R stands for receiver and T for transmitter.	30
3.2	Probability for each dot occurring.	37
3.3	Entropy for each Braille letter rounded to 4 decimal places.	38
4.1	General participant data in the first study.	43
4.2	Results of the Kruskal-Wallis significance tests for the different NasaTLX dimensions with a η^2 Effect Size.	44
4.3	Results of the Kruskal-Wallis significance tests for the different self-assessment dimensions with a η^2 Effect Size.	46
4.4	Statistical Test Results for the direct comparison between the stimuli. * indicates results obtained via Negative Log-Likelihood under H_0	46
4.5	Results of Kruskal-Wallis significance tests for the different Braille characters during learning with a η^2 Effect Size.	48
4.6	Results of the Kruskal-Wallis significance tests for the wordtests “THE”, “OLD”, and “PUB” with a η^2 Effect Size.	49
4.7	Results of Kruskal-Wallis significance tests for the different Braille characters during testing with a η^2 Effect Size.	51
4.8	Second study participant data	54
4.9	Results of Mann-Whitney U Test (MW U test) significance tests for the different NasaTLX dimensions with Cohens d.	56
4.10	Results of the MW U test test for significance grouped by the different self-assessment dimensions with a Cohens d Effect Size.	58
4.11	Statistical Chi-Square Goodness-of-Fit Test (Chi-Square GF) Results for the direct comparison between the stimuli.	58
4.12	Results of the MW U test tests for significance grouped by the different Braille characters during training for the different Encodings with Cohen’s d.	59

4.13 Results of the MW U test tests for significance for the different Braille tests-words with a Cohens d Effect Size.	60
4.14 Results of the MW U test for significance grouped by the different Braille characters during learning for the different Encodings with Cohen's d.	62

1. Introduction

Worldwide, approximately 285 million people are visually impaired (with less than 1.3% vision), and about 39 million are completely blind, according to WHO [60]. In Germany alone, there are about 1.066k visually impaired individuals and approximately 160 thousand that are blind, according to Bertram et al. [9]. Learning Braille remains a significant challenge for blind and visually impaired individuals. While Grade 1 Braille can be learned in a few months, Grade 2 Braille takes more than a year to master. According to the Commission for the Blind of New York State¹. Learning Braille is particularly difficult for those who lose their vision later in life [69]. Braille is more than just a reading system; it is a critical literacy tool directly linked to better educational outcomes and employment opportunities [69, 65]. Ryles et al. note that Braille is the primary medium of literacy for blind individuals and is associated with solid reading habits and a greater likelihood of pursuing post-secondary education [65]. Furthermore, Bell et al. [8] showed, that the daily use of Braille positively impacts employment, salary, and self-esteem. Despite these clear benefits, only 10% of blind individuals learn Braille due to a shortage of certified instructors and resources. As a result, 74% of blind individuals are unemployed [69]. The challenges of Braille literacy are further compounded by the wide variability of teaching approaches, each requiring learners to have ample opportunities to use and develop their understanding of Braille contractions [79]. Modern technologies such as text-to-speech are able to help visually impaired people participate in active life but also cause neglect in Braille instruction [69]. However, excessive reliance on audio learning can negatively affect essential literacy skills such as spelling and composition [25], as full reliance on audio technology is inconsistent with the broader definition of literacy, which also includes writing [84]. In light of these barriers to traditional Braille instruction, several Braille learning devices such as gloves have been invented like the devices by Zaman et al. [91], Ozioko et al. [59], An [4] Cho et al. [14] and other such as Seim et al. [69, 74, 67], Yang et al. [90] or Forsyth et al.[44]. And also different teaching / acquiring methods such as active and passive learning. In our opinion, Passive Haptic Learning (PHL) offers a promising solution due to the lack of active attention needed. PHL enables individuals to learn motor tasks, such as Braille typing, through tactile stimulation without requiring active

¹<https://ocfs.ny.gov/programs/nyscb/assets/docs/BrailleFAQ.pdf>

attention. Research teams have leveraged this concept to design assistive gloves that teach Braille through muscle memory, a form of procedural memory that allows individuals to unconsciously retain skills over time [90, 67]. By using PHL, individuals can passively learn Braille while performing everyday activities, such as walking or commuting, reducing the time and effort required for instruction [90]. The potential of PHL to accelerate Braille learning is further supported by research into the neuroplastic changes that occur during the process. Blind individuals who learn Braille experience cortical changes, including enlargement of the sensorimotor area associated with the reading finger and the recruitment of the occipital cortex, which formerly processed visual information, for tactile tasks [29]. By providing continuous, passive tactile stimulation, PHL systems may enhance these neuroplastic processes, making Braille learning more efficient. In doing so, PHL offers a viable solution to address the "crisis" in Braille literacy [69], providing an innovative method for improving literacy and independence for those who are blind or visually impaired. However, many open questions remain in this domain, such as: **RQ1:** *Is there a difference between affective and discriminative touch for both hands using the Prioritized Overlapping Spatiotemporal Sequence (OST) encoding?* and **RQ2:** *Is there a significant difference between using the OST and the Sequential encoding (SEQ) encoding?* These are the questions this thesis aims to address, with the goal of easing the burden of learning Braille and enabling more individuals to embrace a life of literacy."

2. Background & Related Work

2.1 Passive learning

Learning is often perceived as an active and purposive process; however, this is not always the case. In addition to active learning, there exists a form of passive learning, which stands in contrast to the active approach. Passive learning is often described as being “caught rather than taught” [40], emphasizing its effortless nature. This lack of effort is attributed to the absence of resistance, meaning that neither motivation nor interest is necessary for the acquisition of this type of knowledge [92]. Furthermore, passive learning has been characterized as “typically effortless, responsive to animated stimuli, amenable to artificial aids to relaxation, and marked by an absence of resistance to what is learned” [34, 40]. This suggests that passive learning can occur in environments where learners are exposed to stimuli without actively engaging in the learning process. Zukin et al. [92] demonstrated that exposure to media-rich environments can lead to information being acquired passively. In their study, they examined two groups of subjects who were not initially interested in political information. They found that subjects who were exposed to political content through a media-rich environment were 40% more likely to acquire the information compared to those living in media-poor environments [93, 34]. Later research by Huang et al. [34] extended the concept of passive learning to the acquisition of physical skills. The success of this study contributed to the introduction of the term PHL [62], which further encapsulates the potential for learning in contexts where active engagement is minimal or absent. Over the years a significant body of research has been dedicated to the exploration of PHL. It spanned a wide range of applications, including piano learning [34, 38, 68, 15, 21, 23], the acquisition of typing skills [74, 70, 69, 44], the learning of Braille [69, 44], Morse code [71, 73, 62], multi-limb rhythm coordination [11, 32], skin reading [48, 49], stenography learning [6, 5], and even the effects of PHL on spinal cord injury (SCI) rehabilitation [53]. For a general overview of the background this section outlines, several parameters of passive haptic learning and how they were investigated in previous works.

Paper name	Game	Learning Time
Aveni et al. [6]	SpikeDislike2	4 * 10 min
Caulfield et al. [44]	Not mentioned	10 min
Fang et al. [23]	Gweled	30 min
Fang et al. [21]	Tetris	15 min
Donchev et al. [15]	Gweled	20 min
Hsu et al. [33]	Not mentioned	30 min
Pescara et al. [62]	Gweled Open Hexagon	20 min (5 min training/character)
Luzhnica et al. [49]	Snake Game	32 min
Seim et al. [73]	Fritz	8 or 16 min
Seim et al. [70]	Fritz	15 min
Seim et al. [71]	Fritz	20 min
Seim et al. [68]	Fritz	20 min
Seim et al. [74]	Memory Card Game	30 min
Seim et al. [69]	Fritz	30 min
Bouwer et al. [11]	Reading Comprehension	30 min
Kohlsdorf et al. [38]	Watching a film Playing memory Walking a path	5 min
Huang et al. [35]	Daily task (pilot study) PSAT/SAT (main study)	30 min
Pala et al. [85]	Not mentioned	15-60 min
Huang et al. [34]	Daily task (Reading book/paper, typing at desk)	30 min

Table 2.1: Distraction tasks leveraged in previous literature.

Distraction Task

Apart from the primary challenges of learning new skills or rehabilitation, much of the focus in PHL research has been on distraction tasks, which are crucial to its main selling point. Distraction tasks are those that can be performed concurrently while the primary learning process takes place, allowing the acquisition of information to occur passively. We compared the distraction tasks used in previous literature, along with the time participants spent learning, and summarized them in Table 2.1.

In earlier PHL research, reading comprehension tests [34, 35, 38] were commonly employed as the distraction task. However, this method has largely fallen out of favour. During the development of the Mobile Music Touch (MMT) framework, Kohlsdorf et al. [38] tested three different tasks: watching a film (audio-visual stimulation), playing a memory game (active memory engagement), and walking a designated path (body motion). These tasks were chosen to represent common everyday activities such as relaxing, thinking, and walking.

The results showed no statistically significant difference in the number of PHL sessions required across the different tasks. However, individual differences emerged, with some participants finding certain tasks more challenging than others. Rhythm retention was slightly better after the memory game condition compared to the film condition, though no condition was significantly better or worse overall. Participants reported similar subjective workloads across all conditions, suggesting that the type of primary task does not significantly impact the effectiveness of PHL in learning

piano sequences. The study concluded that while the type of primary task may influence individual performance, there is no clear evidence that one task is superior to others in enhancing PHL effectiveness. This suggests that PHL can be integrated into various everyday activities without being significantly hindered by the nature of the concurrent task.

This was also investigated by Pescara et al. [62], who found that the difficulty level of distraction tasks, such as the games Gweled (easy) and Open Hexagon¹ (hard), did not significantly influence learning outcomes [62]. However, Pescara et al. also noted that participants reported increased fatigue over the course of the study due to the prolonged focus required by these games. This finding suggests that future research should explore alternative distraction tasks that are engaging enough to divert attention from PHL, yet unlikely to induce fatigue during extended periods—a challenge that remains difficult to address.

More recent studies have shifted their focus to other tasks, such as playing the game 'Fritz'², which has become the most frequently used alternative, appearing in five studies, followed by the game 'Gweled,'³ which has been utilized in three studies. Table 2.1 provides an overview of the games used as distraction tasks in previous literature.

PHL Duration

Another crucial factor is the duration of the distraction task and the period during which passive learning occurs, as this may directly influence the effectiveness of the PHL process. As shown in Table 2.1, most studies employ a standard learning period of 30 minutes before subjects undergo further testing or evaluation. Close behind, several studies opt for a slightly shorter 20-minute learning period. However, there is significant variability in session lengths, ranging from as brief as 5 minutes to as long as 60 minutes, indicating no clear consensus on the optimal duration. To explore this further, Seim's study [73] highlighted the benefits of extended learning time. The study demonstrated a notable improvement in learning Morse code between 8-minute and 16-minute exposure conditions, suggesting that longer exposure periods may be more advantageous.

Overlearning

Another aspect closely tied to learning duration is the concept of overlearning. Overlearning refers to the deliberate overtraining of an already learned task, aiming to achieve error-free performance [39]. Numerous psychological studies have examined its effects, particularly on retention [39, 16]. While overlearning can enhance retention, it may also have adverse effects, such as degrading performance, as demonstrated by Langer et al. [43].

In the context of PHL, Donchev et al. [15] deliberately avoided overlearning, citing its unpredictable effects on long-term retention and the potential for distorted results. To mitigate this, they halted the learning session once participants achieved an accuracy of 90

¹Open Hexagon: <https://vittorioromeo.info/Downloads/>

²Fritz!: www.gamesgames.com/game/fitz.

³Gweled: <https://gweled.org>

However, not all studies have avoided overlearning. For example, Seim et al. [72, 69] included overlearning in their experimental design. In their full alphabet study [69], they specifically investigated its effects. Conversely, in another study [67], they avoided overlearning to prevent ceiling effects on shorter phrases. This suggests that the decision to include overlearning in some studies was likely a deliberate choice tailored to the research objectives.

Chunking

When learning information, it is often presented piece by piece. This is called “chunking” and it is a critical concept in cognitive science, especially in memory and learning processes. It involves breaking large pieces of information into smaller, more manageable units to enhance retention. Miller et al. [58] first observed that the average person can hold about seven items in working memory, and that chunking helps organize information into meaningful patterns. Laird et al. [42] emphasized that chunks are the basic units of human memory, allowing the brain to retrieve information from long-term memory more efficiently. Thalmann et al. [80] demonstrated that chunking reduces working memory load, benefiting recall as long as the chunks consist of unique elements.

In passive learning, chunking is widely used to improve learning and retaining efficiency. Markov et al. [53] divided note sequences into four passages of 10-15 notes each. Seim et al. [74] found that random presentation of letters and words did not aid learning, highlighting that chunk size and learning time are crucial factors in passive learning. They taught phrases one at a time. Similarly, Seim et al. [69] applied chunking in language learning with phrases like ”add a bag” (AAB) and ”hike fee” (HF), which involved 15-18 vibrations and 3-4 characters. These phrases were comparable in length to previous work on PHL for piano [38] and typing [74]. Seim et al. continued to use chunking in [67] to teach 4-8 note sequences with chords, finding that optimal learning occurred in sets of 10-17 stimuli. They also used chunking to teach Morse code via a Bone conducting transducer (BCT) introducing one word at a time from the sentence ”the quick brown fox jumps over the lazy dog” [72]. In their keyboard learning research, Seim et al. [70] employed row-wise in contrast to the widely used word-wise chunking. Additionally, in their smartwatch-based Morse code study, Seim et al. presented phrases in manageable chunks for improved retention [73].

Luzhnica et al. [49] applied chunking to teach 10 letters, repeating each letter four times in multiple rounds, while Prescara et al. [62] used chunking to reduce Morse code training time by dividing the 26 patterns into three sets.

Moreover, studies such as the study of Sargent et al. [66] further support chunking’s role in memory, showing that participants recalled spatial information more accurately when it was grouped into smaller chunks.

However not every related work used chunking as a means of transmitting information to the participants. Kohlsdorf et al. [38], Donchev et al. [15], Fang et al. [21, 23], and Huang et al. [34] did not use chunking for note sequences of 6-10 notes, as it was likely unnecessary due to the short sequence length.

Audio-Sensory Timing

Another important consideration is the timing of audio and sensory input—primarily in the form of vibrations—used in previous studies. Cognitive processing can be hindered when individuals are required to perform two perceptual tasks simultaneously, as shown by Gescheider et al. [26]. To mitigate this issue, most PHL research incorporates a delay or offset between audio and sensory inputs, although the specific timings vary across studies [74, 70, 49, 21].

For instance, Seim et al. [74] introduced a 100ms offset, where the audio was followed shortly by the vibration sequence corresponding to the word being learned. In a later study [72], they extended this offset to 1 second, before eventually eliminating it altogether in [70], where stimuli were presented immediately after the text was spoken. Similarly, Luzhnica et al. [49] implemented a brief 50ms delay between auditory and vibrotactile cues.

By contrast, Pescara et al. [62] adopted a simultaneous approach, delivering both sensory input and audio at the same time. Fang et al. [21] opted for a short offset of a few seconds, ensuring that auditory signals were delivered during pauses of the tactile signals, and vice versa.

Glove Design

As previous research shows, PHL is not only constrained to the hand, and there are several appliances, that facilitate the option of learning PHL such as smartwatches [73], wrist bands, google glasses BCT [71], velcro bands at the limbs [11] or even gloves as depicted in Table 2.2.

Various haptic devices have been employed for PHL, including smartwatches [73], Google Glass [71], and Velcro bands applied to the limbs [11] (as can be seen in Table 2.2). However, given that previous research has primarily focused on the hand, the glove has emerged as one of the most extensively studied devices for PHL, followed closely by vector bands, which are predominantly used on the fingers, some glove designs can be seen in Figure 2.1. This trend may also be influenced by the significant number of studies centred on learning to play piano pieces. Within this context, there are notable differences in the types of gloves used, such as fingerless gloves versus standard gloves, as seen in Figure 2.1. A critical factor in selecting gloves for PHL is the placement of actuators. Fingerless gloves are often preferred due to their superior manual dexterity [34], allowing wearers to perform everyday tasks more easily (as demonstrated in the MMT system [53, 38, 35]). Additionally, fingerless gloves are more adaptable to various hand sizes, ensuring that actuators can be precisely positioned [69, 68]. Other important considerations for glove design include weight, breathability, flexibility, and coarseness, all of which contribute to the comfort of the device—an essential factor given the need for extended wear [53, 38, 35, 21]. These considerations might also explain the advantages of using velcro bands as an alternative to gloves.

Special gloves were also invented for braille learning such as the gloves by Yang et al. [90] that use gloves with vibration at the fingertips for typing Taiwanese braille or [44] Caulfield et al., which uses a haptic glove with vibration at the intermediate parallax for typing braille, or even Seim et al. [69] using a stiff glove [74] as well as many more notable mentions such as the ones from Zaman et al. [91], Ozioko et al.

Paper name	Location	Device	Actuator	Chorded input
Aveni et al. [6]	Proximal phalanx (dorsal side)	Fingerless Glove	Vibration	Yes (Staggered)
Caulfield et al. [44]	Center proximal phalanges	Fingerless Glove	Vibration	Yes (didn't work)
Fang et al. [23]	Proximal phalanges close to joint	Velcro bands	Dragging Tapping Vibration	No
Fang et al. [21]	Intermediate phalanges Bottom of distal phalanx (thumb)	Cotton glove	Vibration	No
Fang et al. [22]	Below proximal interphalangeal	Plastic glove	Vibration	No
Fang et al. [19]	Index Finger Proximal Phalanges Index Finger Intermediate Phalanges Outer Wrist and Inner Wrist	Self-adhesive tape Elastic strap	Dragging Tapping Vibration	No
Fang et al. [24]	3 Arm positions	Elastic band	Dragging Tapping Vibration	No
Donchev et al. [15]	Above proximal phalanges Near interphalangeal joint	Glove (Soft, Stretchy)	Vibration	No
Hsu et al. [33]	Fingertips	Velcro-fastening straps	Vibration	No
Pescara et al. [62]	Wrist	Velcro tape fastening	Vibration	No
Luzhnica et al. [49]	Hand (back)	Glove	Vibration	Yes (partly) OST encoding
Seim et al. [73]	Wrist	Smartwatch	Vibration	No
Yang et al. [90]	Fingertips	Glove	Vibration	Yes
Seim et al. [70]	Intermediate phalanges	Fingerless Glove	Vibration	No
Seim et al. [71]	Head	Google Glass	BCT	No
Seim et al. [68]	Proximal phalanges	Fingerless Glove	Vibration	Yes (Staggered) like Seim et al. [69]
Seim et al. [74]	Proximal phalanges	Fingerless Glove	Vibration	Yes (didn't work) (Non-staggered)
Seim et al. [69]	Proximal phalanges	Fingerless Glove (stretchy)	Vibration	Yes (Staggered)
Bouwer et al. [11]	Limbs	Velcro bands	Vibration	Yes
Huang et al. [35]	Proximal phalanges	Fingerless Glove (stiff)	Vibration	No
Pala et al. [85]	Proximal phalanges (Version 1) Intermediate phalanges (Version 2)	Fingerless Glove (abandoned) Patchwork Glove	Vibration	No
Kohlsdorf et al. [38]	Proximal phalanges	Fingerless Glove	Vibration	No
Markow et al. [53]	Proximal phalanges	Fingerless Glove (golf) Fingerless Open Flap Glove Velcro Finger Glove	Vibration	No
Huang et al. [34]	Proximal phalanges	Fingerless Glove (golf)	Vibration	No

Table 2.2: Overview of the devices in previous literature.

[59], An et al. [4], Cho et al. [14], however, they are not specialised for PHL, only for active learning.

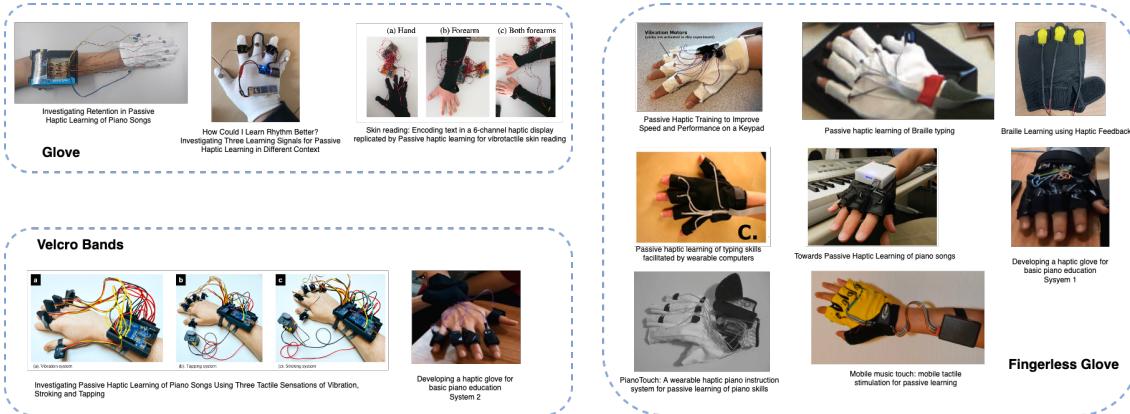


Figure 2.1: Glove variants and designs used in previous works [15, 23, 21, 34, 35, 44, 48, 53, 69, 70, 68, 74, 85].

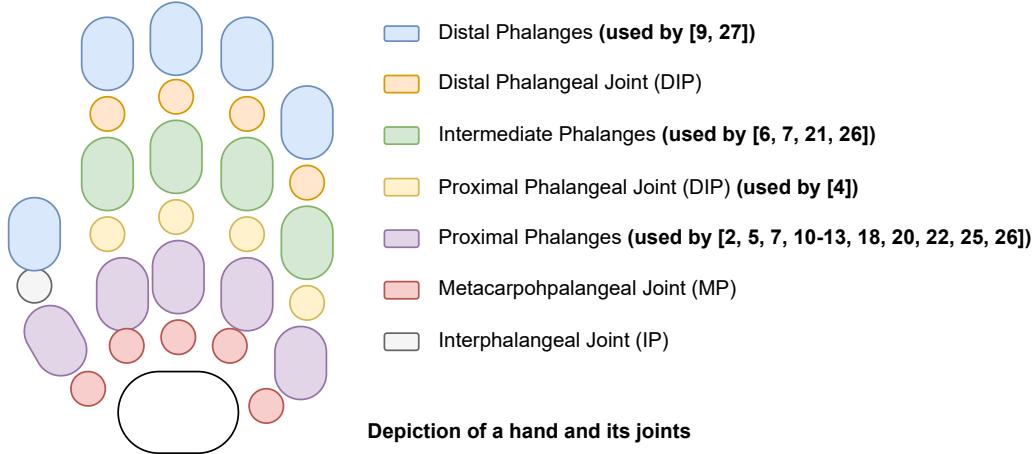


Figure 2.2: Actuator placement on the hand in previous works [44, 23, 21, 22, 19, 15, 33, 90, 70, 68, 69, 74, 35, 85, 38, 53, 34].

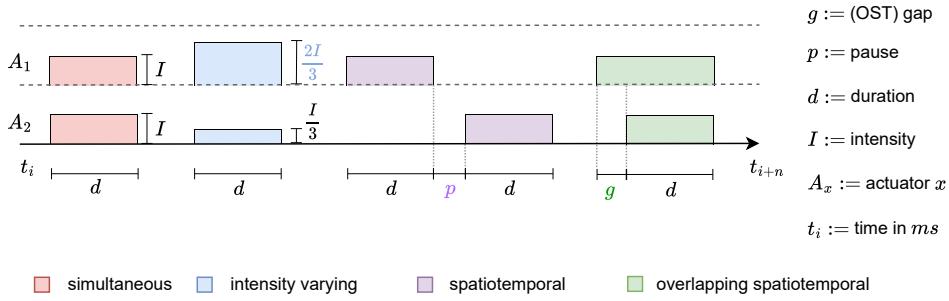


Figure 2.3: Chord encoding schemes used in previous literature [47, 48, 49, 50].

Actuator Hand Placement

The placement of actuators has undergone significant changes in recent research. While some studies have explored more unconventional approaches, such as the BCT used in Google Glass [71], smartwatches [73] worn on the wrist, or Velcro bands applied to the limbs for rhythm learning [11, 32], the majority of research has focused on the skin of the hand (and occasionally the arm) as a successful site for input. In particular, the placement of actuators on the fingers has shown that targeting the proximal phalanges is advantageous [19], but research also explored other areas, such as the fingertips [90] or even the wrist or back of the hand. Figure 2.2 shows the different hand placements and their corresponding papers. Research from Fang suggested, that the response time at the finger is shorter than for the wrist for the stimuli (vibration, taping and stroking) and the perception accuracy at the finger is significantly more accurate than at the wrist, moreover, their experimental results indicated, that the Finger Phalanx achieves higher accuracy than the Outer Wrist [19].

Chorded input

One of the primary challenges associated with Braille typing in the context of passive learning is the chorded input aspect. This refers to the simultaneous pressing of

multiple keys or buttons to generate a single character, which can be particularly demanding in a passive learning environment. Chorded input often requires a high degree of motor coordination and precision, posing unique challenges for learners who lack active engagement during the learning process.

The encoding and execution of chords—actions involving the simultaneous use of multiple limbs or fingers—are central to many real-world tasks, such as playing musical instruments like the piano [74, 68, 34, 38, 35, 69, 85, 15, 21, 23], performing multi-limb rhythms on drums [11, 32], and Braille writing itself [44, 70, 69]. These activities demand the integration of complex motor skills, making them particularly challenging to teach through passive learning. As such, developing effective methods to teach users how to perform chords is crucial.

Several approaches have been explored to encode and teach chorded inputs, as illustrated in Figure 2.3. Seim et al. identified that encoding chords is especially challenging due to the difficulty participants face in accurately distinguishing simultaneous stimuli of multiple fingers, a problem depicted in red in Figure 2.3 [74, 67].

In an attempt to address these challenges, Luzhnica et al. investigated the use of varying stimulus intensities (depicted in blue in Figure 2.3) to differentiate between inputs. However, this approach proved to be ineffective, as the variation in intensity did not provide sufficient clarity for learners to distinguish between stimuli [47].

A more promising method, proposed by Seim et al., involves staggered input, where stimuli are activated or deactivated sequentially rather than simultaneously (depicted in purple in Figure 2.3). This spatiotemporal encoding method, first introduced by Seim et al. [69] and adopted in subsequent studies [74], enables a clearer temporal distinction between stimuli. By presenting stimuli sequentially, learners are better able to recognize and understand chord patterns, improving learning outcomes. However, this approach has limitations, particularly with encoding speed. The sequential nature of the method can slow down the process, especially for complex chords, thereby impacting overall learning efficiency.

To overcome these speed limitations, Luzhnica et al. introduced the OST encoding method, depicted in green in Figure 2.3. This method improves upon the spatiotemporal approach by overlapping the activation of actuators. Specifically, one actuator is turned on, followed by a delay (the OST-gap g) before activating the next, with all actuators remaining active for a fixed duration d before being turned off simultaneously. The OST method not only enhances encoding speed but also ensures that patterns are maintained longer, improving both accuracy and the overall learning experience [49, 50, 47, 48].

Further refinements to the OST encoding method were explored in a follow-up study by Luzhnica et al. [47]. They found that prioritizing more sensitive areas of the skin during the OST encoding process improved accuracy while increasing the delay between activations had little impact on performance. These findings highlight the robustness and effectiveness of the OST method in addressing the challenges of chorded input in passive learning [47].

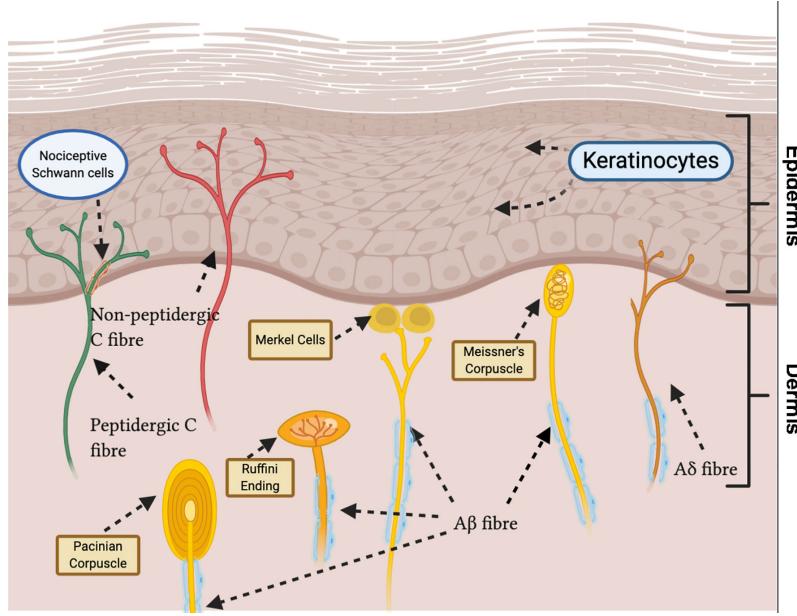


Figure 2.4: Depiction of the human skin [46].

Human skin and the influences of stimulus

The human skin, the largest and most visible organ of the body, serves as a versatile interface for perceiving a wide range of sensations. Beyond its protective functions, the skin provides sensory input from the environment and acts as a medium for communication and feedback. It is capable of detecting mechanical, thermal, chemical, and electrical stimuli, which generate sensations such as pressure, vibration, temperature, and pain. This diversity makes touch one of the most ancient and fundamental senses in the human body [23].

Touch perception begins at the receptors connected to nerve endings within the skin. These receptors respond to external stimuli, converting mechanical energy into nerve impulses that relay somatic sensations to the brain. Somatic sensations are those related to the physical body and include thermal, painful, and pruritic (itch-related) stimuli. The skin itself varies across the body, with glabrous (non-hairy) and hairy regions demonstrating differences in their receptor types as depicted in Figure 2.4, nerve fibre compositions, and the nature of the sensations they evoke. Glabrous skin, such as that on the palms and soles, is associated with discriminative touch and excels in tasks requiring precision and localization. In contrast, hairy skin regions are more attuned to affective touch and often evoke pleasant sensations, as suggested by findings in several studies [23, 2, 1].

Receptors in the skin fall into four major categories, collectively known as low-threshold mechanoreceptors (LTMs): Pacinian corpuscles, rapidly adapting (RA) units, slowly adapting type 1 (SA1), and slowly adapting type 2 (SA2) receptors. Each of these receptors has specialized functions, enabling the conversion of various mechanical stimuli into nerve impulses. For example, Merkel and Meissner cells detect slow pressure and low-frequency vibrations, while Pacinian corpuscles specialize in higher-frequency vibrations (up to 4000 Hz). Ruffini endings respond to skin stretching, highlighting the skin's capacity to detect spatial and temporal resolution in touch [19, 23, 1, 57].

These mechanoreceptors are connected to two types of nerve fibres—myelinated A β fibres and unmyelinated C fibres—each playing distinct roles in touch perception. Myelinated A β fibres, which are wrapped in myelin to increase signal conduction speed (20–80 m/s), project to the primary somatosensory cortex (SI area) and are primarily responsible for discriminative touch. This type of touch is crucial for localization and fine spatial resolution. On the other hand, unmyelinated C fibres, including the C-tactile (CT) afferents, have slower conduction velocities (0.5–2 m/s) and project to the posterior insula. These fibres are integral to the perception of affective touch, which is associated with emotional and social responses [19, 23, 1, 57].

The distinction between discriminative and affective touch is further reflected in the choice of learning devices used for passive haptic learning (PHL). The choice of device is critical to the success of PHL, as it determines the effectiveness of encoding and conveying tactile information. This study examines the impact of different haptic devices and actuator designs, differentiating between two types of input: discriminative and affective. Discriminative input encompasses sensory perceptions such as pressure, vibration, texture, or slip, whereas affective input involves motions such as sliding, tapping, and stroking [23].

Previous research has predominantly focused on vibrational input, with most studies examining discriminative input over affective input. Only a few studies have explored alternative approaches. For example, the BCT device used in Google Glass [71] is a notable example of discriminative input. In contrast, two studies specifically examined affective touch and incorporated tapping and stroking systems [20, 23]. These studies concluded that tapping and stroking systems are more pleasant, natural, and unobtrusive than vibrational methods for conveying information to users [19, 23]. This highlights the potential of affective input methods for improving user comfort and engagement in PHL.

Past work has further explored the skin’s ability to perceive stimuli through diverse actuation principles, such as vibrotactile feedback [20], skin stretching [87], temperature modulation [61], and airflow [83]. Vibrotactile devices, for instance, use actuators to generate vibrations that are perceived by mechanoreceptors like Pacinian and Meissner cells. Low-frequency vibrations are primarily detected by Merkel and Meissner cells, while higher frequencies (up to 400 Hz) are processed by Pacinian corpuscles [19, 45]. Additionally, Ruffini cells detect skin stretching, highlighting how specific receptor types are tuned to different tactile sensations. [19, 45, 19].

2.2 Braille Learning

Braille, a tactile writing system, was developed in 1825 by Louis Braille⁴. It is composed of a six-dot system, as illustrated in Figure 2.6, which allows users to type characters by pressing combinations of six keys simultaneously, as shown in Figure 2.5. Devices like the Perkins Brailler, the most commonly used Braille typewriter, facilitate this process. The Perkins Brailler consists of six main keys for typing, along with a space bar and secondary keys [88]. Despite its utility, teaching

⁴<https://www.dbsv.org/wie-die-brailleschrift-funktioniert.html>

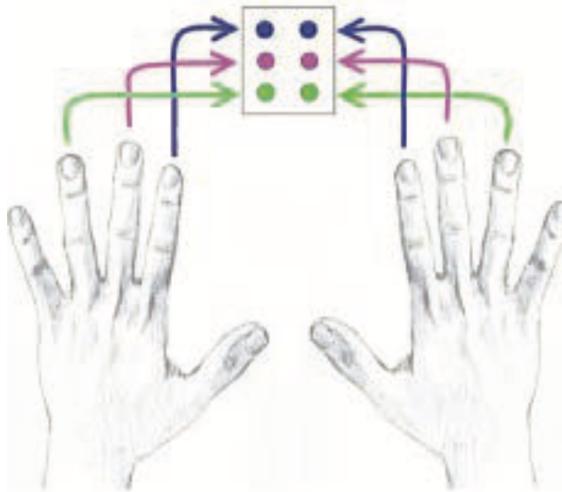


Figure 2.5: Braille finger mapping [69].

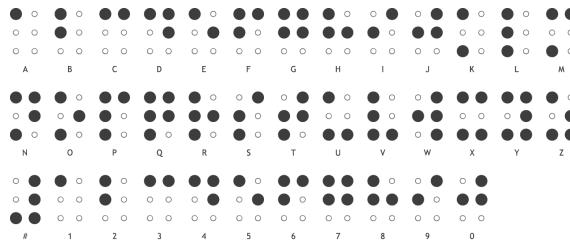


Figure 2.6: English Braille alphabet (Grade One) [63, 81].

and learning Braille remains one of the most significant challenges, particularly due to the time-intensive nature of mastering the system.

The integration of technology in Braille education has gained traction but remains underutilized, especially for senior learners. A 2018 study by Martiniello et al. [54] found that while 62.5% of Teacher of Students with Visual Impairments (TVI) and Rehabilitation Specialists working with younger learners use technology in their instruction, only 26.3% do so with seniors. Rehabilitation Specialists were also found to use technology less frequently than TVI, though TVI reported that technological tools enhance learner motivation and improve outcomes. Among these tools, the Braille Tutor app stands out. Available on multiple platforms, it has been downloaded over 100,000⁵ times. McCarthy et al. [55] demonstrated that the app increased students' learning rates, allowing them to achieve 100% accuracy faster and learn more Braille contractions—a shortened form of Braille words, also called Grade two Braille[81].

In addition to digital methods, non-digital programs such as the Mangold Braille Program [52] and resources from Hadley⁶ play a vital role. The Mangold Program focuses on tactile perception and symbol recognition before introducing the Braille alphabet through 29 progressive lessons. Hadley, endorsed by the New York State Commission for the Blind (NYSCB)⁷, offers self-learning resources but emphasizes

⁵<https://play.google.com/store/apps/details?id=com.lukeneedham.brailletutor&hl=en>
and <https://brailliac.com/>

⁶https://hadleyhelps.org/learn?topic_id=15

⁷<https://ocfs.ny.gov/programs/nyscb/assets/docs/BrailleFAQ.pdf>

that learning Braille, particularly contracted Braille, is a lengthy process, often requiring over a year. Tools like Alpha Boxes⁸, which pair initial letter sounds with Braille symbols, provide additional support for early learners.

Despite these resources, one-to-one teaching between students and teachers remains the dominant method for Braille instruction, as noted by Jawasreh et al. [36], who developed the Braille Finger Puller, a haptic device aimed at innovating the teaching process. Similarly, haptic technologies, such as the Translation Glove by Subathra et al. [89], have been designed to use vibrations to support Braille learning, akin to the gloves developed by Bandodkar et al. [7] and Shivakumar et al. [78]. However, most devices rely on vibration gloves, with few exploring PHL. Like Seim et al. and Caulfield et al., [44] have investigated this technique, though it remains underutilized in existing Braille learning devices. Furthermore, none of the current technologies incorporate OST encoding, a method with significant potential to improve tactile learning efficiency.

Studies have also explored Braille learning among sighted individuals. Bola et al. [10] conducted a nine-month study with 29 sighted adults, mostly Braille teachers, and found that participants could read Braille at an average speed of six words per minute by the course's end. Interestingly, low tactile accuracy did not significantly affect reading speed, indicating that even sighted individuals can adapt their sensorimotor systems to Braille without visual deprivation. Their learning rate was comparable to congenitally or early blind children learning Braille in primary school. Some educators have even employed methods like blindfolding children with residual vision to accelerate their tactile learning [10].

Additional research has focused on variables influencing Braille learning rates. Hall et al. [28] identified study modality (visual or haptic), stimulus discriminability, and test modality as key factors affecting performance during the learning phase. These insights have informed the development of teaching strategies and tools to better accommodate diverse learners.

Despite advancements, learning Braille remains a slow and challenging process, often requiring months or even years to achieve proficiency, particularly in contracted Braille. This underscores the need for further innovation in teaching methods and devices, particularly those incorporating PHL and OST encoding, to enhance the efficiency and accessibility of Braille instruction.

⁸<https://www.pathstoliteracy.org/alpha-boxes/>

2.3 Related Works

2.3.1 Piano Learning

In 2008, Huang et al. [34] investigated the effectiveness of learning piano through passive haptic feedback combined with audio cues. A study was conducted utilizing a specialized glove embedded with vibration motors corresponding to each finger, designed to assess whether passive exposure to a combination of auditory and tactile stimuli could improve piano learning and performance relative to learning through auditory stimuli alone. Participants wore the glove while engaging in a 30-minute distraction task, such as reading or typing, during which piano music was played and corresponding finger vibrations were delivered. Afterwards, they were asked to play the piano pieces they had been exposed to. The results revealed that participants who received both audio and haptic feedback performed significantly better, playing the pieces more smoothly and with fewer errors compared to those who received only audio feedback. The latter group exhibited more hesitation and confusion. The study concluded that PHL can significantly enhance piano skill acquisition by reducing errors and improving performance fluidity. The combination of audio and tactile feedback provided a richer understanding of the musical structure, reinforcing the potential of PHL as a valuable tool for learning physical skills, such as piano playing.

Further investigation into this phenomenon was conducted within the MMT framework. The first work by [35] explored the potential of using PHL to teach piano playing, focusing on whether individuals could learn piano passages through haptic feedback delivered via fingerless vibration gloves and how this method compared to traditional active learning methods. Two studies were conducted. In the first study, novice participants were asked to learn and reproduce a musical passage after a 30-minute session of PHL using the MMT system. During the session, participants engaged in a reading comprehension task while receiving tactile cues via the gloves. The results showed that participants who received tactile stimulation performed better than those in the control group, demonstrating that PHL can effectively teach piano passages. Interestingly, participants without prior musical experience tended to perform better with PHL than those with musical backgrounds. In the second study, the researchers compared the time required to learn a short, randomly generated musical passage using either passive or active learning methods. Participants with no prior piano experience often succeeded in repeating the passage correctly after PHL, while those with musical experience found the process more challenging. This study highlighted the advantages of PHL for novices, as it required fewer attempts to learn the passage compared to active learning, particularly for those without a musical background. The paper also found that while audio alone was insufficient for effective learning, the combination of tactile feedback and passive exposure to musical sequences significantly improved participants' ability to learn and reproduce the music.

The second MMT paper reported by [38] examined the impact of different primary tasks on the effectiveness of PHL in teaching piano note sequences. Three primary tasks were examined while participants received passive haptic feedback to learn a random 10-note piano sequence: watching a film (audio-visual stimulation), playing a memory game (active memory engagement), and walking a designated path

(body motion). These tasks represented common everyday activities like relaxing, thinking, and walking. Participants initially observed and listened to the piano keyboard as it played a 10-note sequence, after which they attempted to replicate the sequence. If they were unable to do so successfully, they proceeded to engage in the primary task for five minutes while receiving targeted finger stimulation via the PHL device. Following this stimulation, participants made another attempt to reproduce the sequence. This cycle was repeated until the participant was able to accurately replicate the sequence with 100% accuracy. The results indicated no statistically significant difference in the number of PHL sessions required across the different primary tasks. However, individual differences were noted, with some participants finding certain tasks more challenging than others. Rhythm retention was slightly better after the memory game condition compared to the film condition, though no condition was significantly better or worse overall. Participants reported similar subjective workloads across all conditions, suggesting that the type of primary task does not significantly impact the effectiveness of PHL in learning piano sequences. The study concluded that while the type of primary task may influence individual performance, there is no clear evidence that one task is superior to others for PHL effectiveness. This suggested that PHL can be effectively integrated into various everyday activities without being significantly hindered by the nature of the concurrent task.

Based on the aforementioned results, [68] investigated the potential of using PHL to teach two-handed, chorded piano melodies, focusing on the effectiveness of PHL in teaching complex motor skills and the necessity of accompanying audio feedback. The study introduced a method of sequentially delivering tactile stimulation to each finger involved in a chord, rather than simultaneous stimulation which has been proven to be ineffective, to facilitate the learning of complex piano pieces[47, 48, 49, 50, 69]. The study comprised two experiments. In the first, participants were exposed to vibration-only and vibration-plus-audio conditions while learning a simple one-handed piano melody. Their performance, assessed using Dynamic Time Warping (DTW), indicated no significant difference between the two conditions, suggesting audio feedback was not essential for effective learning with PHL. In the second experiment, participants without prior piano experience were randomly assigned to one of the following four conditions: no feedback; audio only; vibration only; and audio with vibration. Those in the vibration-only and vibration-plus-audio groups performed significantly better than the control and audio-only groups, indicating the effectiveness of tactile feedback in learning motor skills. However, participants reported higher frustration levels when audio was combined with vibration, as measured by the NASA Task Load Index (NASA TLX). The study concluded that PHL is effective for teaching two-handed, chorded piano melodies, particularly with tactile feedback alone. These findings suggest that passive haptic stimulation can suffice for learning motor skills, even with minimal attention dedicated to the task. The research also has broader implications for teaching other complex motor skills, like Braille typing, through PHL, and reinforced that PHL is most effective when teaching sets of 10-17 stimuli at a time, as explored in previous work [69].

In 2021, Donchev et al. [15] explored the effectiveness of PHL in teaching and retaining piano note sequences, comparing it to active learning methods. The study aimed to determine whether PHL could be as effective as active learning for memorizing and recalling piano sequences and to assess the long-term retention of these

sequences. Participants were taught a 10-note piano sequence through both active and PHL methods and were then tested three days later to evaluate their retention of taught sequences. The study design was based on previous PHL research, particularly the MMT tactile stimulation method, but with modifications to prevent overlearning, as participants were stopped once they achieved 90% accuracy during the learning phase. The results indicated no significant difference in unaided recall between actively and passively learned note sequences when participants were asked to play from memory. However, when provided with auditory and visual cues, participants were significantly better at recalling the passively learned sequences. This suggested that while both learning methods are effective, PHL may offer advantages in cued recall situations. The study also observed a recency effect in PHL, where more recently learned material was better retained. Moreover, the study found that while PHL took longer initially, participants required fewer attempts to learn the sequences and demonstrated a 10% higher retention rate compared to active learning. This suggested that PHL can be a highly effective method for teaching and retaining complex skills like piano playing, especially when cues are provided during recall.

In 2023, Fang et al. [21] investigated the impact of PHL on rhythm learning across different musical instruments, focusing on the keyboard and ukulele. The study also examined whether combining haptic feedback with audio enhances rhythm learning, as measured by accuracy in duration and timing. Participants were divided into three groups: one receiving haptic feedback only, another receiving both haptic and audio feedback, and a third receiving audio feedback only. Inspired by previous research on PHL in piano learning[15, 35], the study offset the haptic and auditory signals by a few seconds to avoid overlap. The results indicated that the effectiveness of learning varied depending on the feedback method and the instrument used. For rhythm duration accuracy, the group that received only haptic feedback performed the best on the keyboard, followed by the group that received both haptic and audio feedback. However, performance across all groups was notably poor on the ukulele, suggesting that haptic feedback alone may be insufficient for learning more complex instruments. Regarding timing accuracy, rhythms played on the keyboard were generally reproduced more accurately, with the group receiving both haptic and audio feedback achieving near-perfect timing. In contrast, the group relying solely on haptic feedback demonstrated the greatest difficulty with timing accuracy, particularly on the ukulele. Interviews with participants further revealed that the combination of haptic and audio feedback was advantageous for rhythm learning, especially when using the keyboard. However, relying exclusively on haptic feedback was found to be the least effective approach, particularly when applied to more complex instruments like the ukulele. The study concluded that while PHL can be effective for rhythm learning, its efficacy is contingent upon the instrument used and the type of feedback provided. The combination of haptic and auditory feedback consistently produced the most favourable outcomes, particularly in terms of timing and duration accuracy. Conversely, haptic feedback alone was insufficient for more complex instruments, such as the ukulele, resulting in the least successful learning outcomes. These findings indicate that integrating both haptic and auditory feedback is crucial for achieving optimal rhythm learning across various instruments.

Following these results, [23] investigated whether other kinds of stimuli apart from vibration might be beneficial for PHL, exploring the effectiveness of different tactile

sensations in PHL for piano songs. The study aimed to determine whether affective tactile sensations are as effective as the more commonly used discriminative sensation of vibration in teaching motor tasks through PHL. Additionally, it examined whether there are differences in learning rates and user perceptions across these tactile modalities. Each participant learned three different note sequences using the three tactile systems (vibration, tapping, and stroking) in a within-study design. After a 30-minute PHL session for each system, participants were tested on their ability to recall and play the sequences. The results indicated no significant differences in the effectiveness of the three tactile systems for PHL, confirming that all three modalities—vibration, tapping, and stroking—are effective for teaching piano sequences. However, tapping and stroking were found to be slightly more effective than vibration, with participants learning more notes and making fewer errors (up to 1.06 fewer errors on average) when using these affective sensations. Additionally, over 50% of participants rated stroking as the most pleasant sensation, while only 11% favoured vibration. The study also highlighted that PHL is particularly beneficial for inexperienced users, consistent with previous research. However, the overall accuracy rate per note sequence was lower than in earlier studies, possibly due to the absence of recall aids during the testing phase, such as auditory or visual cues.

2.3.2 Typing Skills

Building on the success of PHL in the MMT project [53, 38, 35], Seim et al. extended their research to explore its application in typing systems, aiming to use these findings as a foundation for passively teaching Braille typing [74]. They investigated whether complex skills, such as typing and chord recognition, could be effectively taught through tactile interfaces using PHL, and also examined the role of visual feedback in the learning process. Participants in the study were taught typing skills using fingerless gloves embedded with vibration motors. During practice sessions, audio cues were followed by corresponding vibration patterns to stimulate finger presses. Participants then typed the patterns into software that displayed either the actual letters they typed or asterisks as feedback. The study aimed to determine whether visualizing the letters during typing would aid or impede learning. The results showed that visual feedback, where participants saw the letters they typed, actually hindered their performance compared to using asterisks or vibration only. Those using vibration-only feedback achieved better accuracy, though their typing speed was lower. This suggested that visual prompts may not be effective for PHL-based typing and that users might benefit more from audio prompts. The study also found that the random presentation of letters and words did not significantly impact learning, highlighting the importance of session length and information chunk size. However, teaching chords through PHL was unsuccessful, as participants had difficulty distinguishing which fingers were being stimulated. The researchers concluded that accuracy, rather than speed, should be the primary metric for evaluating PHL effectiveness. In a follow-up experiment, a PHL session without active practice was conducted, where participants played a memory card game while receiving training. The results indicated that participants could type with a low error rate and maintain consistent performance, successfully learning to use both hands with PHL. Some even achieved perfect accuracy on new phrases, though at reduced typing speed. This suggested that PHL can effectively teach typing skills, including the mapping of letters to keys. Overall, the study concluded that PHL is a valuable

method for teaching typing skills, particularly when using audio prompts rather than visual feedback. However, its effectiveness in teaching more complex tasks, such as chord recognition, remains limited.

To further investigate the potential of PHL, Seim expanded their research to determine whether it could be applied to a multi-row keyboard rather than the traditional one-finger-to-one-key mapping [70]. The study focused on enhancing the speed and accuracy of a motor task, specifically numeric entry on a randomized keypad. The aim was to assess whether PHL could improve typing speed and reduce reliance on visual cues in a text entry system. The researchers conducted a study using a 4x3 numeric keypad with a randomized key mapping, designed for use with the right hand only. The study included a pretest to establish a baseline, followed by multiple sessions in which participants alternated between a distraction task and a typing test. During the distraction task, participants in the PHL group received passive tactile stimuli corresponding to one row of the keypad at a time, which facilitated chunking and improved spatial memory. The results demonstrated that participants in the PHL group significantly improved their typing speed compared to the control group. Additionally, PHL users looked at the keyboard significantly less during the task, indicating improved familiarity with the key layout and reduced dependency on visual cues. This suggested that PHL can effectively convert tactile stimuli into motor movements and enhance performance in text entry systems. A pilot study included an additional test where participants' hands were covered by a paper screen to assess their knowledge of the keypad layout without visual assistance. This further confirmed the effectiveness of PHL in reinforcing the spatial memory needed for typing. The study concludes that PHL can be a powerful tool for improving motor task performance, particularly in learning and mastering keyboard typing skills. The use of wearable computing devices that provide passive tactile feedback presents a promising solution for training and enhancing the speed and accuracy of text entry tasks.

2.3.3 Braille Learning

Building on the initial success with typing, Seim et al. [69] explored the effectiveness of PHL in teaching Braille typing and reading through wearable technology. The study aimed to determine whether PHL could reduce errors in Braille typing and enhance the recognition and reading of Braille letters compared to traditional learning methods. Participants in the study were passively taught the full Braille alphabet over several sessions using a wearable device that provided haptic feedback. The instruction method utilized a chorded input system based on sequential tapping patterns, a technique that had previously been ineffective with non-sequential patterns [69]. Participants engaged in tactile and visual Braille letter identification tasks, along with a distraction task to rigorously assess their learning. The results demonstrated that participants who received passive haptic instruction exhibited a significant reduction in typing errors when typing phrases in Braille compared to those who did not receive haptic feedback. Moreover, participants were able to recognize and read more Braille letters from the phrases they typed, achieving a high recognition rate of the entire Braille alphabet by the end of the study. These findings suggested that PHL, facilitated by wearable technology, is a feasible and effective method for teaching Braille typing and reading. The study also revealed that PHL allowed participants to learn words and complete their learning more quickly

than those who did not receive haptic feedback. This indicates that typing practice in this context may also serve as effective reading practice, further enhancing the learning experience. The researchers concluded that PHL could be a valuable tool in Braille education, offering a passive yet powerful means of learning complex text entry skills.

Following this success, Caulfield et al. [44] investigated the impact of a PHL glove on the learning rate, proficiency, and recall rate in Braille learners. The study compared the effectiveness of the glove-based PHL method with traditional memorization approaches. The study was conducted in three phases. In the first phase, participants used flashcards to associate letters with Braille cell orientations, serving as a baseline for evaluating their initial proficiency without haptic feedback. The second phase involved a typing exercise using a keyboard, with some participants receiving haptic feedback through the glove while typing. The third phase consisted of a recall test conducted both with and without haptic feedback, followed by a retention test conducted several days later. The results indicated no statistically significant difference in the effectiveness of using PHL via the glove compared to traditional memorization methods. While the glove provided haptic feedback, it did not significantly enhance learning outcomes. In some cases, the glove even appeared to hinder performance, as suggested by longer response times and lower recall rates in participants who used the glove. The study concludes that the PHL system tested may not be an effective tool for improving Braille learning.

2.3.4 Morse Code

In 2016, Seim et al. investigated whether PHL could teach rhythm by using Google Glass to passively teach Morse code through head-based vibrations [71]. The study focused on whether Morse code, a rhythm-based system, could be learned passively through vibrations on the head rather than through hands, which are typically used in haptic feedback studies. Participants were randomly assigned to either a control group or a PHL group. The PHL group received rhythmic haptic feedback via Google Glass's BCT while learning Morse code, while the control group only heard the words without Morse code information. Over four hours, participants engaged in various learning and distraction tasks, including typing and perception tests, to assess their Morse code proficiency. The results showed that PHL could effectively teach Morse code using head-based vibrations. The PHL group achieved 94% accuracy on a pangram typing task, with most participants reaching 100% accuracy by the end of the study. They were also able to recognize and reproduce Morse code rhythms with minimal errors, demonstrating that the rhythm-based nature of Morse code could be learned through head-based haptic feedback. The PHL group outperformed the control group, showing a lower error rate and increased typing speed, which improved from 2.5 words per minute (WPM) to 4 WPM, approaching the target speed of 10 WPM. The study concluded that PHL is a viable method for teaching rhythm-based non-motor skills like Morse code through BCT devices like Google Glass. It highlighted the potential of PHL for eyes-free, silent text entry on mobile devices, offering new possibilities for learning and communication. However, it also noted that some active learning might occur when visual feedback is provided during testing, suggesting that future research should further isolate and measure the effects of PHL alone.

After the success, Seim et al. explored in [73] the potential of using smartwatch haptics to facilitate PHL of new skills, specifically focusing on Morse code. The study aimed to determine whether the subtle haptic feedback typically used for message alerts on smartwatches is sufficient for teaching skills and to compare the effectiveness of different durations of passive stimulation. The researchers conducted a study where participants used a smartwatch to deliver low-amplitude haptic stimuli corresponding to Morse code. Participants underwent a pre-test to assess their initial knowledge of Morse code, followed by a period of PHL where they received haptic feedback while engaged in a distraction task. The study was designed as a between-subject experiment, with participants split into two groups: one receiving 8 minutes of passive stimulation per word and the other receiving 16 minutes. The results demonstrated significant improvements in participants' ability to recall and recognize Morse code from pre-test to post-test, with those in the 16-minute stimulation group showing a 25-75% improvement in accuracy compared to the 8-minute group. This suggested that extended exposure to haptic feedback enhances learning outcomes. A follow-up recall test administered 1-3 days later indicated that the participants retained the information learned during the study. The study concludes that smartwatches, despite their low-amplitude actuators, can effectively support PHL and help users learn new skills like Morse code. The findings suggested that longer durations of haptic stimulation may lead to better retention and performance, indicating that smartwatch haptics could be a viable tool for skill acquisition through PHL. This research opened up new possibilities for using everyday wearable devices for educational and training purposes.

However, [62] suggested that the training and testing procedures used in earlier studies may have leaked information to participants, leading to inadvertent active learning. They revisited and critiqued the design choices of previous studies such as [71, 73], highlighting potential flaws that might have facilitated active learning [62]. To address this, [62] investigated whether PHL could effectively teach Morse code without requiring active attention from learners, building on prior research. The study divided participants into five groups to explore the effectiveness of PHL in teaching Morse code. Participants were exposed to vibration patterns on a wristband, each corresponding to a Morse code character, while also engaging in distraction tasks of varying difficulty to simulate divided attention. The results showed that while it is possible to learn Morse code passively through haptic feedback, learning rates were significantly lower compared to when active attention was involved. The findings suggested that PHL can facilitate the acquisition of simple motor skills with minimal attention but is less effective for complex, non-motor tasks like learning Morse code, which requires declarative memory engagement. The study also found that participants performed better when feedback was provided during learning, though the difficulty level of the distraction tasks did not significantly affect outcomes.

2.3.5 Multi-limb Rhythm Learning

In 2011, the potential of PHL for multi-limb skills was further explored. Bouwer et al. [11] introduced the Haptic Ipot [32, 11], a system designed to teach drumming techniques. In this study, participants wore elastic Velcro bands equipped with haptic vibrotactile devices that delivered rhythmic stimuli to different limbs. The stimuli were played back silently, and during the haptic feedback sessions, participants engaged in a reading comprehension task, similar to those used in previous

studies [34, 35]. Participants were exposed to two different rhythms, and their baseline performance was measured using a MIDI drum kit. Following the PHL session, participants were tested again on the MIDI drum kit to evaluate their accuracy, timing, number of attempts, and errors during their best attempt. A questionnaire was also administered to collect subjective feedback on the learning experience. The preliminary results suggested that PHL of multi-limb rhythms is a promising approach. Participants demonstrated improvements in both rhythm accuracy and timing, indicating that even while focusing on other tasks, individuals can still absorb and reproduce complex rhythmic patterns through haptic feedback.

2.3.6 Skin Reading

Vibrotactile Skin Reading (VSR) [48] is a method of encoding vibrotactile patterns to represent symbols, which can be combined to convey complex messages such as words and phrases [49]. Building on their previous research on VSR, Luzhnica et al. [49] explored the effectiveness of PHL as a training method for skin reading, where information is conveyed through vibrotactile patterns. This study specifically investigated whether PHL can be used to teach participants to comprehend text transmitted via these patterns and examines whether the speed of transmission affects recognition accuracy. The researchers conducted an experiment in which participants underwent 30 minutes of training to learn 10 letters of the German alphabet encoded into vibrotactile patterns. The training utilized a glove with six vibromotors placed on the back of the hand, replicating the design from [48]. Each letter was encoded by activating one or two vibromotors in an OST sequence, which is known to provide better perception than the simultaneous activation of multiple motors. During the training, participants engaged in a distraction task, such as playing a game⁹, while passively receiving vibrotactile cues. Each letter's pattern was repeated multiple times over 12 rounds of training. In addition to the pre-and post-tests, the study conducted a recall test the following day to assess the participants' ability to reconstruct and recognize the letters they had learned [49]. The results demonstrated that participants could recall the learned vibrotactile patterns and accurately reconstruct and recognize the letters immediately after training and one day later. The accuracy of recognition and reconstruction was consistent with previous research, indicating that PHL is an effective method for training skin reading. Additionally, the study found no significant difference in comprehension accuracy across different transmission speeds, suggesting that participants could accurately comprehend the information transmitted at varying speeds. And, henceforth, concludes that PHL is a promising and effective method for training vibrotactile skin reading, offering a viable alternative to more demanding and time-consuming active training methods. The ability to comprehend information regardless of transmission speed further enhances the potential applications of PHL in this domain.

2.3.7 Effects of PHL Practice in Rehabilitation

In their work on the MMT framework in 2010, Markow et al. explored potential improvements in dexterity and sensation for patients with incomplete spinal cord injury (SCI) while learning a new skill set. This research led to their second MMT paper [53], which presented a pilot study on hand rehabilitation in individuals with

⁹The snake game [https://en.wikipedia.org/wiki/Snake_\(video-game_genre\)](https://en.wikipedia.org/wiki/Snake_(video-game_genre))

tetraplegia due to SCI. The study demonstrated that MMT could stimulate afferent nerves, potentially improving motor function and sensory perception through the active learning (piano practice) mode. Participants with tetraplegia indicated progress in sensory tests such as the Semmes-Weinstein monofilament evaluation and the Grasp and Release Test (GRT) after four weeks of practice, consisting of three 30-minute sessions per week. Additionally, three different glove designs were tested: a golf-style glove, an open-flap glove, and a Velcro-finger glove (as depicted in Figure 2.1). The preliminary findings suggested that MMT holds promise as a hand rehabilitation for individuals with tetraplegia resulting from incomplete SCI. The work presented in this paper lays the foundation for future studies to evaluate the broader applicability of MMT in the tetraplegia population.

2.3.8 Stenography Learning

Aveni et al. [6] explored passive haptic learning (PHL) for stenography training, focusing on a system that combines tactile feedback with spatial tasks. The study aimed to teach participants to use a stenotype keyboard, where each key corresponds to an English sound. Over four 10-minute sessions, participants wore two-handed fingerless gloves with a vibration motor on the dorsal side of each hand and played the game "SpikeDislike2" as a distraction¹⁰. The training focused on combining "subchords," or word-parts, to form unfamiliar words. Each finger was responsible for two keys, except the left pinky, and the system used temporal offsets in the vibration patterns to stimulate the fingers from left to right and top to bottom. A distinct tapping rhythm indicated whether the top, bottom, or both keys needed to be pressed simultaneously. Results showed a significant improvement in typing accuracy compared to the control group, based on uncorrected error rates. The study demonstrated that passive tactile feedback can help novices learn stenography, even without explicit instruction on combining subchords. Participants autonomously figured out word formation through the modular training structure, with errors mainly being horizontal or vertical, indicating correct finger placement. This suggests PHL as an effective and intuitive method for teaching complex skills like stenography.

¹⁰<https://gamejolt.com/games/spikedislike2/>

3. Implementation and Design

3.1 Implementation

This section presents the implementation and the key design decisions we made for this project. We begin by describing the hardware apparatus, which includes the actuators and the gloves themselves, as well as the design iterations undertaken during the development of the glove. Next, we outline the software components, detailing the encoding of the actuators, and the communication protocol, and providing a brief introduction to the associated software elements. Finally, we conclude this section by introducing the study design of the two studies conducted to address our research questions.

3.1.1 Hardware

We have divided this subsection into two parts: the first focuses on the actuators used, while the second discusses the design of the Braille gloves.

3.1.1.1 Actuator Design

For the actuators and their setup, we adopted the design and configuration proposed by Fang et al. [23], using Velcro straps. This decision was informed by prior research [53, 38, 35, 21], which highlights the importance of design factors such as weight, breathability, flexibility, and coarseness for user comfort, particularly during extended wear. Velcro straps effectively meet these criteria while enhancing dexterity, a recognized advantage of fingerless glove designs [34]. This design facilitates everyday tasks and accommodates a range of finger sizes, making the gloves adaptable for different users. Furthermore, using the same actuators enables a direct comparison with Fang et al.’s prior work [23], which employed identical actuators in a one-handed, non-chorded piano learning setup.

The actuators consist of six vibration systems (three per hand), with one shown in Figure 3.1. Each system includes a vibration motor (Brand: Grove Seed; Model: ANDA-B1020) housed in a 3D-printed PLA case and secured with Velcro bands. Operating at a frequency of approximately 200 Hz, the vibration motors are directly

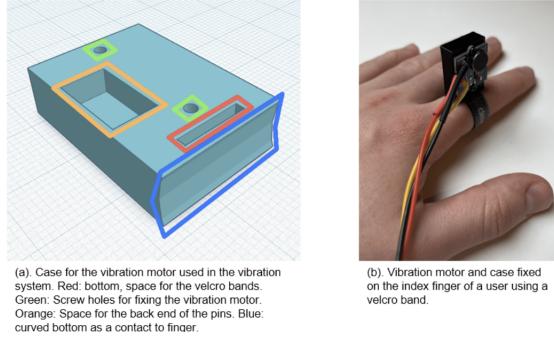


Figure 3.1: 3D model, and the implementation on a users finger of one element of the vibration system from [23]

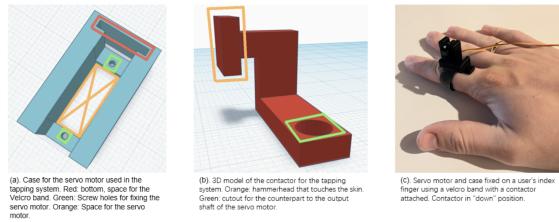


Figure 3.2: 3D models for the case and hammer-shaped contactor, and the implementation on a user's finger of one element of the tapping system from [23]

connected to the glove for control. Each system is mounted in a curved-bottom 3D-printed case for optimal fit, as illustrated in Figure 3.1, where it is demonstrated on a single finger. Consistent with Fang et al.'s design [23], larger contact areas were used to allow easier adjustment for individual comfort. The actuators operate at an amplitude of 1.03 G and weigh 6.6 grams each.

For the tapping and stroking systems, we employed six actuators for each system, utilizing mini-servo motors (Master DS208). These motors provide an actuating force of approximately 0.1 - 0.2 kg and complete a 45° movement in approximately 0.1 seconds. The actuators draw around 5V and 1.75A for stroking, and 5V and 2A for tapping, based on our measurements using a USB Current Voltage Capacity Tester (Model: KWS-V20/V21). Both systems are controlled via Pulse Duration Modulation (PDM) through the glove. The cases for these systems are 3D-printed using PLA. The design of the stroking system is shown in Figure 3.3, while the tapping system is depicted in Figure 3.2.

To enhance wearer comfort during prolonged use, we added a small cushion to the actuator casings for both the tapping and stroking systems. This cushion, which

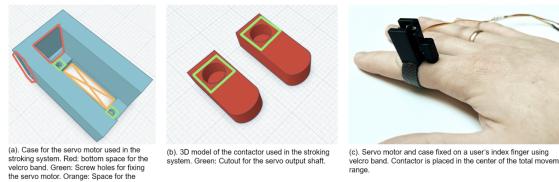


Figure 3.3: 3D models for the case and the contactor, and the implementation on a users finger of one element of the stroking system from [23].

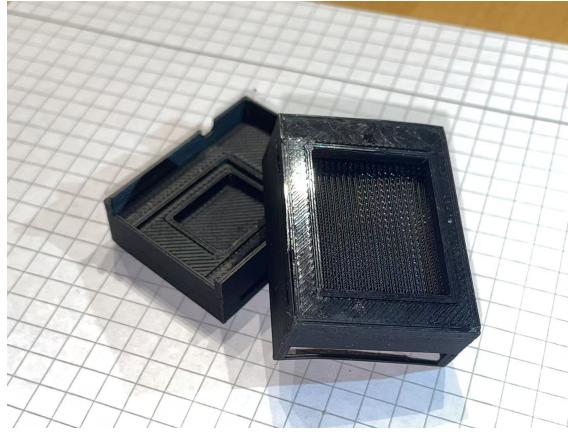


Figure 3.4: Final Glove- Case Design on a squared Din A5 paper for size reference.

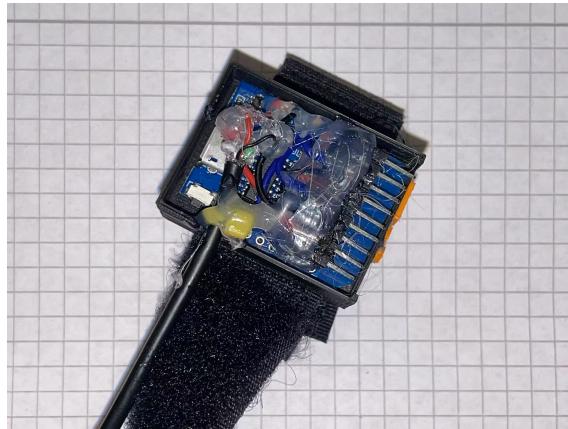


Figure 3.5: Final Glove Design opened on a squared Din A5 paper for size reference.

was not included in Fang et al.’s original design [23], is only used for the contact area of the non-moving part of the actuator and the skin.

The tapping system delivers equal force at the same rate by applying and removing the contact from the user’s skin [23]. Its design follows a hammer-like structure, consisting of a servo motor housed in a PLA case and a contactor. The contactor is an 8×8 mm square plate, which presses against the users’ skin, connected to the servo motor’s output shaft via an L-shaped support. The design is illustrated in Figure 3.2.

The stroking system, shown in Figure 3.3, features a contactor that moves across the user’s skin while simultaneously indenting it slightly, similar to the tapping system. The contactor is a $15 \times 7 \times 5$ mm square with a rounded bottom and is housed in a design similar to the tapping system. The servo motor is mounted on the participant’s hand, and by rotating the motor, the contactor performs a stroking motion across the skin.

All actuators are positioned near the interphalangeal joints of the fingers.

3.1.1.2 Glove Design and Design Iterations

Our final glove design, shown in Figure 3.6, incorporates the actuators described above along with a wristband. The wristband consists of a Velcro strap mounted



Figure 3.6: Final Glove Design on a squared Din A5 paper for size reference.

Protocol	Range	EE (R)	EE (T)	Throughput	Latency	Overhead	OSI-Layer
ESP-NOW	220m	489 mW	1042 mW	1 Mbps	1ms	Small	Layer 2
TCP / UDP	100m	214 mW	538 mW	54 Mbps	3.3ms	Medium	Layer 4
Bluetooth	60m	141 mW	441 mW	784 Kbps	6ms	High	Layer 2

Table 3.1: Comparison of Wi-Fi, Bluetooth and Esp-Now [18].

EE stands for Energy Efficiency, R stands for receiver and T for transmitter.

onto a 3D-printed PLA casing with a cushion on the bottom to enhance comfort during extended wear. Therefore, we left a small hole in the bottom to fit the cushion into it due to the cushion being not soft enough due to the clue pressing directly against the users' skin. The case design is shown in Figure 3.4.

The casing measures 37.6 mm × 28.75 mm × 15 mm, making it comparable in size to the Xiaomi Mi Watch Lite smartwatch (dimensions: 41 mm × 35 mm × 10.9 mm, weight: 35 g with strap, 21 g without strap)¹. Also, the bottom is fitted, so that the ESP8266 can fit even without glue in there and won't move. With an open case, the design is depicted here Figure 3.5. The 9 outputs are the same as shown in the circuit diagram in Figure 3.8.

This design achieves our goal of creating a compact wearable device comparable to a modern smartwatch.

For the microcontroller, we chose to use devices from the ESP family due to their compatibility with the ESP-Now protocol. This decision was based on the protocol's advantages in terms of latency, overhead, and throughput, as highlighted in the comparison by Eridani et al. [18], with their results shown in Table 3.1. We identified those as the most essential factors for solving our soft-real time² requirements, as we need to get the ms timings right and in order.

In our initial design iteration, we used the ESP8266 microcontroller, but it was later replaced with the ESP8266 D1 Mini due to several advantages. These include its low cost (approximately €1), lightweight design (3 g)³, and compact size. Both microcontrollers offer built-in Wi-Fi capabilities that provide sufficient connectivity for the entire software system. The affordability and accessibility of the ESP8266

¹<https://www.mi.com/de/mi-watch-lite/specs/>

²Soft-Real Time as defined in computational theory such as by Shin et al. [77]

³<https://www.smart-prototyping.com/Mini-D1-PRO-Development-Board-ESP8266-4M-16M>

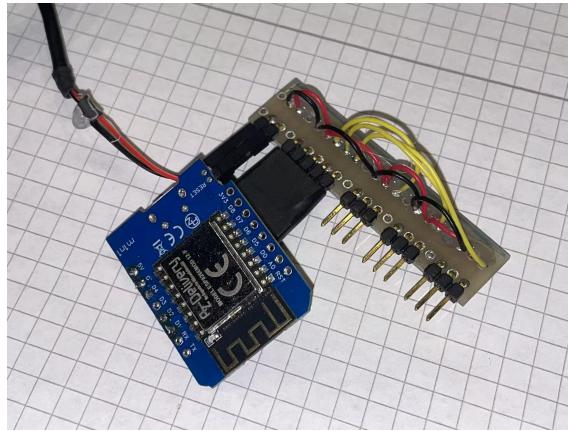


Figure 3.7: Old design of the circuit.

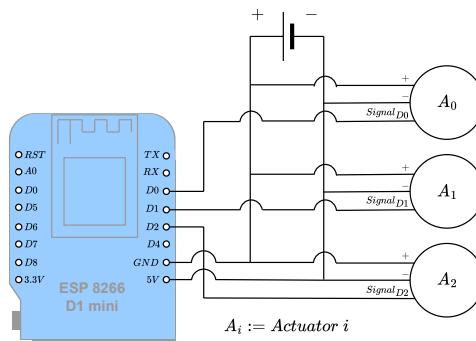


Figure 3.8: Glove Circuit Diagram.

D1 Mini make it particularly suitable for use in low-income households, enhancing the device’s feasibility and reach.

The first alpha prototype version with the esp8266 D1 mini is shown in Figure 3.7. As it is the Minimal Viable Prototype (MVP), it is rather bulky with the cables attached to it. Nevertheless, the same circuit diagram as in Figure 3.8 applies to it, and it is fully operational.

Due to the high current demands of the tapping and stroking systems, the on-board power supply of the ESP8266 was insufficient. To resolve this, we soldered an additional USB cable to the board to provide an external power supply, as shown in Figure 3.8, that can also be seen on Figure 3.7 for the MVP and in Figure 3.5 for the current one. In the first experiment, the actuators were interchangeable and could be of the vibration, tapping, or stroking type. We utilized the pins D0, D1, and D2 because of their PDM capabilities.

The USB cable was connected to a standard phone charger. For testing, we used the original 10W Xiaomi USB-A charger (model: MDY-09-EW), which has a maximum output voltage of 5V and 2.0A. This served as the general power source for the system, with one charger used per glove. The design also works with a power bank, however, due to our extended experiment times we didn’t use a power bank in our study.

Furthermore, we added wiring to simplify mounting the actuators onto the wristband glove, ensuring better usability and stability during operation. This can be seen in the open version of the glove design depicted in Figure 3.5 so that we can fit the actuators directly on it.

3.1.2 Software

This software section is divided into two parts, the websites created for the experiment (one on the glove and one on an external laptop for testing) and the communication protocol that is used for the communication between the gloves.

3.1.2.1 Website

Two websites were developed for the study, adhering to the Material Design guidelines for button design and usability⁴. One website was displayed on a mobile phone (Xiaomi A2 Lite), which was hosted by the glove to control the experiment and play audio data, while the other was used to assess the participants' knowledge.

The website for controlling speech output and vibrations is shown in Figure 3.9. It was designed using a responsive framework, enabling compatibility with other devices capable of running modern browsers. During the study, we used the Google Chrome browser on the smartphone.

The website could be accessed within the "Master Glove" Wi-Fi network (SSID: Master Glove) using the URL 192.168.4.1. The preset buttons on the website correspond to those used in the studies. Upon pressing a button, the master controller receives the associated word or letter, as well as whether OST-Encoding is activated (inactive for sequential input). The master controller then sends this data to the slave controller.

The website plays the corresponding audio for the selected character using a JavaScript text-to-speech converter, as the master controller was not connected to the internet. After the specified offset detailed in the audio-vibration offset section, the vibration begins, aligned with the encoding chords and tailored to finger sensitivity. Both, the audio and vibrations automatically stop after five minutes, providing a break for the conductor to test the participant, as outlined in the study protocol.

The second website, shown in Figure 3.10, was designed solely for testing participants' knowledge. It ran on a Firefox browser on a Fujitsu laptop (model: VFY A5440M15B70E) with Ubuntu.

Additionally, instead of displaying the pressed character, we only showed asterisks ("*") to avoid distracting the user. This approach followed the idea of the "stars-only feedback" condition from Seim et al. [74], allowing participants to focus on the order rather than the specific characters.

The same laptop was also used to run Gwelled, the game employed in Fang et al.'s study [23], during the learning session.

⁴<https://m3.material.io/>

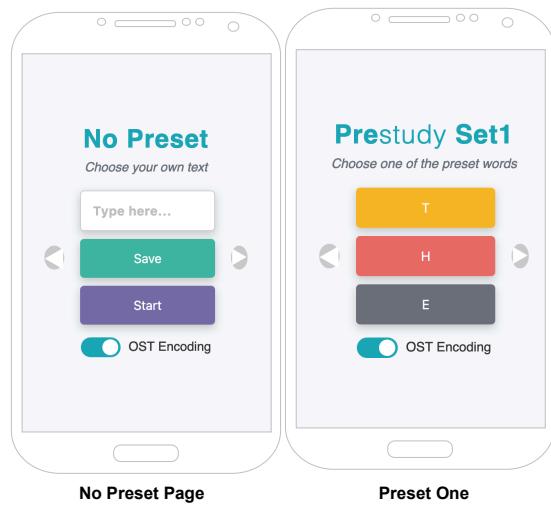


Figure 3.9: Website Design in a Mobile Phone.

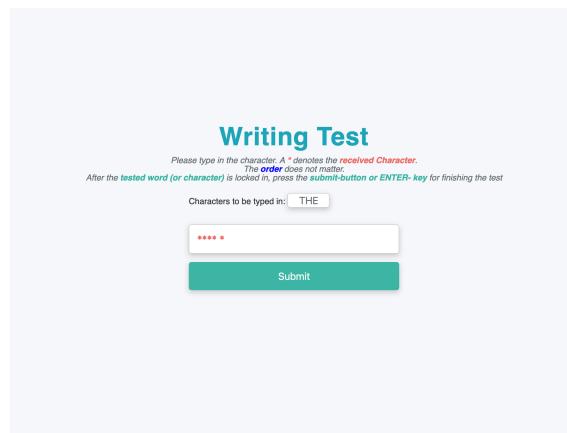


Figure 3.10: Testing Site for the Writing Test.

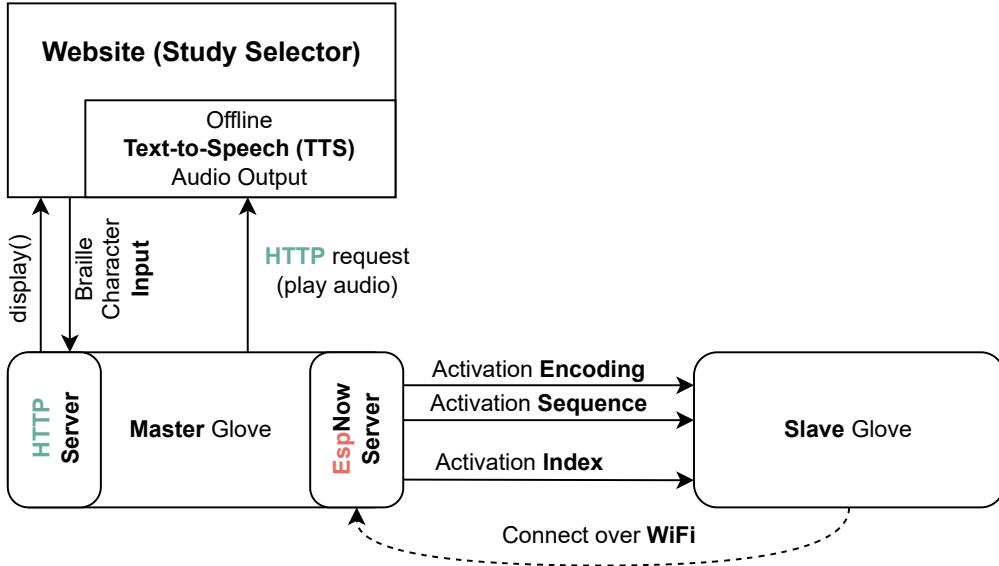


Figure 3.11: Communication Architecture.

3.1.2.2 Communication between the gloves

Both gloves operate using a master-slave configuration depicted in Figure 3.11, with the left glove functioning as the master and the right glove as the slave. To ensure flexibility in actuator motor types and encoding schemes, we implemented a layered architecture within both the master and slave gloves.

For communication, the slave glove employs a listener that, upon receiving a message, triggers a callback function to determine how the data should be processed.

The slave glove can receive two types of data. The first type is the activation sequence, which consists of a series of activation requests and pauses in between. Once this sequence is received, the slave waits for the second type of data—a timing index indicating when the next character should be played.

This approach ensures precise synchronization, as the timing index is transmitted during the pauses between characters, preventing significant timing discrepancies. To meet the requirements of low overhead, fast latency, and high throughput, as outlined in section 3.1.1.2 and illustrated in Table 3.1, we leverage this speed to maintain accurate timing without the need to wait for a connection to be fully established.

3.1.3 Encoding Scheme

This section provides an overview of the encoding methods used in our study. First, we introduce the encoding of chords, which we employ in both of our studies. Here, we differentiate between the sequential approach that we use and the OST encoding approach.

The section also discusses the finger activation sequence to ensure alignment with previous works. The second subsection addresses the offset between the audio and the activation sequence employed, explaining which method we use and the rationale behind our choice.

The third part focuses on the selection of isograms for the words used during training. We explain why we believe these words to be the most appropriate and demonstrate, using information theory, that they have similar entropy. This selection ensures that the words used for learning are of comparable complexity. Additionally, we explain why our chosen words form a partial pangram.

3.1.3.1 Encoding Chords

Encoding Braille words as tactile chords is not straightforward because several considerations must be taken into account, such as how to encode a chord in a way that prevents all fingers from vibrating simultaneously, as this was shown to be ineffective by Seim et al. [74], who demonstrated that participants often struggle to distinguish stimuli. Additionally, when offsetting each of the tactile sensations, further considerations must be made, such as: "How long are the sequences activated?" "In which order are the tactile sensations delivered to the fingers?" "How long and where are breaks placed during activation?" and "What activation protocol should we use?" To address these questions, we orient ourselves based on previous works.

For the activation protocol, we use two different encodings, which we compare against each other in the second study. We employ the OST encoding developed by Luzhnica et al. [49, 50, 47, 48], as shown in Figure 2.3, to encode the chords. The OST encoding uses a gap p of 10 ms, following the value named (g) used in [49], with the same finger stimuli order and tactile thresholds that align with the findings of [17]. Additionally, we incorporate the sequential encoding approach used by Seim et al.

The OST encoding has several advantages, such as enhanced throughput, as previously outlined. Furthermore, compared to simultaneous encoding, which often leads to difficulties in distinguishing stimuli [74], the OST encoding has proven more beneficial for learning [49]. In the first study, we use only the OST encoding.

Luzhnica et al. [47] found that the order in which tactors are activated during overlapping spatiotemporal stimulation impacts the ability to accurately identify stimuli. Prioritizing the activation of tactors, starting with the most sensitive areas, significantly improves accuracy. Building on these findings, we prioritize the fingers according to their known sensitivity order (from index to ring finger), as described by [47], [31], [86], and [17]. This prioritization follows the approach outlined by [47] to enhance perception accuracy.

Studies on temporal acuity indicate that individuals can discriminate between successive taps on the skin with a gap as small as 5 ms [47, 37]. Luzhnica et al. found that gaps of 10 ms and 20 ms between taps did not significantly impact perception accuracy. Based on this, we chose a gap of 10 ms, as shown in Figure 3.12, which is greater than the minimum discriminative gap of 5 ms established by [47]. This 10 ms gap has been used for OST encodings in previous studies [49, 48].

During both studies, we use the same intensity for vibration, as [47] found that varying vibration intensities between tactors do not lead to higher accuracy, even when prioritization by sensitivity is applied. Therefore, we maintain consistent intensities across all tactile sensations.

For the base duration d , we use 200 ms, with a between-letter gap (bl) based on the average durations of dots (100 ms) and dashes (300 ms) from [73] and dots (200

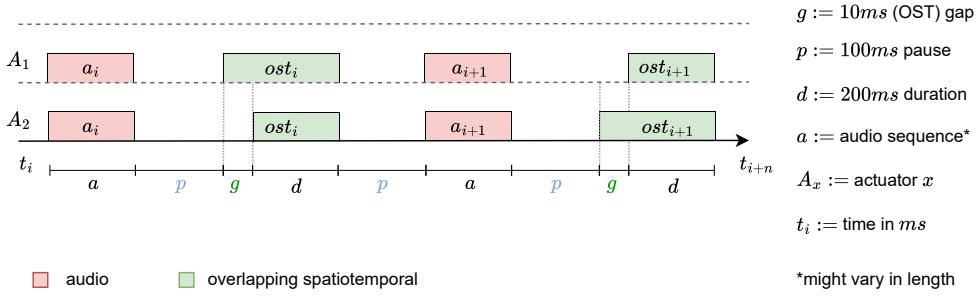


Figure 3.12: Audio vibration offset.

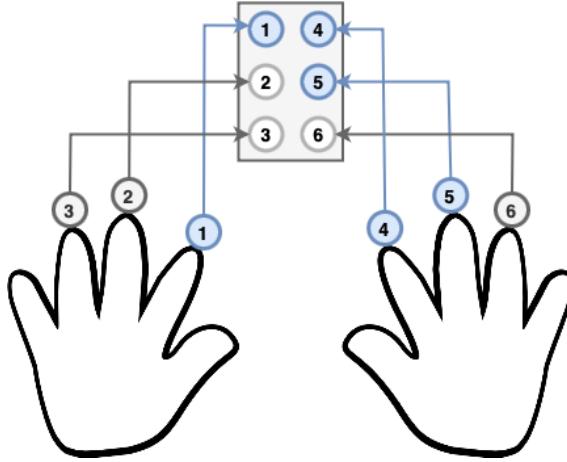


Figure 3.13: Encoding of the character D as an example for hand encodings.

ms) from [62]. The 200 ms duration aligns with the recommendations of [49], who suggest this interval to separate subsequent letters. While this duration is shorter than those used in some language-teaching studies, such as [69], it fits well within the 100–300 ms range used for keypad learning chords by Seim et al. [70].

3.1.3.2 Audio-Chord Offset

For the offset between audio and vibration, we adopt the same value used in [70] for Braille learning, which is 100 ms, as shown in Figure 3.12.

For stroking and tapping, we follow the setup described by [23], where each finger is stroked or tapped once. However, we use the OST encoding with the same OST gap and pause time, as illustrated in Figure 3.12, so the only difference between the affective and discriminative touch setups lies in the base duration d . Since this is the first study, to our knowledge, investigating OST with stroking or tapping for affective touch, we use this pattern without any additional prior timing guidelines, except for the passive learning encoding found in Fang et al. [23].

3.1.3.3 Isogram Selection and Carry-Over Effect Minimisation

When participants are passively learning to type using different actuators, we use a segment of a pangram [12], following the methodology of Seim et al. [73, 72]. This approach is intended to mitigate the “carryover effect” [51, 13], which occurs when participants are influenced by previously learned data, either through stress or prior knowledge.

To ensure a fair comparison and avoid the carryover effect, we taught participants different characters with equal complexity for each actuator. Pescara et al. [62] defined complexity by creating patterns of equivalent length and difficulty, based on the number of dash and dot transitions in Morse code. Inspired by this approach, we use entropy, as defined in information theory [27, 75, 76], to quantify the underlying complexity.

To achieve this, we encoded each Braille dot with a number from 1 to 6, following the methodology of [90]. The dots correspond to positions on the left hand (index to middle finger) and right hand (index to middle finger), as illustrated in Figure 3.13 for the Braille character “D”. Each character is thus represented as a set of numbers corresponding to the Braille dots.

Using this encoding, we calculated the probability $P(d)$, where d represents a “dot at position i .“ We used the standardized English Braille alphabet, consisting of 26 characters. The probability distribution for each dot being present in a character is calculated as:

$$P(d = X) = \frac{\|\{d \in c \mid c \in A\}\|}{\|A\|}$$

Where A represents the 26-letter English alphabet. The results are summarized in Table 3.2, showing the occurrence of each Braille dot and its corresponding probability across the alphabet.

Dot d	①	②	③	④	⑤	⑥
Occurrences	20	14	15	15	13	6
$P(d)$	0.7692	0.5384	0.5769	0.5769	0.5	0.2307

Table 3.2: Probability for each dot occurring.

Using these probabilities for each dot $P(d)$, we then computed the entropy $H(c)$ for each character c using the entropy formula:

$$H(c) = \sum_{d \in C} P(d) \times \log_2 P(d)$$

This measures the amount of information in bits per character. The calculated entropies for each character c are presented in Table 3.3.

We evaluated words used in previous studies, such as “add,” “a,” and “bag” from Seim et al. [69, 74], with entropy values of 2.7891, 0.2912, and 2.793 bits, respectively, and the words “The,” “Lazy,” and “Dog” from Seim et al. [73], with entropy values of 3.9597, 5.4531, and 4.2278 bits, respectively.

Next, we searched for a partial pangram composed of three words for the three actuators by going through the English dictionary with a word length of 3^5 , while ensuring that the words did not share the same characters and had similar complexity and character length, and are commonly used⁶. We selected the words “the,” “old,”

⁵<https://www.dictionary.com/e/word-finder/3-letter-words/>

⁶As we didn’t interview native speakers we needed to ensure they knew the words

Character c	• A	•• B	••• C	•••• D	••••• E	•••••• F	••••••• G	•••••••• H	••••••••• I
$H(c)$ in bits	0.2912	0.6458	0.749	1.249	0.7912	1.1036	1.6036	1.1458	0.8124
Character c	••• J	•• K	•• L	••• M	•••• N	••••• O	•••••• P	••••••• Q	•••••••• R
$H(c)$ in bits	1.3124	0.749	1.1036	1.2068	1.7068	1.249	1.5614	2.0614	1.6036
Character c	•• S	••• T	•• U	••• V	•••• W	••••• X	•••••• Y	••••••• Z	
$H(c)$ in bits	1.2703	1.7703	1.2372	1.5918	1.8006	1.695	2.195	1.7372	

Table 3.3: Entropy for each Braille letter rounded to 4 decimal places.

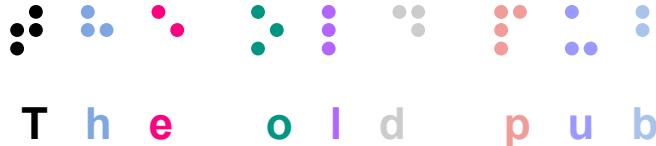


Figure 3.14: Sentence used in the pre-study and its braille part.

and “pub,” as shown in Figure 3.14, with entropy values of 3.9597, 3.728, and 3.6969 bits, respectively. These words were deemed more suitable for our task due to their similar entropy values and simplicity, as many of our participants are non-native English speakers. These words were used in the first and second studies (for the second study, we used “old” and “pub” due to their closer similarity in entropy).

3.2 Study Design

Our study is inspired by the work of Pescara et al. [62] and Fang et al. [23], and it is divided into two distinct phases. The first phase addresses our first research question: ”RQ1: Is there a difference between affective and discriminative touch for both hands using the OST encoding?” This phase is followed by a pre-study. The second phase aims to answer our second research question: ”RQ2: Is there a significant difference between using the OST and the SEQ encoding?” In both studies, we focus on teaching uncontracted, alphabetic English Braille, known as Grade One Braille [82, 3].

Similar to Seim et al. [72, 73], our studies focus on learning words. However, we use a different set of words than those employed in their research. In the first study, we

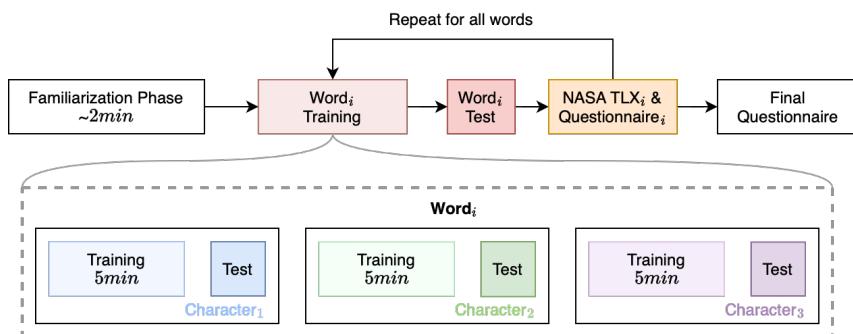


Figure 3.15: Study design.

aim to assess the effectiveness of various stimuli and examine the impact of affective versus discriminative touch using the OST encoding. This will be combined with different stimuli to teach Grade One Braille. In the second study, we investigate the differences between using the OST and SEQ encodings.

For both studies, we employed a balanced randomized Latin square design, similar to the method used by Huang et al. [35], a technique frequently applied in educational and psychological research [64]. The study procedures are illustrated in Figure 3.15. As shown in the figure, each study begins with a familiarization phase lasting approximately 2 minutes. This phase includes using the testing website Figure 3.10 and its input method to familiarize participants with the setup, followed by a brief session of the game Gwelled to help participants acclimate to the game.

The familiarization phase is followed by word training, during which participants use the specific actuator attached to their fingers. For this, we used a Velcro band, similar to the setup used in previous studies [85, 23], enabling comparability with [23], which also investigated discriminative and affective touch. For the first study, we used the respective actuator according to the balanced Latin square design, consisting of vibration, tapping, and stroking, with the OST encoding employed. In the second study, we used only the vibration actuator, but the encoding was changed according to the balanced Latin square design to either SEQ or OST.

During word training, each word is taught letter by letter. The training phase for each letter is followed by a test. In the letter training phase, participants play Gwelled, which was used in previous studies by Fang et al. [23], Donchev et al. [15], and Pescara et al. [62] for 5 minutes. This serves as a distraction task while they receive their respective stimuli. Throughout this phase, we log user inputs, clicks, game scores, and the time played. This data allows us to assess participant focus in relation to the type of actuator used and evaluate the test results.

To ensure data validity, we monitored the average click count to avoid significant drops between letters with the same stimulus. For the character test, we use the testing site shown in Figure 3.10.

After participants learn three characters, they complete a word test consisting of a word formed from the three learned characters. The word test is conducted on the same website.

During the testing phase, participants do not see their typed information to minimize distractions and encourage better performance, as detailed in subsubsection 3.1.2.1. For each test, participants are given three attempts to reproduce the Braille character chord, following the setup used in previous works [23, 67, 21]. After all three characters of a word (as shown in Figure 3.14) have been learned, participants complete a NASA TLX [30] questionnaire, as well as our own questionnaire assessing the perceived usefulness of the system. Once all conditions (each actuator for the first study or each encoding for the second) are completed, participants fill out a final questionnaire directly comparing the conditions to each other. This final questionnaire aims to gather objective scores for the conditions and determine participants' preferences and feedback. The questionnaires are provided in the appendix.

Since we only have two conditions for the second study, we used only the two Braille words (OLD) and (PUB), as depicted in Figure 3.14, for learning/testing.

4. Analysis

This section analyzes the results of the collected data from the first and second studies. For both studies, we begin by analyzing the participant data, followed by an assessment of how the participants perceived the different tests in terms of difficulty, using the NASA-TLX and questions related to the comparison of the setups. Specifically, we focus on which setup participants found to be better. Next, we examine the actual performance results to compare perceived performance with actual performance.

To describe the Braille-dot components, we represent the keys using their respective numbers within a dot, as shown here: \textcircled{i} for character i , similar to the figures presented previously.

4.0.1 First Study

In the first study, we interviewed 12 participants (3 female, 9 male), aged between 22 and 55, with an average age of 28.67 and a median age of 27 years. Of these, 11 were right-handed, and one was left-handed, as shown in Table 4.1. None of the participants had prior knowledge of Braille.

First, we assessed the validity of our data by ensuring that the participants were focused on the game and not on the sensations themselves. To do so, we measured the click rate for each character to detect any differences in performance. Given that participants tended to become more fatigued later in the game, we compared the click rates with those from the previous round to determine whether the data showed a 40% improvement or decline, as indicated by the two red lines in Figure 4.1. As shown, the data passed the test, with the exception of participant 7, where the observed difference can be attributed to the stimulus change and the completion of questionnaires between sessions.

The raw NASA-TLX scores are presented in Figure 4.2, which displays boxplots for the different stimuli and their corresponding NASA-TLX scores, grouped by the respective NASA-TLX dimensions.

Overall, the medians for the dimensions are similar, with the most notable difference observed in the "performance" dimension. Specifically, the medians are 25.0 for tapping, 50.0 for stroking, and 50.0 for vibration.

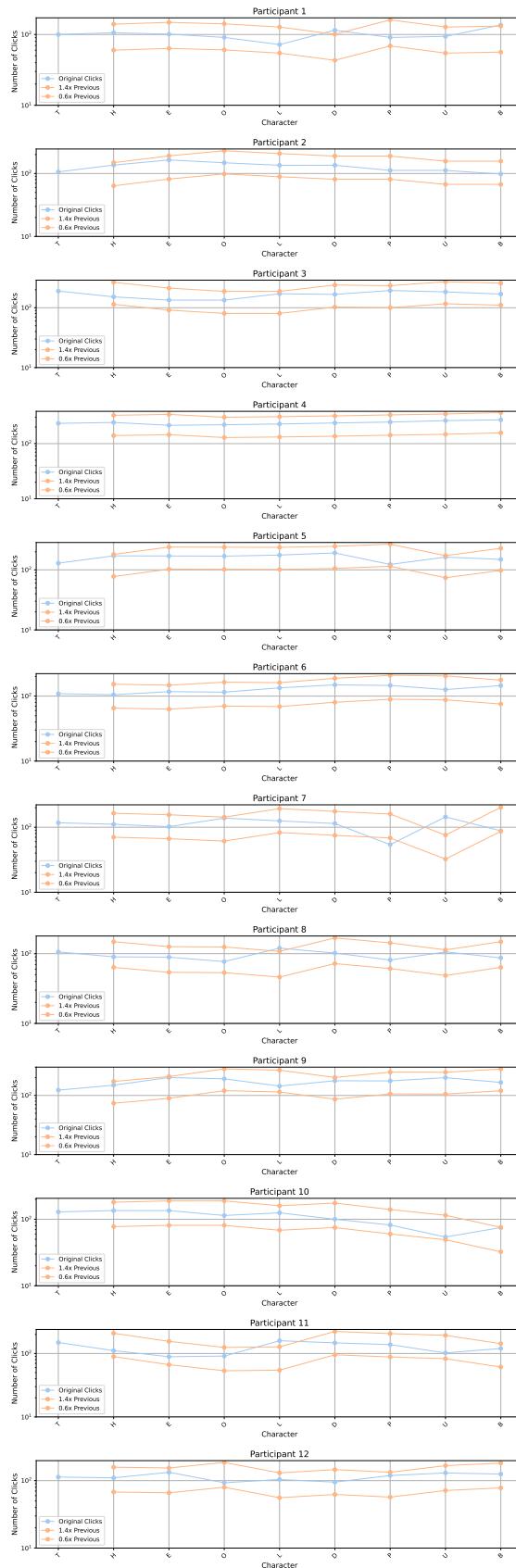


Figure 4.1: Participant Click-differences.

Gender	Age	Dominant Hand	Previous Braille Knowledge
M	27	R	No
M	27	R	No
M	22	R	No
M	22	R	No
M	26	R	No
M	27	R	No
M	28	R	No
W	28	R	No
W	27	R	No
M	30	L	No
M	25	R	No
W	55	R	No

Table 4.1: General participant data in the first study.

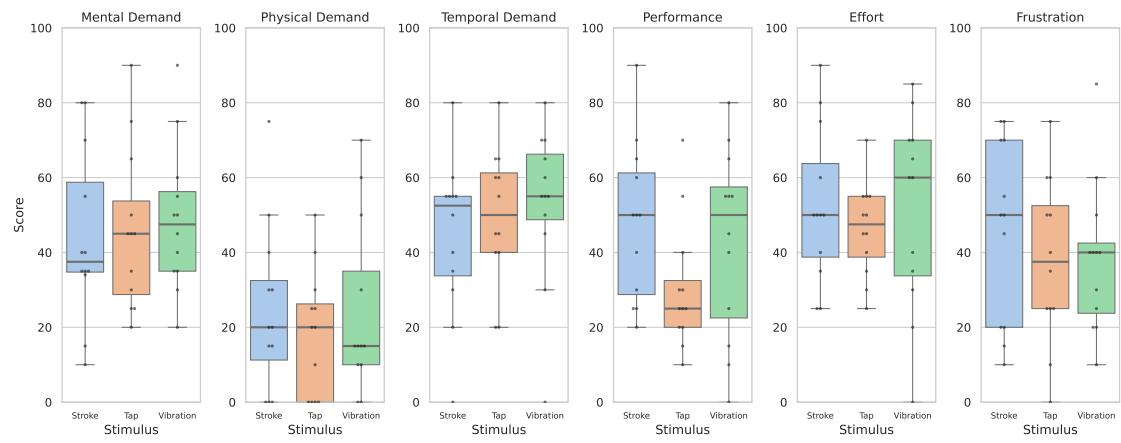


Figure 4.2: Raw NASA TLX scores for the different Stimuli grouped by the NASA TLX dimensions.

Each dot represents one participant.

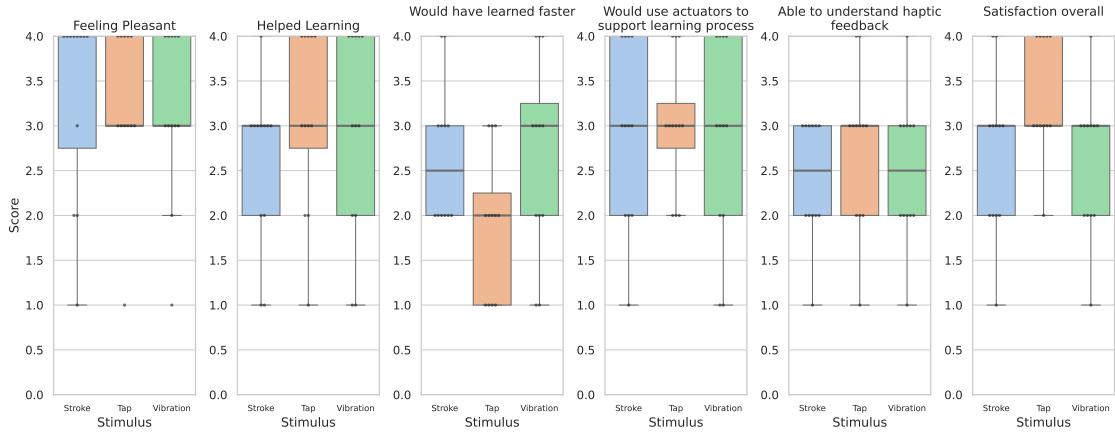


Figure 4.3: Self-assessment Results of the different Stimuli grouped by the self-assessment categories.

4 is the best score and 0 the worst score.

Each dot represents one participant.

In the "physical demand" dimension, a noticeable difference in the quantiles is apparent. The quantile for tapping is slightly larger, indicating that it performed worse on average. Similarly, in the "effort" dimension, slight differences in the quantiles and medians are observed. The medians for stroking and tapping are 50 and 47.5, respectively, while the median for vibration is 60.

In the "frustration" dimension, the quantile range is larger, particularly for the box-plot representing stroking, which has a quantile range of Q1 = 20, Q3 = 70, with a median of 50. In contrast, tapping has a Q1 of 25, Q3 of 55, and a median of 37.5. Vibration shows the smallest quantile range, with a Q1 of 23.5, Q3 of 42.5, and a median of 40.

Subsequently, we tested for significant differences between the sets using Kruskal-Wallis significance tests, the results of which are tabulated in Table 4.2. The results indicate no significant differences between the sets, with p-values exceeding the threshold value of $\alpha = 0.05$. The closest p-value to passing the threshold is found in the "Performance" dimension, with a p-value of 0.1496, which is not close to being statistically significant.

Question	H-Statistic	p-value	Significance	Effect Size
Mental Demand	0.5311	0.7668	Not Significant	0.0152
Physical Demand	0.358	0.8361	Not Significant	0.0102
Temporal Demand	1.6356	0.4414	Not Significant	0.0467
Performance	3.7994	0.1496	Not Significant	0.1086
Effort	0.7655	0.6820	Not Significant	0.0219
Frustration	0.9098	0.6345	Not Significant	0.0260

Table 4.2: Results of the Kruskal-Wallis significance tests for the different NasaTLX dimensions with a η^2 Effect Size.

After the Task Load Index, we surveyed five dimensions to assess how the participants perceived learning and usability with the different actuators, comparing the stimuli across six different dimensions, as shown in Figure 4.3.

As shown in the figure, there are larger differences in the dimensions “Helped learning”, “Would have learned faster”, “Would use actuators to support the learning process”, and “Satisfaction overall”.

For the “Feeling pleasant” dimension, the median values differ by 4 for stroking, and 3 for tapping and vibration. However, the Q1-Q3 quantile ranges are similar, with ranges of 3 to 4 for tapping and vibration, and 2.75 to 4 for stroking. Although the median for stroking is better, there are more outliers for stroking compared to the other two stimuli.

In the “Helped learning” dimension, the medians are identical for all stimuli, each with a value of 3. However, the quantile ranges differ slightly, with a Q1-Q3 range of 2 to 3 for stroking, 2.75 to 4 for tapping, and 2 to 4 for vibration.

For the “Would have learned faster” dimension, the medians differ: 2.5 for stroking, 3 for vibration, and 2.0 for tapping, as shown in orange.

In the “Would use actuators to support the learning process” dimension, the medians are the same for all three stimuli. However, the variance differs considerably, with Q1-Q3 intervals of 2 to 4 for stroking and vibration, while the Q1-Q3 interval for tapping is 2.75 to 3.25.

For “Satisfaction overall”, the Q1-Q3 intervals are identical for stroking and vibration, ranging from 2 to 3, and from 3 to 4 for tapping. The medians, however, are the same (3.0) for all three stimuli in this dimension.

In the “Able to understand haptic feedback” dimension, there is no difference in the Q1-Q3 quantile range. However, the medians differ, with 2.5 for stroking and vibration, compared to 3.0 for tapping.

To assess statistical differences, we conducted non-parametric Kruskal-Wallis tests, the results of which are presented in Table 4.3. As shown in the table, no statistically significant differences were found between the stimuli for the dimensions, as the p-values for each Kruskal-Wallis test exceed the threshold value of $\alpha = 0.05$.

However, the dimensions closest to the threshold are “Satisfaction overall” ($p\text{-value} = 0.0504$) and “Would have learned faster” ($p\text{-value} = 0.0882$). Given their relatively low p-values and η^2 effect sizes of 0.1707 and 0.1387 for “Satisfaction overall” and “Would have learned faster”, respectively, which are considered large, these dimensions are regarded as “approaching significance”.

After completing all the learning sessions for the different stimuli, the participants directly compared the stimuli based on the two dimensions presented in Figure 4.4, with the questions “Which actuator is the most comfortable” on the left and “Which actuator helped most in learning” on the right. 41.67% of the participants found the tapping actuator to be the most comfortable, followed by the vibration actuator, as shown in the left figure, while approximately 16.67% preferred the stroking actuator. This indicates that, according to the participants’ judgments, the vibration and tapping actuators were considered superior to the stroking actuators in terms of comfort.

Question	H-statistic	p-value	Significance	Effect Size
Feeling Pleasant	0.706	0.7026	Not Significant	0.0202
Helped Learning	1.942	0.3787	Not Significant	0.0555
Would have learned faster	4.855	0.0882	Not Significant	0.1387
Would use actuators to support learning process	0.038	0.9812	Not Significant	0.0011
Able to understand haptic feedback	1.241	0.5377	Not Significant	0.0355
Satisfaction overall	5.975	0.0504	Not Significant	0.1707

Table 4.3: Results of the Kruskal-Wallis significance tests for the different self-assessment dimensions with a η^2 Effect Size.

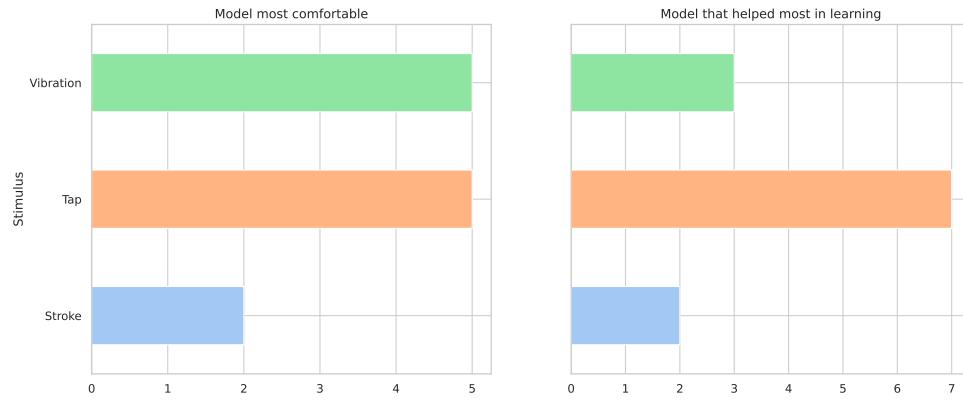


Figure 4.4: Results of the direct comparison between the different stimuli.

In the “Which actuator helped most in learning” category, the participants selected the tapping actuator as the most helpful, with 58.33% of participants voting for it, followed by the vibration actuator with 25%, and the stroking actuator with 16.67%. The stroking actuator was generally perceived as the least effective compared to the other two.

To test for significant statistical differences, we conducted two tests: first, the Chi-Square GF, and, as the sample sizes were relatively small and the expected values might be less than 5, we performed an additional Exact Multinomial Goodness-of-Fit Test (Exact MGF), as suggested by McDonald et al. [56], because it is likely more accurate. The results of these tests are presented in Table 4.4. As shown, the p-values for the first question, “Most comfortable model”, are 0.4724 for the Chi-Square GF and 0.4568 for the Exact MGF, both of which exceed the threshold value of 0.05. The same holds for the question “Model that helped most in learning”, with p-values of 0.1738 for the Chi-Square GF and 0.278 for the Exact MGF, indicating that there is no statistically significant difference between the stimuli for those questions.

Question	Test	Test- Statistic	p-value	Significance
Model most comfortable	Chi-Square GF	1.5	0.4724	Not Significant
	Exact MGF	3.464*	0.4568	Not Significant
Model that helped most in learning	Chi-Square GF	3.5	0.1738	Not Significant
	Exact MGF	4.206*	0.278	Not Significant

Table 4.4: Statistical Test Results for the direct comparison between the stimuli.

* indicates results obtained via Negative Log-Likelihood under H_0 .

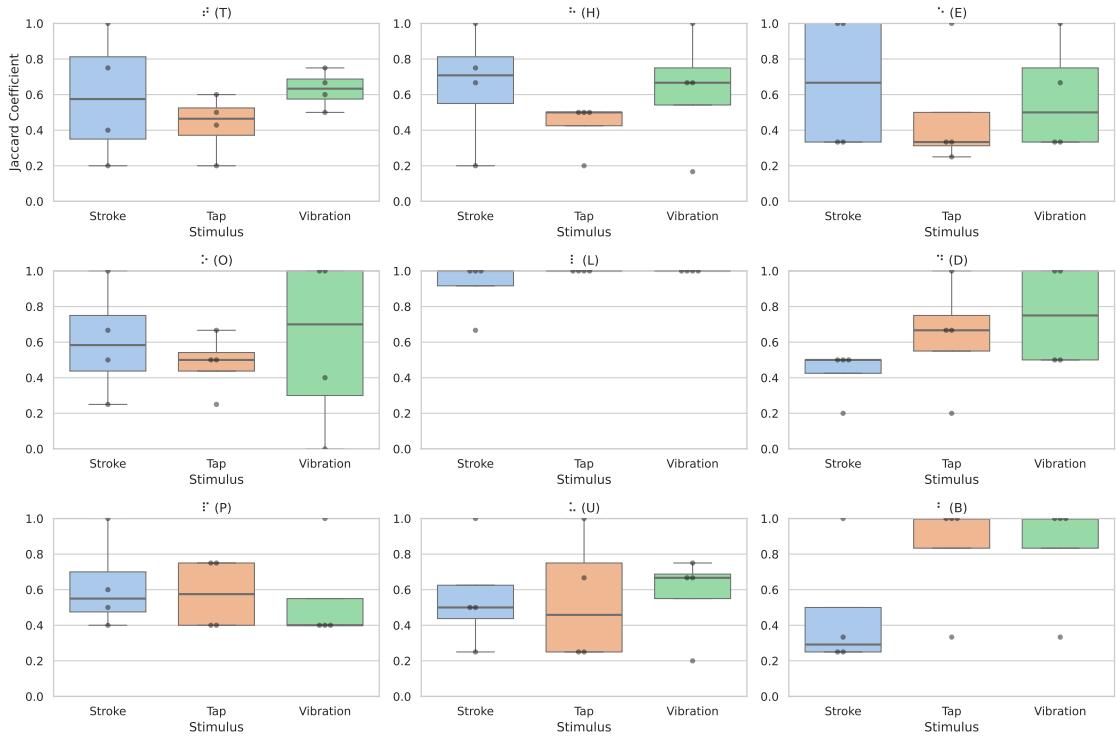


Figure 4.5: Jaccard coefficient results grouped by the Braille character during learning for the different stimuli.

Each dot represents one participant.

After passively learning a character using a specific stimulus, a test was conducted to assess the performance of the characters immediately following the learning session. The test results are shown in Figure 4.5, where the stimuli are plotted with their respective Jaccard indices, grouped by the specific characters learned in the session.

The most significant difference is observed for the character ⠼ (B), where the median for stroking is 0.3, while the medians for tapping and vibration are 1. The quantile ranges for tapping and vibration are 0.82 to 1, while the quantile range for stroking is 0.25 to 0.5.

A similar trend is observed for the character ⠼ (L), where both tapping and vibration perform perfectly while stroking has an outlier at 0.675. However, all medians are the same at 1.

For the character ⠼ (H), a larger difference is evident between tapping and the other two stimuli. While tapping has a median of 0.5, the medians for the other two stimuli are approximately 0.7. All three stimuli had a poor outlier, with a score of 0.2.

Another notable difference in medians appears for the character ⠼ (D), where the median for stroking is 0.5, compared to medians of 0.675 for tapping and 0.75 for vibration. Additionally, the quantile ranges differ: vibration has the largest range, from 0.5 to 1, due to two participants scoring 0.5 and 1, respectively. In contrast, only one participant achieved a perfect score for tapping, and both tapping and stroking have worse participant scores of 0.2.

A further difference can be observed for the character $\text{:}\ddot{\text{:}}$ (T), where the median for stroking is approximately 0.6, 0.65 for vibration, and 0.475 for tapping.

To test for significance, we used the Kruskal-Wallis tests. The results, however, did not show any significant differences, as depicted in Table 4.5. As shown in the “p-value” column, all p-values for the tests exceed the threshold value of $\alpha = 0.05$, indicating no statistically significant difference between the Jaccard index results of the stimuli for any of the characters.

Question	Test Statistic	p-value	Significance	Effect Size
$\text{:}\ddot{\text{:}}$ (T)	1.9406	0.3790	Not Significant	0.1764
$\text{..}\ddot{\text{:}}$ (H)	2.2817	0.3195	Not Significant	0.2074
$\text{..}\cdot\text{..}$ (E)	1.1068	0.5750	Not Significant	0.1006
$\text{..}\cdot\text{..}$ (O)	0.2790	0.8698	Not Significant	0.0254
$\text{..}\text{..}$ (L)	2.0000	0.3679	Not Significant	0.1818
$\text{..}\text{..}\ddot{\text{:}}$ (D)	2.9298	0.2311	Not Significant	0.2663
$\text{..}\text{..}\ddot{\text{:}}$ (P)	0.7068	0.7023	Not Significant	0.0643
$\text{..}\text{..}$ (U)	0.0299	0.9852	Not Significant	0.0027
$\text{..}\text{..}$ (B)	3.6667	0.1599	Not Significant	0.3333

Table 4.5: Results of Kruskal-Wallis significance tests for the different Braille characters during learning with a η^2 Effect Size.

After the passive learning sessions for all characters using a single stimulus, we conducted a word test for the characters learned during the previous passive learning sessions with that stimulus. The Jaccard score results, compared across the stimuli for each word, are depicted in Figure 4.6. As shown, the differences in performance are smaller than those observed for the individual characters.

For the word $\text{:}\ddot{\text{:}}\text{..}\text{..}$ (THE), the medians are 0.375 for stroking, 0.425 for tapping, and 0.425 for vibration. The quantile ranges are 0.35-0.5 for stroking, 0.3-0.6 for tapping, and 0.475-0.45 for vibration, respectively.

For the word $\text{..}\text{..}\text{..}\ddot{\text{:}}$ (OLD), the medians are 0.62 for tapping and 0.625 for vibration, compared to 0.475 for stroking.

For the word $\text{..}\text{..}\text{..}\text{..}$ (PUB), the median for stroking (0.45) is somewhat lower than that for tapping (0.56) and vibration (0.61).

Additionally, it can be observed that the quantile range for tapping is almost twice as large as that of the other two stimuli, with an approximate range of 0.2 compared to 0.1 for both vibration and stroking.

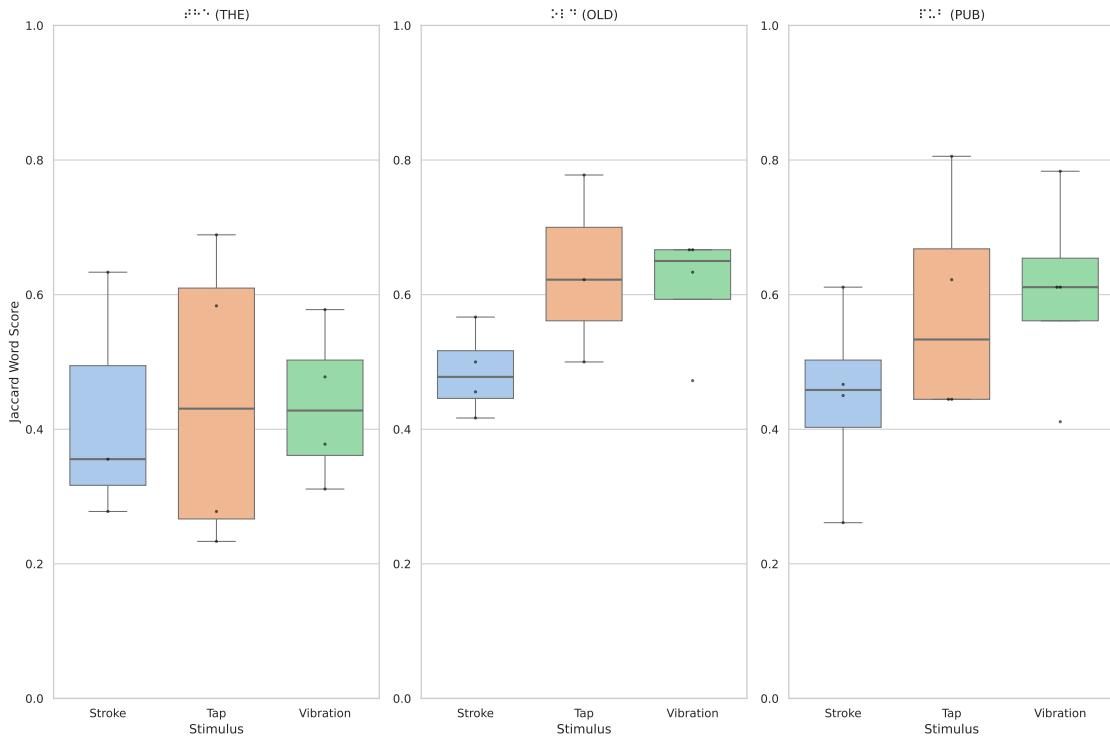


Figure 4.6: Jaccard Word-Test results grouped by the results for the Braille test-words “THE”, “OLD” and “PUB” for different stimuli.

To test for significance, we performed a Kruskal-Wallis test, the results of which are depicted in Table 4.6. The results showed that all p-values are well above the threshold α , with the closest value being 0.1371 for the word ⠼⠼⠼⠼ (OLD). This indicates that there was no statistically significant difference between the Jaccard index results for the different stimuli in relation to the word tests.

Question	Test Statistic	p-value	Significance	Effect Size
⠼⠼⠼⠼ (THE)	0.0361	0.9821	Not Significant	0.0036
⠼⠼⠼⠼ (OLD)	3.9736	0.1371	Not Significant	0.1371
⠼⠼⠼⠼ (PUB)	1.0569	0.5895	Not Significant	0.0961

Table 4.6: Results of the Kruskal-Wallis significance tests for the wordtests “THE”, “OLD”, and “PUB” with a η^2 Effect Size.

We further investigated the results by breaking them down for each individual character and analyzing them by examining false positives and false negatives in the construction of the Jaccard score. We regarded the decision to press a key or not as a classification task. Thus, a ”missed character” is classified as a false negative, and a ”surplus character” is classified as a false positive. Using this approach, we calculated precision and recall to derive the Jaccard score. These values are plotted in Figure 4.7.

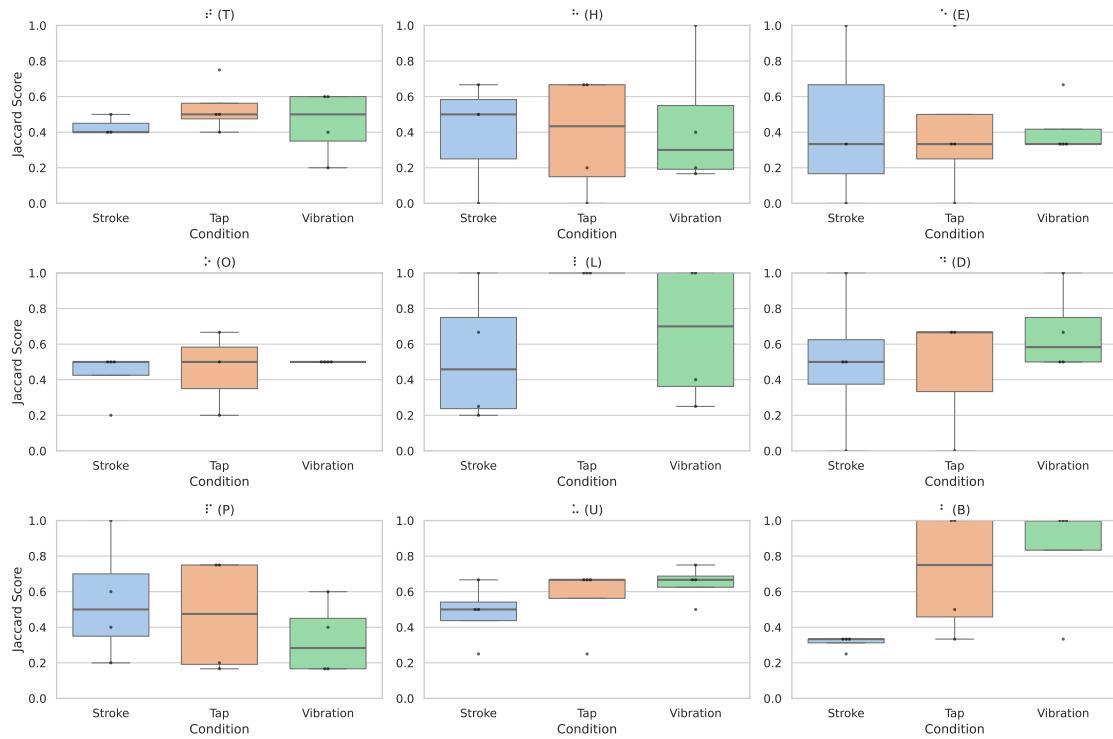


Figure 4.7: Jaccard Score comparison for the different Stimuli grouped by the Braille test-word characters.

As shown in the plot, the Jaccard score values do not differ significantly across most of the boxplots. The largest differences are observed for the character ⠼ (L), where tapping performed the best with a median of 1 while stroking performed the worst with a median of 0.45 and vibration had a median of 0.7. Although perfect scores are observed for all stimuli, stroking had more low data points, with Jaccard scores of 0.2 and 0.25.

The character ⠼ (B) showed a different pattern, with a median of approximately 0.325 for stroking, 0.75 for tapping, and 1 for vibration. None of the stroking participants were able to press the correct keys, whereas 2 participants in the tapping condition and 3 in the vibration condition succeeded in learning the character.

Additional differences were noted for the characters ⠼ (D) and ⠼ (P). For ⠼ (P), the median for stroking was higher than the other stimuli, with a median of 0.5 compared to 0.45 for tapping and 0.3 for vibration.

For ⠼ (D), stroking was the worst-performing stimulus, with a median of 0.5 compared to 0.6 for tapping and 0.58 for vibration. It is important to note that there was only one perfect score for both vibration and stroking, while there were also scores of 0 for both stroking and tapping.

However, when testing for statistical significance using Kruskal-Wallis tests, which are tabulated in Table 4.7, no significant differences were found for any stimulus across the characters, with the exception of ⠼ (B), which approached significance with a p-value of 0.0559 and a large η^2 effect size of 0.3906.

Question	Test Statistic	p-value	Significance	Effect Size
•• (T)	1.0203	0.6004	Not Significant	0.1131
•• (H)	0.0136	0.9932	Not Significant	0.0017
•• (E)	0.0979	0.9522	Not Significant	0.0121
•• (O)	0.5309	0.7669	Not Significant	0.0622
•• (L)	3.3764	0.1849	Not Significant	0.2968
•• (D)	0.5290	0.7676	Not Significant	0.0620
•• (P)	1.6124	0.4465	Not Significant	0.1519
•• (U)	2.5488	0.2796	Not Significant	0.2207
•• (B)	5.7683	0.0559	Not Significant	0.3906

Table 4.7: Results of Kruskal-Wallis significance tests for the different Braille characters during testing with a η^2 Effect Size.

To analyse the data that contributed to the Jaccard scores previously presented, we further examined the missed and surplus characters—those that were either missed or incorrectly submitted in addition to the required characters during the test. The results for the missed and surplus characters are depicted in Figure 4.8, grouped by the stimulus.

As shown for the false negative characters (missed characters), marked in blue on the left side, the first two missed characters are always ① [F] and ③ [S], followed by ④ [K] for both the vibration and tapping stimuli. For the stroking stimulus, ② [D] follows, and then ④ [K]. The character ⑥ [L] was the least missed, as it does not appear among the missed characters for the vibration stimulus and ranks last for both the stroking and tapping stimuli. Next, the character ② [D] appears, which is ranked last for vibration and second-to-last for tapping. Following this, ④ [J] is the second-to-last missed character for the vibration and stroking stimuli, and ranks third from the bottom for the tapping stimulus.

For the false positives (surplus characters), shown in red on the right, the most frequently added character is ⑥ [L]. This indicates that, in most cases, the character ⑥ [L] was added too often. However, the specific differences between the actuators vary. The ① [F] character appears last for the vibration stimulus, second-to-last for the stroking stimulus, and was never added as a surplus for the tapping stimulus.

After analysing the missed and surplus characters, we now dive deeper into the specific relationships between each tested character and the corresponding surplus or missed character. These details are depicted in Figure 4.9.

The diagram shows each Braille character under the category “tested character”, with the corresponding pressed keyboard characters on the left. The blue sections

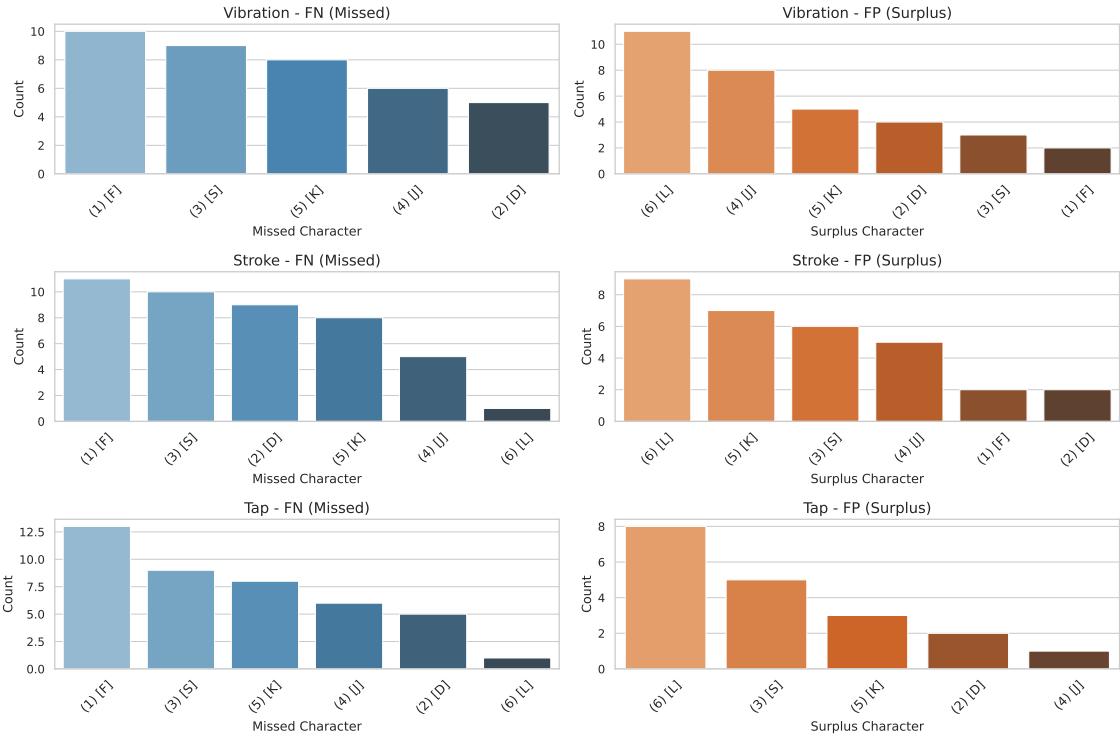


Figure 4.8: FN (Missed) and FP (Surplus) key(s) for each stimuli.

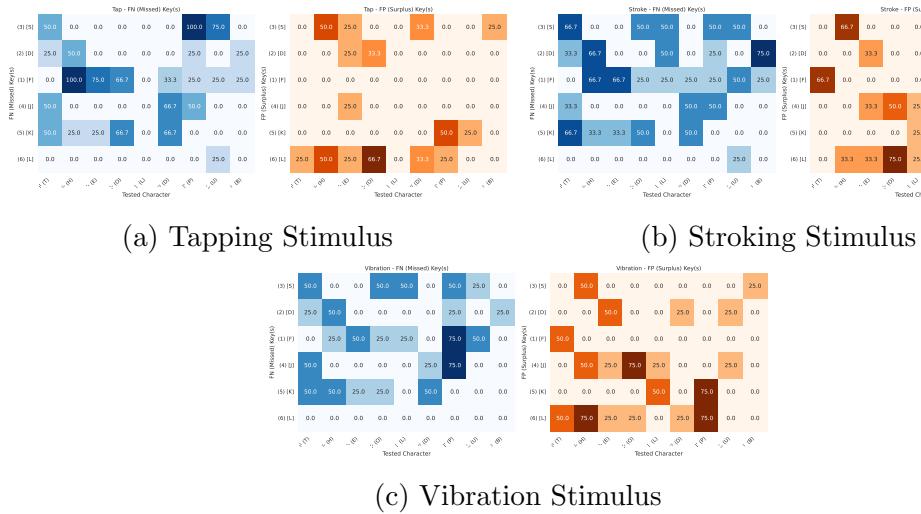


Figure 4.9: FN (Missed) Character in blue and FP (Surplus) keys in red in percent for each Braille character grouped by stimulus.

represent the percentage of missed keys when typing a character, while the red sections indicate surplus pressed keys for each character.

It is important to note that both Figure 4.9 and Figure 4.8 are related. Each column in Figure 4.8 corresponds to one row of missed or surplus characters in the same stimulus image, with matching colours for the same character. Thus, Figure 4.9 provides a more detailed, lower-level abstraction of the data shown in Figure 4.8.

For the surplus (red) side, significant differences are observed for the Braille characters ⠼ (B) and ⠼⠼ (U). For ⠼ (B), the key ③ [S] was consistently pressed incor-

rectly across all stimuli. However, for the Stroking stimulus, the keys ⑤ [K] and ⑤ [L] were also pressed incorrectly, with percentages of 50% and 25%, respectively.

Another notable difference occurs for the Braille character ⠼⠼ (U), where the key ④ [K] was pressed incorrectly for the Tap and Stroking stimuli, and the keys ④ [J] and ② [D] were pressed incorrectly for the Stroking and Vibration stimuli.

For the missed characters (FN, in blue), several differences are evident for the Braille characters ⠼⠼ (L) and ⠼⠼ (B). There were no missed characters for the Tapping stimulus, but for the Stroking and Vibration stimuli, the keys ③ [S] and ① [F] were frequently missed. In the case of Stroking, the key ② [D] was missed in about 50% of the trials.

A larger difference is seen with the key ⑥ [L], which was never missed for the Vibration stimulus but was missed in about 25% of cases for both the Stroking and Tapping stimuli.

Lastly, a one-hot encoding vector was created for the pressed keys for each stimulus, similar to a column in Figure 4.9. In order to visually represent the differences between the errors. We then calculated the cosine similarity for each stimulus character vector embedding against the ground truth, which is depicted by the black dotted line in Figure 4.10. To present the cosine similarity in a visually appealing manner, we used PCA to reduce the dimensionality to two dimensions for plotting.

The cosine similarity and PCA analysis, as shown in the figure, indicate that despite noise reduction through PCA, the vectors align in a similar direction. The most noticeable differences were observed for the braille characters ⠼⠼ (U), ⠼⠼ (E), and ⠼⠼ (O). But their Cosine similarity scores were still very similar with cosine scores of 0.81 (Vibration), 0.76 (Tapping) and 0.75 (Stroking) for the braille character ⠼⠼ (E), cosine scores of 0.82 (Vibration), 0.72 (Tapping) and 0.74 (Stroking) for the ⠼⠼ (O). And lastly 0.9 (Tapping), 0.93 (Vibration) and 0.9 (Stroking) for the braille character ⠼⠼ (U)

4.0.2 Second Study

For the second study, we interviewed 8 participants (5 male, 3 female) aged between 4 and 61 years, with an average age of 29.125 years and a median age of 24.5 years. Of these, 7 participants were right-handed and 1 was left-handed, as shown in Table 4.8. None of the participants had prior knowledge of Braille.

Consistent with the first study, we conducted a NASA TLX test after each encoding sequence to assess the task load experienced by the participants. The results of the NASA TLX are presented in Figure 4.12, where each encoding is displayed as a box plot grouped by the NASA TLX dimensions.

As shown, the respective box plots for the dimensions appear similar, with medians of 40 for SEQ and 35 for “ost” under the “Mental Demand” category. The Q1-Q3 quantiles for SEQ range from 20 to 82, while for “ost”, they range from 20 to 65.

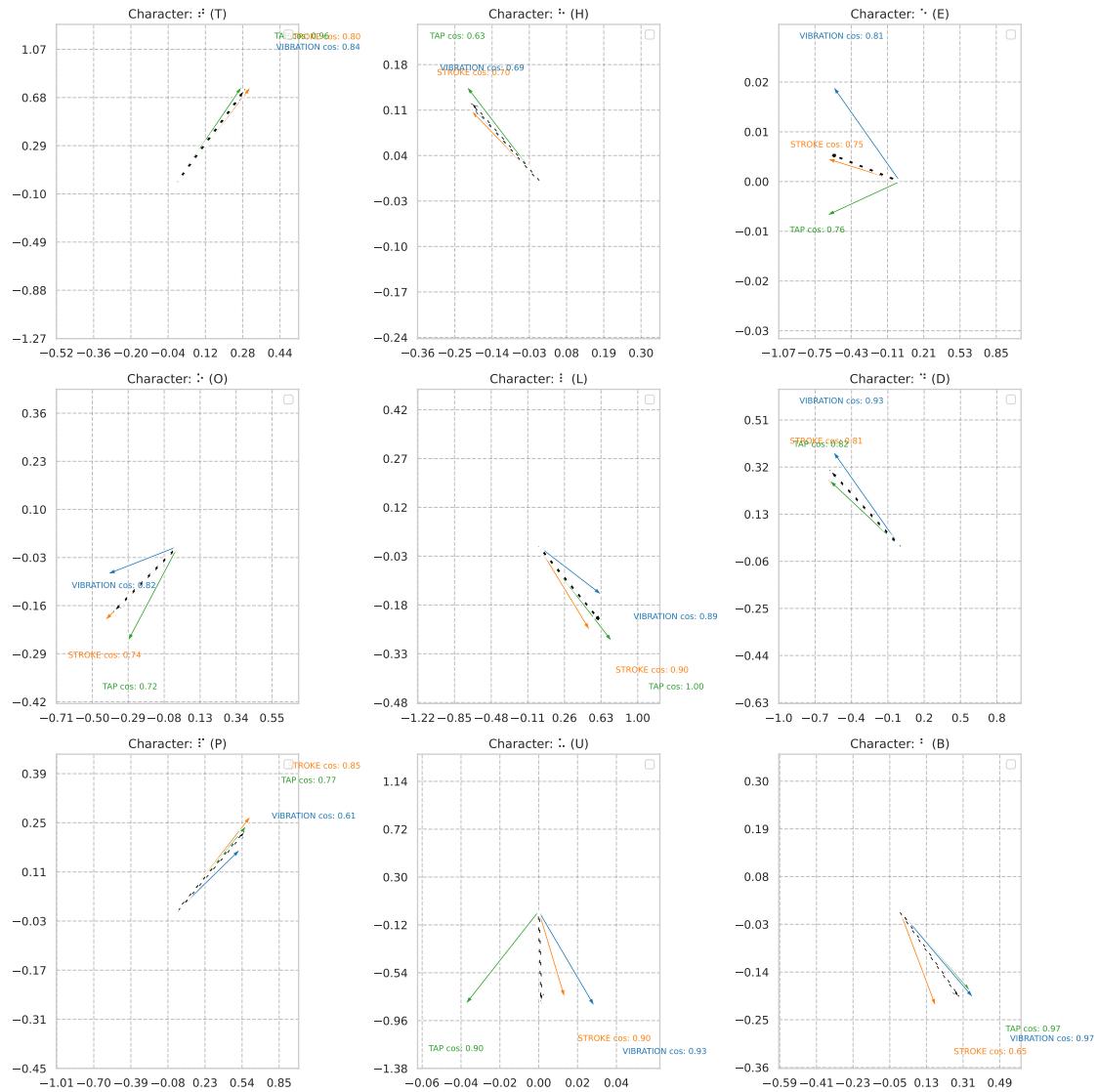


Figure 4.10: Cosine Similarity for each of the Stimuli.
Plotted using a PCA dimensionality reduction.

Gender	Age	Dominant Hand	Previous Braille Knowledge
F	21	R	No
M	61	L	No
M	23	R	No
F	27	R	No
F	29	R	No
M	23	R	No
M	26	R	No
M	23	R	No

Table 4.8: Second study participant data

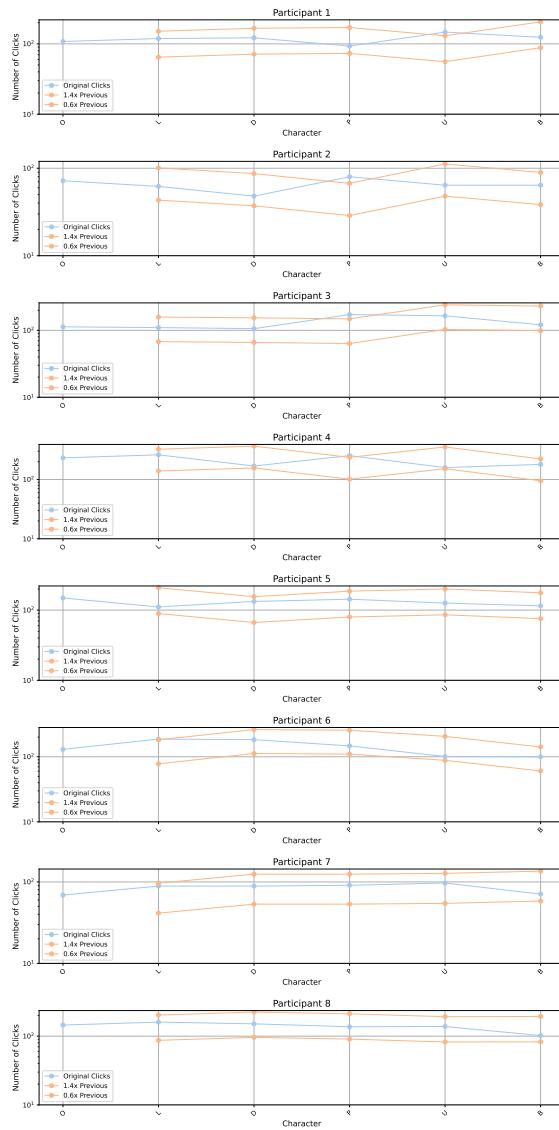


Figure 4.11: Participant Click-differences.

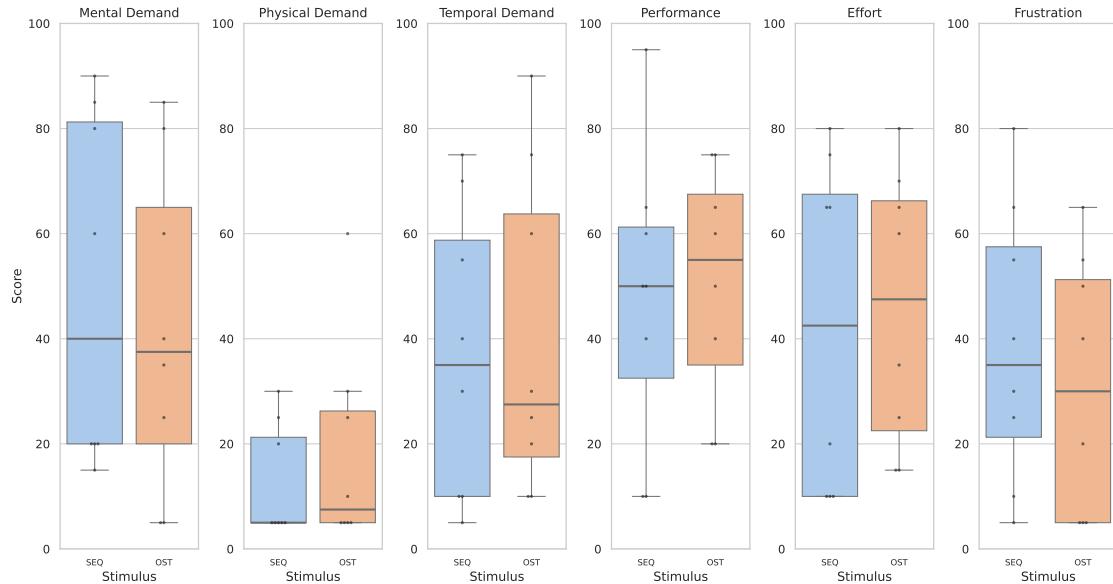


Figure 4.12: Raw NASA TLX scores of the different Encodings grouped by the NASA TLX dimensions.

For the “Physical Demand” category, the median for OST is slightly lower at 5, compared to the median of approximately 7.5 for SEQ. The Q1-Q3 quantiles start at 5 for both encodings, but SEQ extends up to 22.5, while “ost” reaches 25.

In the “Temporal Demand” category, the medians are 35 for SEQ and 30 for “ost”, with similar quantile ranges—10 to 57.5 for SEQ and 17.5 to 65 for “ost”.

Similar to the previous categories, the median for SEQ in the “Frustration” category is higher, at 35, compared to the median of 30 for “ost”.

For the “Performance” and “Effort” categories, the medians show a similar trend. The median for SEQ is 50 in the “Performance” category, while “ost” has a median of 55. For “Effort”, the median for SEQ is 42.5, whereas “ost” has a median of 47.5.

To assess the significance of the NASA TLX results, we conducted MW U test significance tests, with the outcomes presented in Table 4.9. As shown, all p-values are relatively high, indicating that the null hypothesis (H_0) was not rejected.

Question	Test Statistic	p-value	Significance	Effect Size
Mental Demand	35.500	0.7513	Not Significant	0.2141
Physical Demand	27.000	0.6019	Not Significant	0.3559
Temporal Demand	29.0000	0.7911	Not Significant	0.1065
Performance	27.5000	0.6721	Not Significant	0.1228
Effort	27.500	0.672	Not Significant	0.1285
Frustration	39.0000	0.4907	Not Significant	0.3168

Table 4.9: Results of MW U test significance tests for the different NasaTLX dimensions with Cohens d.

Following the NASA TLX task load, participants were asked to evaluate their experiences with the two different encodings. Their evaluations were plotted across six different dimensions, as shown in Figure 4.13.

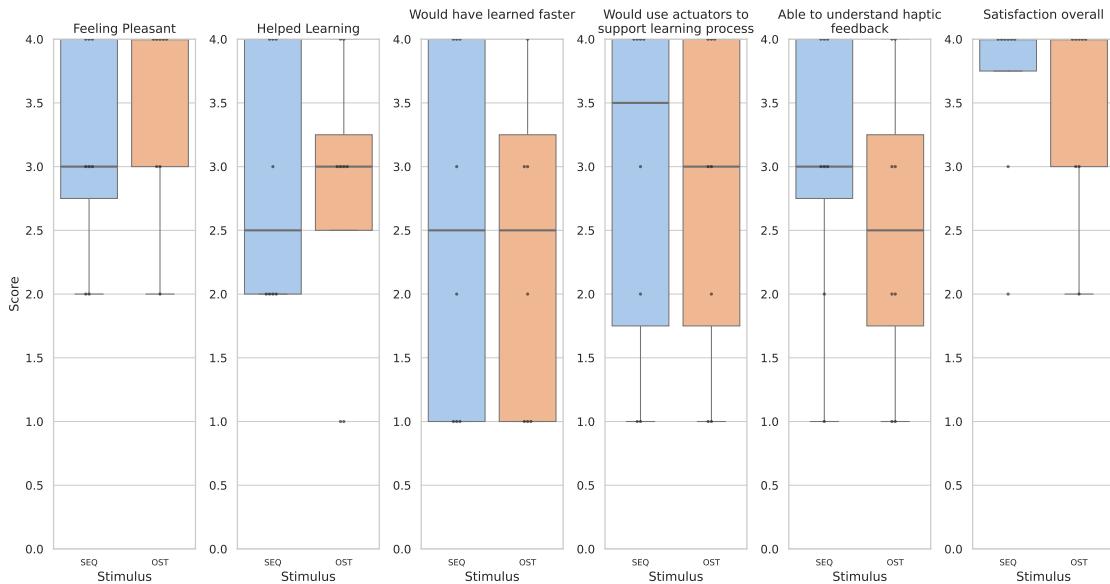


Figure 4.13: Self-assessment Results of the different Stimuli grouped by the self-assessment categories.

The largest differences in medians were observed in the categories: “Helped Learning”, with medians of 2.5 for SEQ and 3 for OST; “Would use actuators to support the learning process”, with 3.5 for SEQ and 3 for OST; “Able to understand haptic feedback”, with 3 for SEQ and 2.5 for OST; and “Satisfaction overall”, with 3.75 for SEQ and 3 for OST.

The medians for the categories “Feeling Pleasant” (3) and “Would have learned faster” (2.5) were the same for both encodings.

The Q1-Q3 quantile ranges differed notably in the “Helped Learning” category, where SEQ ranged from 2-4 and OST from 2.5-3.25. In “Satisfaction overall”, the difference was also noticeable, with SEQ ranging from 3.75-4 and OST from 3-4.

For the “Would have learned faster” category, the quantile ranges showed a significant difference, with SEQ and OST both starting at Q1 = 1, but SEQ extending to 4 and OST to 3.

Finally, the quantile ranges for the “Able to understand haptic feedback” dimension were nearly identical, with SEQ ranging from 2.75-4 and OST from 1.75-3.25.

For the self-assessment tests, we also conducted MW U test significance tests, and the results are presented in Table 4.10. The lowest p-value was found for the “Feeling Pleasant” dimension; however, with a p-value of 0.3596, it remains too high to indicate statistical significance. Therefore, there is no significant difference between the two encodings in terms of self-assessment for usability and their effectiveness in aiding learning.

After the study, we asked the participants to compare the two encoding methods, and the results are presented in Figure 4.14. The comparison reveals that the SEQ encoding was perceived as more distinguishable, with 62.5% of participants agreeing, and it was also considered more helpful for learning with the same proportion. However, the OST encoding was regarded as more comfortable, with 62.5% of participants reporting it as more comfortable than the SEQ encoding.

Question	U-statistic	p-value	Significance	Effect Size
Feeling Pleasant	23.5000	0.3596	Not Significant	0.2232
Helped Learning	33.0000	0.9565	Not Significant	0.0263
Would have learned faster	32.5000	1.000	Not Significant	0.0131
Would use actuators to support learning process	34.5000	0.8244	Not Significant	0.0656
Able to understand haptic feedback	40.0000	0.4139	Not Significant	0.2100
Satisfaction overall	35.5000	0.7001	Not Significant	0.0919

Table 4.10: Results of the MW U test test for significance grouped by the different self-assessment dimensions with a Cohens d Effect Size.

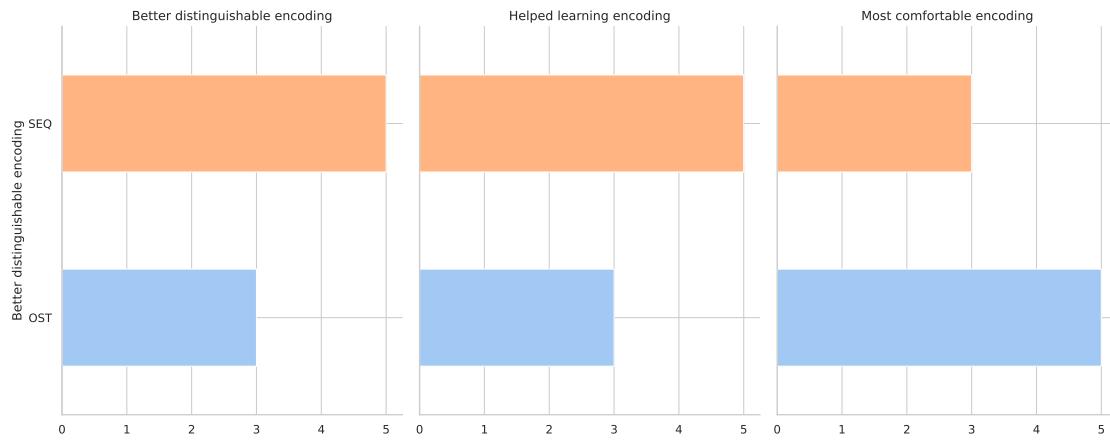


Figure 4.14: Results of the direct comparison between the different encodings.

A statistical analysis, presented in Table 4.11, showed that conducting the Chi-Square GF study resulted in no significant difference. The Chi-Square GF was chosen due to insufficient data for a Chi-Squared test.

During the learning process, we measured performance using the Jaccard and Dice scores. The Jaccard results after learning each character are shown in Figure 4.15, as they are more stringent than the Dice scores.

The charts reveal larger differences in the medians for **• :** (D), with a median of 0.95 for SEQ and 0.55 for OST. Similarly, for the **• :** (U) test, the median difference is substantial, with SEQ showing a median of about 0.45 and OST performing better with a median of 0.825. OST also outperformed SEQ for the character **• :** (L), with a median of 0.825 compared to 0.575 for SEQ. For the character **• :** (B), OST showed better performance, with a median of 1, which was consistent across the Q1 and Q3 quantiles. In comparison, SEQ had a median of 0.825, with Q1 equal to

Question	Chi-Square GF	p-value	Significance
“Better distinguishable encoding”	0.5	0.4795	Not Significant
“Helped Learning encoding”	0.5	0.4795	Not Significant
“Most comfortable encoding”	0.5	0.4795	Not Significant

Table 4.11: Statistical Chi-Square GF Results for the direct comparison between the stimuli.

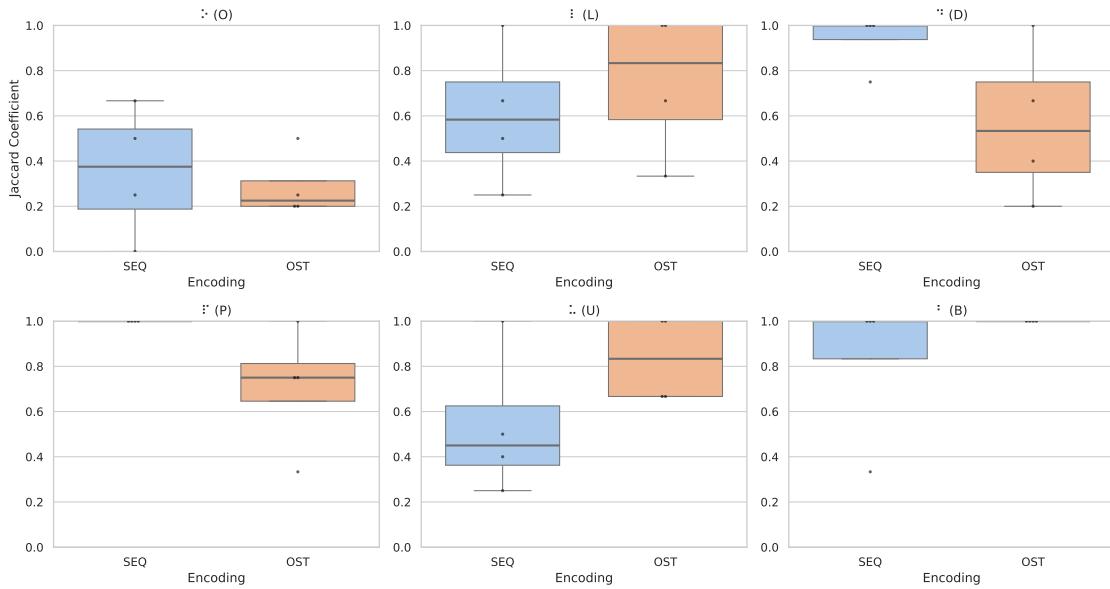


Figure 4.15: Jaccard coefficient results grouped by the Braille characters during learning for the different Encodings.

that value and Q3 at 1. However, for the character $\bullet\bullet$ (P), SEQ performed better, with a median, Q1, and Q3 of 1, compared to OST, which had a median of 0.75, Q1 of 0.65, and Q3 of 0.82.

Afterwards, we conducted the appropriate MW U test tests for significance, and the results are shown in Table 4.12. However, none of the tests showed statistically significant differences. The lowest p-value was observed in the \bullet (B) test, with a value of 0.067, which also had a Cohen's d effect size of 1.492, indicating a relatively large effect.

Question	Test Statistic	p-value	Significance	Effect Size
$\bullet\bullet$ (O)	10.000	0.659	Not Significant	0.290
\bullet (L)	5.500	0.552	Not Significant	0.460
$\bullet\bullet$ (D)	13.500	0.124	Not Significant	1.424
$\bullet\bullet$ (P)	14.000	0.067	Not Significant	1.492
\bullet (U)	3.000	0.180	Not Significant	1.108
\bullet (B)	6.000	0.453	Not Significant	0.707

Table 4.12: Results of the MW U test tests for significance grouped by the different Braille characters during training for the different Encodings with Cohen's d.

After learning each word using one of the encodings, we tested the word itself, with the results shown in Figure 4.16, to determine whether there was a significant difference in testing the entire word after learning all the individual characters.

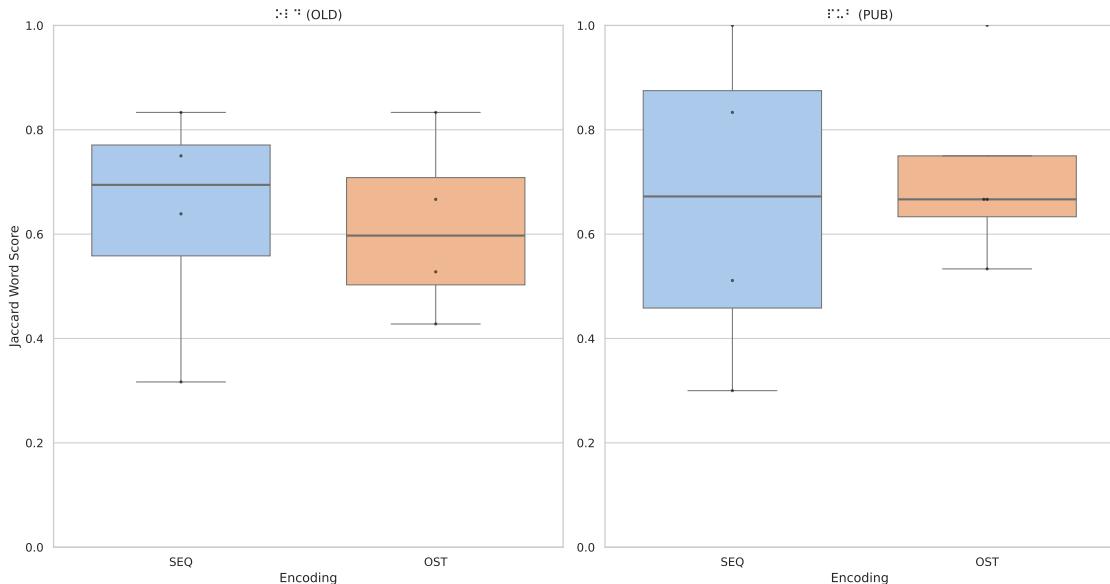


Figure 4.16: Jaccard Word-Test results grouped by the Braille test-words for the different stimuli.

Interestingly, no significant difference was observed in the median. However, the Q1 and Q3 values for the word "pub" differed, with an interval of 0.62-0.85 for OST compared to 0.45-0.875 for SEQ. Nevertheless, the median remained the same for both encodings, at 0.675.

We conducted MW U test tests for the resulting words, and the results showed that no p-value was close to the threshold value of 0.05, as depicted in Table 4.13. This indicates that there was no significant difference between the sets, with p-values of 1.0 and 0.77.

Question	Test Statistic	p-value	Significance	Effect Size
• • • (OLD)	8.500	1.000	Not Significant	0.103
• • • (PUB)	6.500	0.770	Not Significant	0.211

Table 4.13: Results of the MW U test tests for significance for the different Braille tests-words with a Cohens d Effect Size.

Similarly to the first study, we analyzed the Jaccard scores for the different characters in the second study. The most significant differences were observed for the characters ‘•’ (B), followed by ‘••’ (P), ‘•’ (L), and ‘••’ (D).

For the character ♡ (B), the OST encoding performed better, achieving a perfect score, while the SEQ encoding had a median of 0.675 and a Q1-Q3 quantile range of approximately 0.3 to 1, as half of the participants did not achieve a perfect score.

In contrast, for the character ‘•’ (P), the OST encoding performed worse, with a median around 0.5, while SEQ had a median of 1. Similarly, for the character ‘◦’ (D), the SEQ encoding had a median of 1, while OST had a median of 0.7. Notably, only

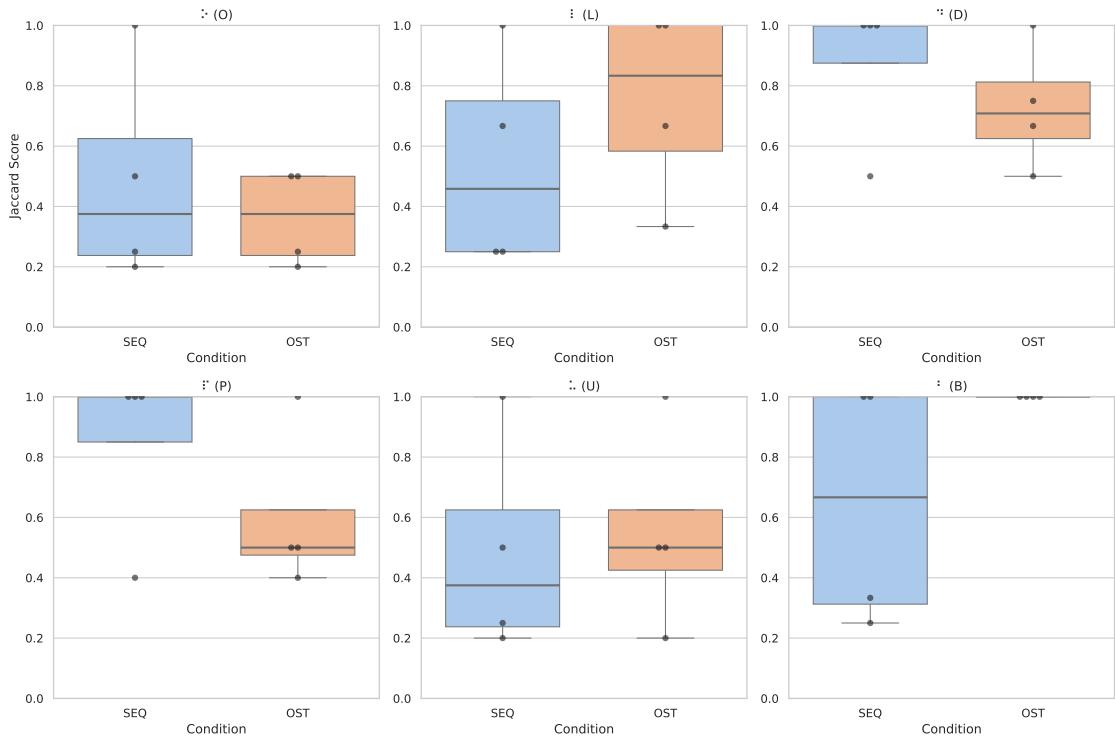


Figure 4.17: Jaccard Score comparison for the different Encodings grouped by Braille character.

one participant in the SEQ group did not achieve a perfect score, with a score of 0.4.

It is also worth noting that only one participant had a non-perfect score for : (D) using the SEQ encoding.

For the character : (L), the OST encoding had a median of approximately 0.825, with half of the participants achieving a perfect score, whereas the SEQ encoding had a median of about 0.45.

Upon analyzing each character individually, no significant differences were found between the datasets. The lowest p-value was observed for : (B), with a value of 0.186, which is significantly higher than the threshold value. Therefore, the null hypothesis (H_0) cannot be rejected.

Further analysis, shown in Figure 4.18, reveals that ③ [S] is the most frequently missed character, while ② [D] is the most frequently in surplus. In contrast, ④ [J] and ⑥ [L] were the least missed characters, while ② [S] and ④ [J] were the least in surplus.

A closer analysis reveals that for the false positives (FP), the characters : (B), : (L), : (D), and : (P) exhibited the most notable differences.

For : (B), the OST encoding had no errors, while in the SEQ encoding, the ⑤ [K] and ③ [S] keys were mistakenly pressed with the ③ [S] key in 50% of the cases.

Question	Test Statistic	p-value	Significance	Effect Size
•• (O)	9.000	0.881	Not Significant	0.443
•• (L)	4.500	0.369	Not Significant	0.609
•• (D)	11.000	0.439	Not Significant	0.634
•• (P)	11.000	0.436	Not Significant	0.875
•.. (U)	7.000	0.881	Not Significant	0.179
• (B)	4.000	0.186	Not Significant	1.221

Table 4.14: Results of the MW U test for significance grouped by the different Braille characters during learning for the different Encodings with Cohen's d.

For •• (L), there were no false positives in the OST encoding, but half of the participants incorrectly pressed the ⑥ [L] key in the SEQ encoding.

For •• (D), a larger difference is evident, with 25% of participants missing ③ [S] and ⑥ [L] in the OST encoding, while the ② [D] key was incorrectly pressed in the SEQ encoding.

For •• (P), the ⑥ [L] key was incorrectly pressed in 25% of the cases in the OST encoding, while the ⑤ [K] key was mistakenly pressed in the SEQ encoding.

Regarding the false negatives (FN), the most significant differences were observed for the characters •• (P), • (B), •• (O), and •• (L).

For •• (P), the SEQ encoding performed better, with only the ④ [J] and ② [D] keys missed 25% of the time. In contrast, the OST encoding also missed the ① [F] and ③ [S] keys.

For • (B), no keys were missed with the OST encoding, but in the SEQ encoding, the ② [D] key was missed 50% of the time.

For •• (O), the ① [F] key was missed in 75% of the cases with the OST encoding, while both the ③ [S] and ⑤ [K] keys were missed in both encodings. Notably, the ⑤ [K] key was missed in 75% of the cases in the SEQ encoding but only 25% of the time in the OST encoding.

For •• (L), both the ① [F] and ③ [S] keys were missed in both encodings, though the SEQ encoding also missed the ② [D] key 25% of the time.

Analysis of the missed keys shows the largest differences for the ① [F] and ② [D] keys.

The ① [F] key was missed in the •• (L) test in the SEQ encoding, and also for •• (O) and •• (P), affecting half of the characters in the OST encoding.

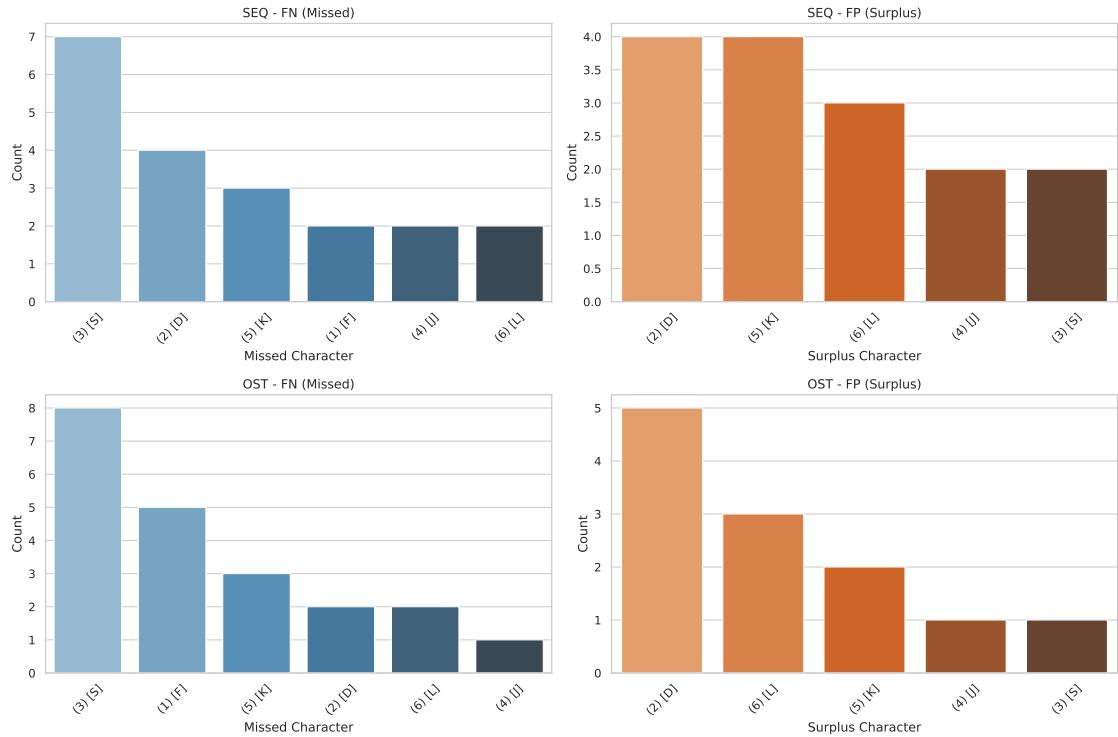


Figure 4.18: FN (Missed) and FP (Surplus) Key(s) for each Braille Character by Encoding.



Figure 4.19: FN (Missed) and FP (Surplus) Key(s) in percent for each Braille character grouped by Encoding.

For the ② [D] key, it was missed for ⠄ (L), ⠄⠄ (P), and ⠄⠄⠄ (B) in the SEQ encoding, but only in 50% of the cases for ⠄⠄⠄ (B) in the OST encoding.

The cosine similarity and PCA analysis, as shown in Figure 4.20, indicate that despite noise reduction through PCA, the vectors align in a similar direction. The most noticeable differences were observed for the braille characters ⠄⠄⠄ (O) and especially ⠄ (L). However, their cosine similarity scores are still rather similar with 0.69 for the OST and 0.78 for SEQ for the braille character ⠄⠄⠄ (O). For the Braille character ⠄ (L), the cosine similarity is even smaller with 0.96 for OST and 0.88 for SEQ.

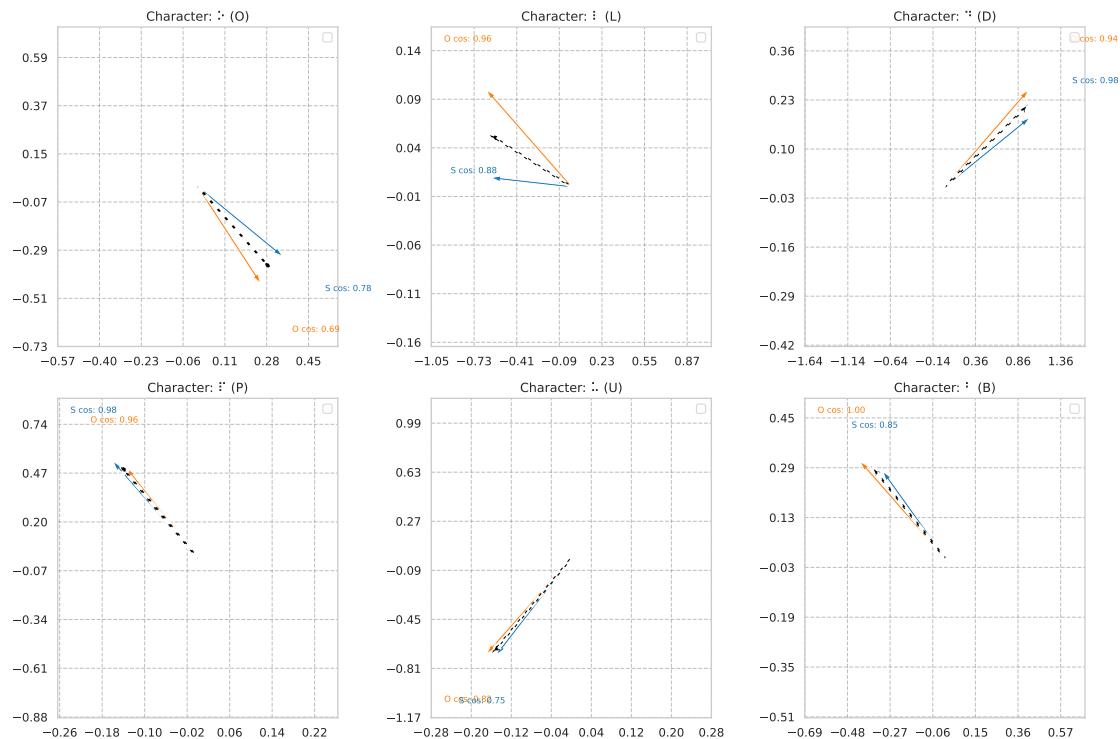


Figure 4.20: Cosine Similarity for each Encoding.
Plotted using a PCA dimensionality reduction.

5. Evaluation

This section is used to interpret the data gathered in the analysis section and answer the two research questions “RQ1: Is there a difference between affective and discriminative touch for both hands using the OST encoding” and “RQ2: Is there a significant difference between using the OST and the SEQ encoding”.

5.0.1 First Study

In the first study, we compared the task load of the participants using the NASA TLX task load index.

By analyzing the six different task load dimensions for each stimulus, and testing for significant differences between the stimuli, we found no significant differences.

However, it is evident that there is a notable difference in the median performance statistics, suggesting that the “Performance” dimension was perceived more favourably in the stroking and vibration conditions.

After completing the NASA TLX, participants were asked to self-assess how they perceived the stimulus on various dimensions, including “Feeling Pleasant”, “Helped Learning”, “Would Have Learned Faster”, “Would Use the Actuators to Support the Learning Process”, “Able to Understand Haptic Feedback”, and “Satisfaction Overall”, as depicted in Figure 4.3.

A Kruskal-Wallis test was conducted on these responses. The results showed that the p-value for “Satisfaction” was 0.0504. In combination with the effect size of η^2 , this indicates a borderline significant difference, particularly for the tapping stimulus. Almost half of the participants rated it as very satisfying, resulting in a better Q1-Q3 quantile range compared to the other two stimuli. This suggests that participants were generally happier with the tapping stimulus, though the difference was not statistically significant.

Furthermore, the dimension “Would Have Learned Faster” yielded a p-value of 0.0882 and an effect size of 0.1387, which is also borderline significant, with more participants expressing dissatisfaction with the tapping stimulus.

After the tests were completed, participants were asked to directly compare the stimuli and select which one they perceived as the best for each of the two dimensions: “Model Most Comfortable” and “Model That Helped Most in Learning”, as shown in Figure 4.4.

The results indicate that the tapping and vibration stimuli were consistently rated better than the stroking stimulus in direct comparisons. In terms of comfort, both the tapping and vibration stimuli were perceived equally, while for learning, the tapping stimulus was preferred by 7/12 of the participants.

However, after conducting a Chi-Square GF and an Exact MGF, the results, presented in Table 4.4, reveal that the perceived differences between the stimuli were not statistically significant.

Participants were also asked to provide comments after the study. The comments received were as follows:

“Stroking is better than vibration, and tapping is better than stroking in both comfort and learning.”

“For vibration, it is sometimes difficult to identify which finger is vibrating.”¹

“The vibration was unclear, as it was difficult to tell which fingers were vibrating due to interference from other vibrators. The stroking was hard to feel.”

Lastly, “I think the tapping was the most comfortable, and I was able to distinguish the fingers. I sometimes couldn’t feel the stroker.”²

The participants’ comments consistently indicate that tapping was preferred over stroking, followed by vibration. This preference seems to be due to stroking being difficult to feel and vibration being hard to distinguish. In contrast, tapping was favoured for its distinguishability.

In summary, we observed that performance was perceived as better for the stroking and vibration conditions in the NASA TLX. This is likely because the tapping actuator was more difficult to grasp, with an average of three fingers being stimulated for each character. This may have confused participants due to the number of taps involved.

The second questionnaire revealed that the tapping stimulus was borderline significant for “Satisfaction”, with participants rating it as the most satisfying. This finding is further supported by the comments provided by the users.

Interestingly, participants expressed dissatisfaction with the tapping stimulus in relation to “Would have learned faster”. This may stem from the same issue observed in the NASA TLX results—too much simultaneous stimulation.

However, in the “Helped learning” dimension, the tapping stimulus was still perceived as helpful, with nearly half of the participants rating it as very helpful for learning.

In a direct comparison of which stimulus was most helpful in learning, the tapping stimulus performed better. Additionally, its comfort level was rated similarly to

¹Translated from: “Bei Vibration ist manchmal schwer zu finden, welche Finger vibriert.”

²Translated from: “Ich empfand den Tapper am angenehmsten und man konnte die Finger gut unterscheiden. Den Stroker habe ich manchmal nur kaum gespürt.”

the vibration stimulus, suggesting that from a qualitative perspective, it is a strong contender.

The vibration stimulus faced the issue of being difficult to distinguish, while the stroking stimulus generally performed worse. It was challenging to feel and distinguish and also underperformed in the “Helped learning” section of the usability questionnaire.

For the objective data, we first gathered the results from all character learning tests, which are shown in Figure 4.5. After conducting Kruskal-Wallis tests for all the Braille characters, we found that there was no statistically significant difference between the sets, with the lowest p-value of 0.1599 for the character ⠼ (B). In this case, the stroking stimulus performed worse than the other two stimuli, but the results were essentially the same for the other stimuli.

The character “::” (D) also showed a p-value of 0.2311 with an effect size of 0.2663, which is relatively high and reflects a slight difference. Here, the stroking stimulus was again perceived as slightly worse than the other stimuli; however, this difference was also far from statistically significance.

Lastly, we conducted a word test to assess performance with complete words after learning. The results are shown in Figure 4.6. This analysis revealed that the stroking stimulus consistently performed worse for each word, followed by the tapping and vibration stimuli, which were similar for the word :• :• • (THE). For the other two words, :• : : (OLD) and :• :• : (PUB), the median score was slightly better for the vibration stimulus, though the difference was small.

However, no statistical significance was found, as detailed in Table 4.6, where the lowest p-value was 0.1371 for the word  (OLD). It was also noted that there was always at least one participant who achieved the best score with tapping. In general, tapping performed better than the other two stimuli for the outliers, except for the word  (THE).

Vibration also performed well, ranking second for the words (OLD) and (PUB) when considering the best performers.

After further analyzing the data, we found that for the ♦ (L) character, tapping performed the best, with no errors, followed by stroking, which also had some participants who made no errors.

For the ♦ (B) character, vibration outperformed both tapping and stroking, and this difference was borderline significant.

An interesting observation was that when all fingers on one hand needed to be stimulated, tapping appeared to be better than vibration, likely due to its higher distinguishability.

The error analysis revealed that the errors were mostly consistent across stimuli. For false negatives (FN), the most frequent error was ① [F], followed by ③ [S] and

⑤ [K] for both vibration and tapping and ② [D] and ⑤ [K] for stroking. The least frequent false negative was ⑥ [L].

The false positives (FP) also showed similar patterns. The most frequently added character was ⑥ [L], while the least frequent false positive was ① [F].

This indicates that ⑥ [L] was pressed almost constantly, even when not needed for some characters, while ① [F] was pressed less often and was mostly missed across all actuators.

A detailed analysis revealed that the errors were similar for both the vibration and stroking stimuli. For example, in the case of the character ։ (U), the ⑤ [K] key was pressed incorrectly for both stimuli. However, for the vibration stimulus, the ④ [J] and ② [D] keys were also pressed incorrectly.

In terms of false negatives (FN), the ⑥ [L] character was never missed with the vibration stimulus but was missed in 1/4 of the cases for tapping and stroking.

5.0.2 Second Study

The second study was conducted to see the differences between the different encodings OST and SEQ.

Similarly to the first study, we analyzed the subjective feelings of the participants using the NASA TLX, and the statistical significance of these results.

As shown in the plot and table, there is no significant difference between the two encodings, as measured by the Mann-Whitney U test (MW U test), with all p-values above 0.4.

This indicates that both encodings resulted in similar task load perceptions.

The self-assessment results of the participants and the corresponding significance tests, revealed no significant difference between the perceived quality of the different encodings, suggesting that they are essentially the same.

However, there is one notable difference in the “Feeling Pleasant” category, where the SEQ encoding had a median of 3, while the OST encoding scored a 4.

For the “Satisfaction” dimension, a larger difference can be observed in the Q1-Q3 quantile range, but this is attributed to one participant who rated the SEQ encoding as more satisfying and did not provide a score of 3. Therefore, the encodings are effectively the same, as reflected by the p-value of 0.7 for this dimension.

The direct comparison, shown in Table 4.11, indicates that the SEQ encoding was rated better for “Better distinguishable encoding” and “Helped learning encoding”, with 5/8 participants rating it higher for both categories. However, for “Most comfortable encoding”, the OST encoding scored worse, with 3/8 participants rating it lower.

None of these differences were statistically significant, as indicated by the p-value of 0.4795 for all dimensions.

In general, there is no significant difference between the two encodings in terms of the participants’ self-assessments. This is true for the task load measured by the

NASA TLX and the self-assessment questionnaire, where neither dimension showed statistically significant differences.

Additionally, the direct comparison of which encoding was perceived as better after the study was not significant, as the differences were limited to just one participant per dimension. Therefore, none of the qualitative assessments showed significant differences.

After the characters were learned using one of the encodings, we conducted tests, with the Jaccard results shown in Figure 4.15 and the results of the MW U test significance tests tabulated in Table 4.14.

An observed difference was tested using the character $\bullet\bullet$ (P), which showed a Cohen's d effect size of 1.492, with the SEQ encoding performing better. For the character $\bullet\bullet$ (D), the SEQ encoding also performed better, with a median of 1 compared to the OST encoding, which had a median of 0.425.

For the characters $\bullet\bullet$ (L) and $\bullet\bullet$ (U), the OST encoding performed better. Interestingly, for all Braille characters containing ④ (J) or ⑤ (K), the SEQ encoding outperformed the OST.

After learning all the words, the word test was conducted, and the results are depicted in Figure 4.16. The significance tests are tabulated in Table 4.13.

As seen from the significance tests, with p-values over 0.7, there is no significant difference between the encodings. Additionally, the plot shows that the worst-performing SEQ encoding performed worse for both words than the worst-performing OST encoding. However, the best-performing SEQ encodings resulted in slightly better participant scores than the best OST encodings, indicating a wider variance in performance.

We then analyzed the individual characters as before, which are plotted in Figure 4.17, with their significance tests tabulated in Table 4.14.

As shown, there are larger differences for the characters \bullet (B), $\bullet\bullet$ (P), $\bullet\bullet$ (L), and $\bullet\bullet$ (D); however, none of these differences were statistically significant.

We then tested the false positives (FP) and false negatives (FN) for each of the characters, as shown in Figure 4.18.

The results indicate that many FN errors were associated with ③ [S]. For the FP errors, both encodings showed ② [D], ⑤ [K], and ⑥ [L].

We then analyzed the errors for each character, with the plots available in Figure 4.19 for both the SEQ and OST encodings.

The analysis of the plots revealed differences for FP in the characters \bullet (B), $\bullet\bullet$ (L), and $\bullet\bullet$ (D). For FN, the differences were observed in the characters $\bullet\bullet$ (O), $\bullet\bullet$ (L), $\bullet\bullet$ (P), and \bullet (B).

The largest differences for FN were seen with the Braille character $\bullet\bullet$ (P), where the keys ③ [S] and ① [F] were often missed. For FP, the largest differences were

with the Braille character ⠼ (B), where the keys ③ [S] and ⑤ [K] were pressed too frequently.

The comments evaluating the different encoding schemes were:

“For OST, I don’t perceive the vibration as accurately.”, “I had difficulties to register which finger did vibrate.”, “If I had to learn with one method with the goal of having learned something in the end, I would choose SEQ. If it’s just for fun, I would choose OST.”, “I had difficulties to register which finger did vibrate.”, “OST was easier to ignore. SEQ was harder to ignore, more irritating during the game.”, “In the second section, I learned the Braille better because the devices of each finger didn’t vibrate at the same time.”,

This shows that the users seem to prefer the SEQ encoding over the OST by saying it is more distinguishable.

5.0.3 Threats to validity

5.1 Threats to Validity

We identified several potential threats to validity in both of our studies, which are categorized into internal, external, and construct validity, following the framework outlined by Lago et al. [41] which are illustrated in Figure 5.1.

5.1.1 Internal Validity

One key threat to internal validity is the sample size. In the **first study**, an *a priori* power analysis using the g* power software determined that a sample size of **36** was required to achieve **80% power**. However, only **12** samples were used, and a *post hoc* power analysis revealed an achieved power of only **0.34**. This low statistical power increases the risk of a **Type II error**, meaning that true effects may not have been detected.

Similarly, in the **second study**, the *a priori* power analysis indicated that a sample size of **45** was necessary for adequate statistical power. However, the *post hoc* power analysis showed that the actual power achieved was only **0.356**. These findings suggest that both studies were underpowered, limiting the reliability of their conclusions.

Additionally, we used a relatively young participant group, with a median age of **28.67 years** in the first study and **24.5 years** in the second study. Both studies also included only **one left-handed participant**. Furthermore, the gender distribution was imbalanced, with only **three female participants** in each study. This lack of diversity may limit the generalizability of our findings across different populations.

5.1.2 External and Construct Validity

Hand size emerged as a potential factor affecting external and construct validity. Differences in hand size may influence the placement of actuators, as they could sit differently on individuals with larger or smaller hands. This variation in actuator positioning could have introduced slight inconsistencies in the stimuli delivered, potentially influencing our results.

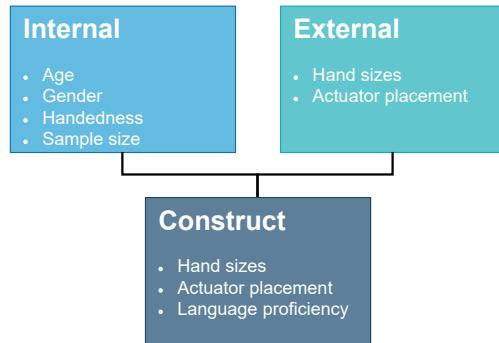


Figure 5.1: Threats to validity

Another construct validity concern relates to stimulus perception. Some participants reported that they did not perceive the **stroking stimulus** as effectively as the **vibration** or **tapping** stimuli. This perception discrepancy could impact the interpretation of the stimulus' effects and must be considered when evaluating the results.

Lastly, none of the participants were native English speakers. Although the words used in the experiments were simple, short, and commonly encountered, some participants may have had minor spelling difficulties. However, we consider this issue to have a negligible impact on the findings.

6. Conclusion and Future Work

We conclude the first study with that the tapping and vibration stimuli performed similarly overall, while the stroking stimulus appeared to perform slightly worse. Based on both the quantitative and qualitative data, we found no statistically significant difference between two-handed OST encoding for affective versus discriminative touch stimuli. Nevertheless, there is a small difference indicating that both the tapping and vibration stimuli were slightly more effective, both in terms of performance and the perceived usefulness reported by participants. For the second study, there are no significant differences between the encodings. However, the SEQ encoding was slightly better than the OST encoding in the tests, and the comments were more positive regarding SEQ. Nevertheless, the direct comparison revealed that there is no large difference between the two encodings. Some participants expressed strong opinions against SEQ due to its distinguishability, while others preferred it for being more comfortable. This suggests that both encodings are valuable for passive haptic learning. Additionally, there appears to be no substantial difference in the number of repetitions between the two encodings. Although the OST encoding involved more repetitions, the SEQ encoding did not result in a higher number of repetitions within the same time frame, as the OST encoding was faster. Therefore, we conclude that time, rather than the number of repetitions, is the key difference between the two encodings.

In future studies, tapping as a stimulus could be further explored for passive haptic learning, as it is not yet commonly utilized. Additionally, the interaction between audio and vibration offsets, as well as the length of stimulus activation, presents an interesting area for investigation. The current setup could also be adapted to explore the potential for learning two-handed instruments, such as the flute, using passive haptic learning with chorded pieces or even other activities that require multi-finger coordination.

Another direction for future research involves testing the SEQ encoding with the tapping stimulus to determine whether the combination of these two factors yields a slightly better learning outcome compared to other encoding methods. While our current findings suggest that time, rather than the number of repetitions, is a key

factor in the efficacy of different encodings, further studies are needed to investigate this relationship in greater detail.

Additionally, the relatively low error rate in single-finger tasks opens up the possibility of employing artificial intelligence to predict the braille characters, which could potentially shorten the learning time for braille. It would also be valuable to explore whether different teaching methods can better drill muscle memory for braille learning using PHL. These avenues could provide deeper insights into the optimization of passive haptic learning systems and their application in diverse learning contexts.

7. Summary

Bibliography

- [1] Rochelle Ackerley, Helena Backlund Wasling, and Francis McGlone. “The touch landscape”. In: *Affective Touch and the Neurophysiology of CT Afferents* (2016), pp. 85–109.
- [2] Rochelle Ackerley et al. “Quantifying the sensory and emotional perception of touch: differences between glabrous and hairy skin”. In: *Frontiers in behavioral neuroscience* 8 (2014), p. 34.
- [3] Mrim Alnfiai and Srinivas Sampalli. “Improved Singeltapbraille: Developing a Single Tap Text Entry Method Based on Grade 1 and 2 Braille Encoding.” In: *J. Ubiquitous Syst. Pervasive Networks* 9.1 (2017), pp. 23–31.
- [4] Sang Sup An et al. “A pair of wireless braille-based chording gloves”. In: *Computers Helping People with Special Needs: 9th International Conference, ICCHP 2004, Paris, France, July 7-9, 2004. Proceedings* 9. Springer. 2004, pp. 490–497.
- [5] Timothy J Aveni. “Passive Haptic Learning for Computer Stenography”. In: (2019).
- [6] Timothy J. Aveni, Caitlyn Seim, and Thad Starner. “A preliminary apparatus and teaching structure for passive tactile training of stenography”. In: *2019 IEEE World Haptics Conference (WHC)*. 2019, pp. 383–388.
- [7] Mukul Bandodkar and Virat Chourasia. “Low cost real-time communication braille hand-glove for visually impaired using slot sensors and vibration motors”. In: *Int. J. Electr. Comput. Energ. Electron. Commun. Eng* 8.6 (2014), pp. 973–980.
- [8] Edward C Bell and Natalia M Mino. “Blind and visually impaired adult rehabilitation and employment survey: Final results”. In: *Journal of blindness Innovation and Research* 3.1 (2013), pp. 1–35.
- [9] Bernd Bertram. “Blindheit und Sehbehinderung in Deutschland: Ursachen und Häufigkeit”. In: *Der Augenarzt* 39.6 (2005), pp. 267–268.
- [10] Lukasz Bola et al. “Braille in the sighted: Teaching tactile reading to sighted adults”. In: *PloS one* 11.5 (2016), e0155394.
- [11] Anders Bouwer, Mat Dalglish, Simon Holland, et al. “The haptic iPod: passive learning of multi-limb rhythm skills”. In: *Workshop ‘When Words Fail: What Can Music Interaction Tell Us About HCI*. Citeseer. 2011.
- [12] Maxey Brooke. “Pangrams”. In: *Word Ways* 20.2 (1987), p. 11.
- [13] Joseph L Brooks. “Counterbalancing for serial order carryover effects in experimental condition orders.” In: *Psychological methods* 17.4 (2012), p. 600.

- [14] Myung-Chul Cho et al. “A pair of Braille-based chord gloves”. In: *Proceedings. Sixth International Symposium on Wearable Computers*, 2002, pp. 154–155.
- [15] Rumen Donchev, Erik Pescara, and Michael Beigl. “Investigating Retention in Passive Haptic Learning of Piano Songs”. In: *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5.2 (June 2021), pp. 1–14. ISSN: 2474-9567.
- [16] James E Driskell, Ruth P Willis, and Carolyn Copper. “Effect of overlearning on retention.” In: *Journal of Applied Psychology* 77.5 (1992), p. 615.
- [17] Robert O Duncan and Geoffrey M Boynton. “Tactile hyperacuity thresholds correlate with finger maps in primary somatosensory cortex (S1)”. In: *Cerebral Cortex* 17.12 (2007), pp. 2878–2891.
- [18] Dania Eridani, Adian Fatchur Rochim, and Faiz Noerdiyan Cesara. “Comparative performance study of ESP-NOW, Wi-Fi, bluetooth protocols based on range, transmission speed, latency, energy usage and barrier resistance”. In: *2021 international seminar on application for technology of information and communication (iSemantic)*. IEEE. 2021, pp. 322–328.
- [19] Likun Fang et al. “DragTapVib: An On-Skin Electromagnetic Drag, Tap, and Vibration Actuator for Wearable Computing”. In: *Augmented Humans 2022*. AHs 2022 (AHs. ACM, Mar. 2022).
- [20] Likun Fang et al. “FLECTILE: 3D-printable soft actuators for wearable computing”. In: *Proceedings of the 2020 International Symposium on Wearable Computers*. UbiComp/ISWC ’20. ACM, Sept. 2020.
- [21] Likun Fang et al. “How Could I Learn Rhythm Better? Investigating Three Learning Signals for Passive Haptic Learning in Different Context”. In: *Proceedings of the 16th International Conference on PErvasive Technologies Related to Assistive Environments*. PETRA ’23. ACM, July 2023.
- [22] Likun Fang et al. “Investigate the Piano Learning Rate with Haptic Actuators in Mixed Reality”. In: *Augmented Humans 2022*. AHs 2022. ACM, Mar. 2022.
- [23] Likun Fang et al. “Investigating Passive Haptic Learning of Piano Songs Using Three Tactile Sensations of Vibration, Stroking and Tapping”. In: *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7.3 (Sept. 2023), pp. 1–19. ISSN: 2474-9567.
- [24] Likun Fang et al. “Investigation of On-Skin Electromagnetic Actuator for Signaling Direction via Tactile Cues”. In: *Proceedings of the 15th International Conference on PErvasive Technologies Related to Assistive Environments*. PETRA ’22. ACM, June 2022.
- [25] Emerson Foulke. “Increasing the braille reading rate”. In: *Journal of Visual Impairment & Blindness* 73.8 (1979), pp. 318–323.
- [26] George A Gescheider, Lawrence C Sager, and Lydia J Ruffolo. “Simultaneous auditory and tactile information processing”. In: *Perception & Psychophysics* 18 (1975), pp. 209–216.
- [27] Robert M Gray. *Entropy and information theory*. Springer Science & Business Media, 2011.

- [28] Anthony D Hall and Slater E Newman. "Braille learning: Relative importance of seven variables". In: *Applied Cognitive Psychology* 1.2 (1987), pp. 133–141.
- [29] Roy H Hamilton and Alvaro Pascual-Leone. "Cortical plasticity associated with Braille learning". In: *Trends in Cognitive Sciences* 2.5 (1998), pp. 168–174. ISSN: 1364-6613.
- [30] Sandra G Hart and Lowell E Staveland. "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research". In: *Advances in psychology*. Vol. 52. Elsevier, 1988, pp. 139–183.
- [31] Eve Hoggan, Sohail Anwar, and Stephen A Brewster. "Mobile multi-actuator tactile displays". In: *Haptic and Audio Interaction Design: Second International Workshop, HAID 2007 Seoul, South Korea, November 29-30, 2007 Proceedings* 2. Springer. 2007, pp. 22–33.
- [32] Simon Holland et al. "Feeling the beat where it counts: fostering multi-limb rhythm skills with the haptic drum kit". In: *Proceedings of the fourth international conference on Tangible, embedded, and embodied interaction*. 2010, pp. 21–28.
- [33] Hsiu-Yun Hsu et al. "Effects of Passive Haptic Learning in Music-Supported Therapy on Sensorimotor Performance in Older Adult Hands: A Randomized Crossover Trial". In: (July 2021).
- [34] Kevin Huang, Ellen Yi-Luen Do, and Thad Starner. "PianoTouch: A wearable haptic piano instruction system for passive learning of piano skills". In: *2008 12th IEEE International Symposium on Wearable Computers*. 2008, pp. 41–44.
- [35] Kevin Huang et al. "Mobile music touch: mobile tactile stimulation for passive learning". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. CHI '10 of. ACM, Apr. 2010.
- [36] Zaid Haron Musa Jawasreh, Noraidah Sahari Ashaari, and Dahlila Putri Dahnil. "The acceptance of braille self-learning device". In: *International Journal on Advanced Science, Engineering and Information Technology*. <https://doi.org/10.18517/ijaseit> 10 (2020), p. 10263.
- [37] David Katz and Lester E Krueger. *The world of touch*. Psychology press, 2013.
- [38] Daniel Kohlsdorf and Thad Starner. "Mobile Music Touch: The effect of primary tasks on passively learning piano sequences". In: *International Symposium on Wearable Computers (ISWC) 2010*. 2010, pp. 1–8.
- [39] William Charles Frederick Krueger. "The effect of overlearning on retention." In: *Journal of Experimental Psychology* 12.1 (1929), p. 71.
- [40] Herbert E Krugman and Eugene L Hartley. "Passive learning from television". In: *Public Opinion Quarterly* 34.2 (1970), pp. 184–190.
- [41] Patricia Lago et al. "Threats to Validity in Software Engineering – hypocritical paper section or essential analysis?" In: *Proceedings of the 18th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement*. ESEM '24. Barcelona, Spain: Association for Computing Machinery, 2024, 314–324. ISBN: 9798400710476.

- [42] John E Laird, Paul S Rosenbloom, and Allen Newell. "Towards Chunking as a General Learning Mechanism." In: *AAAI*. 1984, pp. 188–192.
- [43] Ellen J Langer and Lois G Imber. "When practice makes imperfect: Debilitating effects of overlearning." In: *Journal of personality and social psychology* 37.11 (1979), p. 2014.
- [44] Braille Learning et al. "Braille Learning using Haptic Feedback". In: *2024 Systems and Information Engineering Design Symposium (SIEDS)* |. IEEE, 2024.
- [45] J Lo, Roland S Johansson, et al. "Regional differences and interindividual variability in sensitivity to vibration in the glabrous skin of the human hand". In: *Brain research* 301.1 (1984), pp. 65–72.
- [46] Daniel B Lowy, Preet GS Makker, and Gila Moalem-Taylor. "Cutaneous neuromodulatory interactions in peripheral neuropathic pain states". In: *Frontiers in Immunology* 12 (2021), p. 660203.
- [47] Granit Luzhnica and Eduardo Veas. "Vibrotactile patterns using sensitivity prioritisation". In: *Proceedings of the 2017 ACM International Symposium on Wearable Computers*. 2017, pp. 74–81.
- [48] Granit Luzhnica, Eduardo Veas, and Viktoria Pammer. "Skin reading: Encoding text in a 6-channel haptic display". In: *Proceedings of the 2016 ACM International Symposium on Wearable Computers*. 2016, pp. 148–155.
- [49] Granit Luzhnica, Eduardo Veas, and Caitlyn Seim. "Passive haptic learning for vibrotactile skin reading". In: *Proceedings of the 2018 ACM International Symposium on Wearable Computers*. ISWC '18. Singapore, Singapore: Association for Computing Machinery, 2018, 40–43. ISBN: 9781450359672.
- [50] Granit Luzhnica, Eduardo Veas, and Caitlyn Seim. "Passive Haptic Learning for Vibrotactile Skin-Reading: Comparison of Teaching Structures". In: (2018).
- [51] Halliday J MacFie et al. "Designs to balance the effect of order of presentation and first-order carry-over effects in hall tests". In: *Journal of sensory studies* 4.2 (1989), pp. 129–148.
- [52] Sally Mangold. *Mangold Braille Program: Tactile Perception and Braille Letter Recognition*. Accessed: 2024-09-02. Deutscher Blinden- und Sehbehindertenverband e. V., n.d.
- [53] T. Markow et al. "Mobile Music Touch: Vibration stimulus in hand rehabilitation". In: *2010 4th International Conference on Pervasive Computing Technologies for Healthcare*. 2010, pp. 1–8.
- [54] Natalie Martiniello, Walter Wittich, and Anne Jarry. "The perception and use of technology within braille instruction: A preliminary study of braille teaching professionals". In: *British Journal of Visual Impairment* 36.3 (2018), pp. 195–206.
- [55] Tessa McCarthy et al. "An artificial intelligence tutor: A supplementary tool for teaching and practicing braille". In: *Journal of Visual Impairment & Blindness* 110.5 (2016), pp. 309–322.
- [56] John H McDonald. "Handbook of biological statistics". In: (2014).
- [57] Francis McGlone, Johan Wessberg, and Håkan Olausson. "Discriminative and affective touch: sensing and feeling". In: *Neuron* 82.4 (2014), pp. 737–755.

- [58] George A Miller. "The magical number seven, plus or minus two: Some limits on our capacity for processing information." In: *Psychological review* 63.2 (1956), p. 81.
- [59] Oliver Ozioko et al. "SmartFingerBraille: A tactile sensing and actuation based communication glove for deafblind people". In: *2017 IEEE 26th International Symposium on Industrial Electronics (ISIE)*. 2017, pp. 2014–2018.
- [60] Donatella Pascolini and Silvio Paolo Mariotti. "Global estimates of visual impairment: 2010". In: *British Journal of Ophthalmology* 96.5 (2012), pp. 614–618.
- [61] Roshan Lalitha Peiris et al. "Thermalbracelet: Exploring thermal haptic feedback around the wrist". In: *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 2019, pp. 1–11.
- [62] Erik Pescara et al. "Reevaluating passive haptic learning of morse code". In: *Proceedings of the 2019 ACM International Symposium on Wearable Computers*. ISWC '19. New York, NY, USA: Association for Computing Machinery, 2019, 186–194. ISBN: 9781450368704.
- [63] PharmaBraille. *The Braille Alphabet – PharmaBraille*. PharmaBraille website, <https://www.pharmabraille.com/pharmaceutical-braille/the-braille-alphabet/>. Accessed: 2024-12-15. n.d.
- [64] John TE Richardson. "The use of Latin-square designs in educational and psychological research". In: *Educational Research Review* 24 (2018), pp. 84–97.
- [65] Ruby Ryles. "The impact of braille reading skills on employment, income, education, and reading habits". In: *Journal of Visual Impairment & Blindness* 90.3 (1996), pp. 219–226.
- [66] Jesse Sargent et al. "Chunking in spatial memory." In: *Journal of Experimental Psychology: Learning, memory, and cognition* 36.3 (2010), p. 576.
- [67] Caitlyn Seim, Tanya Estes, and Thad Starner. "Towards Passive Haptic Learning of piano songs". In: *2015 IEEE World Haptics Conference (WHC)*. 2015, pp. 445–450.
- [68] Caitlyn Seim, Tanya Estes, and Thad Starner. "Towards Passive Haptic Learning of piano songs". In: *2015 IEEE World Haptics Conference (WHC)*. 2015, pp. 445–450.
- [69] Caitlyn Seim et al. "Passive haptic learning of Braille typing". In: *Proceedings of the 2014 ACM International Symposium on Wearable Computers*. UbiComp '14. ACM, Sept. 2014.
- [70] Caitlyn Seim et al. "Passive Haptic Training to Improve Speed and Performance on a Keypad". In: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1.3 (Aug. 2017).
- [71] Caitlyn Seim et al. "Tactile taps teach rhythmic text entry: passive haptic learning of morse code". In: *Proceedings of the 2016 ACM International Symposium on Wearable Computers*. UbiComp '16. ACM, Sept. 2016.
- [72] Caitlyn Seim et al. "Tactile taps teach rhythmic text entry: passive haptic learning of morse code". In: *Proceedings of the 2016 ACM International Symposium on Wearable Computers*. UbiComp '16. ACM, Sept. 2016.

- [73] Caitlyn Seim et al. “Towards haptic learning on a smartwatch”. In: *Proceedings of the 2018 ACM International Symposium on Wearable Computers*. ISWC ’18. Singapore, Singapore: Association for Computing Machinery, 2018, 228–229. ISBN: 9781450359672.
- [74] Caitlyn E. Seim, David Quigley, and Thad E. Starner. “Passive haptic learning of typing skills facilitated by wearable computers”. In: *CHI ’14 Extended Abstracts on Human Factors in Computing Systems*. CHI ’14. ACM, Apr. 2014.
- [75] Claude Elwood Shannon. “A mathematical theory of communication”. In: *The Bell system technical journal* 27.3 (1948), pp. 379–423.
- [76] Claude Elwood Shannon. “A mathematical theory of communication”. In: *ACM SIGMOBILE mobile computing and communications review* 5.1 (2001), pp. 3–55.
- [77] Kang G Shin and Parameswaran Ramanathan. “Real-time computing: A new discipline of computer science and engineering”. In: *Proceedings of the IEEE* 82.1 (1994), pp. 6–24.
- [78] BL Shivakumarl and M Rajasenathipathi. “Braille Glove Vibration System For Diabetic Affected Disabled Persons”. In: *Journal of Engineering and Applied Sciences* 8.8 (2013), pp. 635–641.
- [79] Anna M Swenson. *Beginning with braille: Firsthand experiences with a balanced approach to literacy*. American Foundation for the Blind, 1999.
- [80] Mirko Thalmann, Alessandra S Souza, and Klaus Oberauer. “How does chunking help working memory?” In: *Journal of Experimental Psychology: Learning, Memory, and Cognition* 45.1 (2019), p. 37.
- [81] Marjorie Troughton. “Guidelines for Better Braille Literacy”. In: (1992).
- [82] Marjorie Troughton. “Guidelines for Better Braille Literacy”. In: (1992).
- [83] Wen-Jie Tseng et al. “A skin-stroke display on the eye-ring through head-mounted displays”. In: *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 2020, pp. 1–13.
- [84] DW Tuttle. “Point/counterpoint.” In: *Journal of Visual Impairment & Blindness* 90.3 (1996).
- [85] Vaio. “Developing a haptic glove for basic piano education”. In: *World Journal on Educational*. 2019.
- [86] Francisco Vega-Bermudez and Kenneth O Johnson. “Differences in spatial acuity between digits”. In: *Neurology* 56.10 (2001), pp. 1389–1391.
- [87] Chi Wang et al. “Masque: Exploring lateral skin stretch feedback on the face with head-mounted displays”. In: *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology*. 2019, pp. 439–451.
- [88] Wikipedia. *Punktschriftmaschine — Wikipedia, die freie Enzyklopädie*. [Online; Stand 12. September 2024]. 2023.
- [89] Subathra Y et al. “An Intelligent Braille Communication using Translation Glove”. In: *2024 Tenth International Conference on Bio Signals, Images, and Instrumentation (ICBSII)*. 2024, pp. 1–5.

- [90] Tao-Jen Yang et al. “Tactile Braille learning system to assist visual impaired users to learn Taiwanese Braille”. In: *SIGGRAPH Asia 2017 Posters*. SA ’17. ACM, Nov. 2017.
- [91] Hasan U. Zaman et al. “A Low Cost Wireless Braille System Hand Glove for Real Time Communication”. In: *2019 4th International Conference on Electrical Information and Communication Technology (EICT)*. 2019, pp. 1–6.
- [92] Cliff Zukin and Robin Snyder. “Passive learning: When the media environment is the message”. In: *Public Opinion Quarterly* 48.3 (1984), pp. 629–638.
- [93] Cliff Zukin and Robin Snyder. “Passive learning: When the media environment is the message”. In: *Public Opinion Quarterly* 48.3 (1984), pp. 629–638.