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Textile Icons: Investigating Shape Properties to Improve Haptic Recognition

Master's Thesis
submitted to the
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Abstract

Textile interfaces enable rich and natural interactions on readily accessible surfaces in daily life. An advantage of textile interfaces is that they can be designed to be discoverable and usable without vision. This makes them suitable for secondary tasks to be executed while vision and hearing are focused on something else. While research already exists on other textile interface elements, it is not clear how graphical icons should be realized on textiles to allow reliable, fast, and easy haptic recognition.

In this thesis, we show the design and fabrication of 120 textile icon samples, which correspond to 20 shapes in 6 fabrication variants. Four of these variants use a height difference to make the shape haptically perceivable via a raised filled shape, raised outline, recessed filled shape, or recessed outline. The two remaining variants use a texture difference achieved by embroidering either a yarn outline or a filled yarn pattern. We present findings from a haptic shape discrimination study that we conducted using a subset of 14 textile icon samples per variant. We analyze performance measures and participant ratings per variant, and identify groups of shapes that are easily confusable. Finally, we use these results to formulate six initial guidelines on texile icon design.

Results show that a height difference makes shape recognition more reliable, faster, and easier in comparison to icons with a texture difference. This is especially true when using raised filled shapes, but even for these, recognition still requires several seconds. Shapes with a large number of sharp convex and sharp concave vertices have been identified as easily confusable.

Überblick

Textile Interfaces ermöglichen reichhaltige und natürliche Interaktionen auf leicht zugänglichen Oberflächen des alltäglichen Lebens. Ein Vorteil textiler Interfaces liegt darin, so gestaltet werden zu können, dass sie erkund- und benutzbar sind, ohne die Augen zu benutzten. Dies macht sie für sekundäre Aufgaben geeignet, die ausgeführt werden können, während Augen und Ohren anderweitig beschäftigt sind. Während es bereits Forschungsergebnisse zu anderen texilen Interface-Elementen gibt, ist es noch unklar, wie grafische Icons auf Textilien realisiert werden sollten, damit sie zuverlässig, schnell, und leicht haptisch erkannt werden können.

In dieser Arbeit zeigen wir das Design und die Herstellung von 120 textilen Icon-Exemplaren, die 20 Formen in 6 Herstellungsvarianten entsprechen. Vier dieser Varianten nutzen einen Höhenunterschied, um die Form über eine erhöhte Füllung, erhöhte Kontur, abgesenkte Füllung oder abgesenkte Kontur haptisch wahrnehmbar zu machen. Die zwei verbleibenden Varianten nutzen einen Unterschied in der Textur, der über eine aufgestickte Garn-Kontur oder ein gefülltes Garn-Muster erreicht wird. Wir präsentieren die Ergebnisse einer Studie zur haptischen Unterscheidung von Formen, die wir mit einer Teilmenge von 14 Formen pro Herstellungsvariante durchgeführt haben. Wir analysieren Performanzmaße und Bewertungen der Studienteilnehmenden pro Variante und identifizieren Gruppen von Formen, die leicht verwechselbar sind. Schließlich nutzen wir diese Ergebnisse, um sechs erste Leitlinien für das Design textiler Icons zu formulieren.

Die Ergebnisse zeigen, dass ein Höhenunterschied Formen zuverlässiger, schneller, und leichter erkennbar macht im Vergleich zu Icons mit einem Unterschied in ihrer Textur. Dies gilt insbesondere für Formen mit erhöhter Füllung, aber selbst für diese benötigt eine Erkennung mehrere Sekunden. Formen mit einer großen Anzahl spitzwinkliger konvexer und spitzwinkliger konkaver Ecken konnten als leicht verwechselbar identifiziert werden.

Acknowledgements

First, I would like to thank Prof. Dr. Jan Borchers for the opportunity to write my thesis with the Media Computing Group at RWTH Aachen. Secondly, I would like to thank Prof. Dr. Michael Haller for accepting to be my second examiner.

I would also like to thank my supervisors, Oliver Nowak and René Schäfer, for awakening my interest in research on textile icons, as well as for their support and patience over the whole course of this thesis.

Besides, I would like to thank everyone at the chair for their assistance or just for having a chat during a long day of user studies. In particular, I would like to thank Sebastian Pettirsch for providing equipment for my study and some guidance on getting an Arduino to do what I would like it to do.

Special thanks to everyone who took the time to participate in my study. I really appreciate it.

There are numerous other people I would like to thank, although they shall remain unnamed here, for being there for me in stressful times when I did not have much time to be there for them.

Two final thanks: Thanks, Mom! And thanks, my love. I love you.

Conventions

Throughout this thesis we use the following conventions.

Definitions of technical terms or short excursus are set off in coloured boxes.

EXCURSUS:
An *excursus* is a detailed discussion of a particular point in a book, usually in an appendix, or a digression in a written text.

Definition: *Excursus*

HISTORY AND ETYMOLOGY OF EXCURSUS:
Early examples of works of literature using excursus date back to around 500 BC. Some authors like to use excursus to feature interesting etymologies. The word "excursus" itself originates from Latin "excursus", perfect passive participle of the verb "excurrere", which may be translated as "something that has been extended".

Excursus: *History and Etymology of Excursus*

File names and URLs are written in `typewriter-style text`.

The whole thesis is written in Canadian English.

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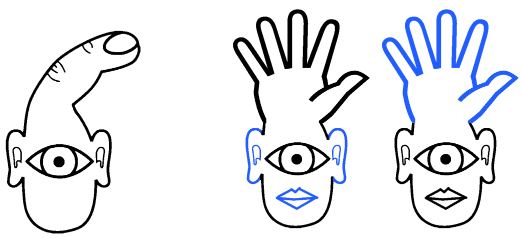
Chapter 1

Motivation

From the start, engaging with interactive systems like desktop computers and (smart)phones has been a multimodal—albeit vision-centered—process: Looking at the interface usually is the main information channel for both perceiving system output and understanding how to provide user input. System output has always included sound as an additional modality; user input further requires touch to control a keyboard, mouse, touchscreen, or other input device. O'Sullivan and Igoe [2004] visualize this as shown in Fig. 1.1(a). With gamepads and smartphones, tactile feedback in the form of vibration has become a common output modality as well (in addition to the static haptic feedback created by merely using the input device).

Computers and (smart)phones have always been multimodal, but depend on vision for output and input.



(a) **(b)**

Figure 1.1: (a) How the computer sees us;, taken from O'Sullivan and Igoe [2004]. (b) Two possible "modal splits" into primary (black) and secondary (blue) tasks when using modern smart devices; adapted from the same source.

Modern smart devices allow interactions that are independent of vision, making these suitable for secondary tasks.

Nowadays, smart devices on the go and in the home leverage multimodality further: Speech recognition allows the use of *audio* as a natural input modality that, crucially, does not need to be used in combination with vision. This enables users to perform secondary tasks, like adjusting room lighting or listening to the news, even if visual and haptic modalities are occupied by the primary task (for instance, loading the dishwasher) and/or with less attention shift from the primary task (for instance, working on a desktop computer). In the same spirit, swipe and multi-finger gestures on touchscreens and touchpads utilize *haptics* as an input modality for secondary tasks (suited for primary tasks like spoken discussions or watching movies). In both cases, modalities are split between tasks, as seen in Fig. 1.1(b). Arguably, even keyboard shortcuts use this "modal split", albeit requiring established knowledge in the head and muscle memory for eyes-free activation without attention shift.

Input devices for secondary tasks further must be readily accessible.

While using a different modality benefits the effortless execution of secondary tasks, a hard requirement is that the corresponding input device be readily accessible. This is true for the input techniques mentioned above, and is also one reason for the appeal of wearable devices, especially smart watches: their interfaces are always reachable on the wrist, while smartphones hide in pockets. This accessibilty is desirable even with vision (and touch) for user input.

Textile interfaces fulfil these requirements as well. Additional benefits are rich channels and high visual and haptic discoverability.

Textile interfaces offer another way to use haptics as an input modality, and are well suited for secondary tasks. Applications include wearables like clothing and backpacks, as well as smart home objects like sofas and pillows; thus, textile interfaces can be assumed to be readily accessible. What makes them stand out is the large number of textile properties (for instance, roughness, softness, color, texture, form, height difference) that can be varied. Resulting channels for haptic perception and haptic user input are both richer and more natural compared to touchscreens. Furthermore—and unlike speech interfaces, touch gestures, and keyboard shortcuts—textile interface can be designed to have *high discoverability*. In particular, visual discoverability and haptic discoverability can both be high individually, but also benefit each other. In doing so, they allow users to compensate for several disadvantages of

Visual discoverability can compensate for disadvantages of haptic perception.

haptic perception using knowledge effortlessly obtained by repeated visual perception of the interface. Such disadvantages include sequentiality (the area perceived haptically at each point in time is small) and low resolution (details must be larger to be perceived haptically compared to vision).

Existing research on textile interface elements has mostly focused on textile sliders [Nowak et al., 2022] and textile-specific affordances [Mlakar et al., 2021]. Examples illustrating the richness of textile properties and the benefits of visual discoverability are shown in Fig 1.2 for textile sliders and in Fig. 1.3 for textile-specific affordances.

Existing research on textile interface elements focuses on sliders and textile-specific affordances.

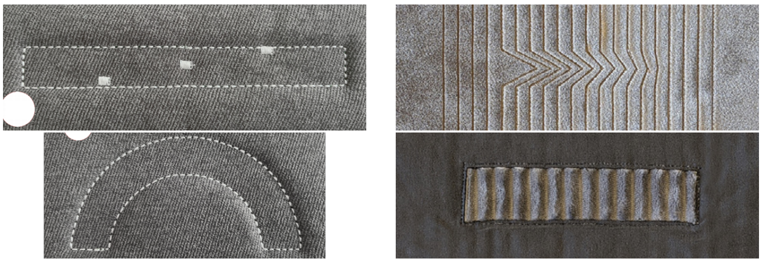


Figure 1.2: Several textile slider designs from Nowak et al. [2022] (left) and Mlakar et al. [2021] (right) varying many different textile properties. The sliders are clearly visually discoverable, which allows the user to easily understand their position and design when learning how to use the interface. While using a slider, the user gets haptic feedback, which they can connect with their visual knowledge of the slider. We argue that as experience increases, the user will need less and less effort to recognize the interface elements using only the haptic modality.

Figure 1.3: Several textile interface elements from Mlakar et al. [2021] that use textile-specific affordances: stroking (left) and pinching (right). Also here, visual discoverability will initially be useful while building up haptic experience.

There is a need for textile interface elements that identify a discrete entity out of a set of entities.

Another useful type of textile interface element is one to trigger atomic actions, to indicate the spatial position of objects, or to label other interface elements like sliders. Such interface elements face a challenge: they should be able to convey the information *which* action they trigger, *which* object's position they indicate, or *what* the labeled interface element is used for. The set of actions or object types, however, is often large or unknown. To be able to communicate which discrete entity out of a large set of entities is meant (the *intended meaning*), we need a rich communication channel—which textile interfaces can provide. We theorize that when designed appropriately, they would allow to effortlessly receive this information haptically, even as part of secondary tasks. To this day, however, very little research exists on textile interface elements with a discrete intended meaning.

In classical vision-centered interfaces, *graphical icons* are a very common approach to convey such rich information. In this thesis, we will define them as follows[1]:

Definition: *(Visual graphical) Icon*

(VISUAL GRAPHICAL) ICON:
An icon is a compact symbol that represents a discrete object, action, or idea. Icons are meant to be read at a glance and are typically created on a square (1:1) canvas.

By "symbol", we understand the core aspect that makes these icons graphical: the *graphical shape* that the icon depicts is what conveys the icon's *intended meaning* (i.e., what the icon represents). These two concepts usually differ: consider, for instance, a pair of scissors representing "cut" or two sheets of paper representing "copy". While less common, there are also non-graphical icons: icons that convey their intended meaning not via graphical shape, but in other ways.

Graphical icons could be adapted for such textile interface elements.

Adapting graphical icons for textile interfaces with a discrete intended meaning has the benefit that not only the interface element itself is visually discoverable, but also its meaning. This is especially true if *visually familiar* graphical

[1] `https://uxdesign.cc/foundations-of-iconography-f95d7233a3e6` (accessed on June 5, 2022)

shapes are chosen. Thus, the amount of knowledge obtainable by repeated visual perception is even higher, compensating for the fact that the disadvantages of haptic perception carry even more weight in the context of *shape recognition*. One part of this knowledge will be the set of shapes (representing the set of discrete entities, or meanings) used on a particular interface, which then turns the haptic shape recognition task into an (easier) shape discrimination task.

We call these icons "textile icons" and investigate how to design and fabricate them in this thesis.

This thesis aims to establish *textile icons* as **visually familiar graphical icons for textile interfaces that allow effortless haptic discrimination**. After we motivated them, the basic research question of this work is how to actually make them easily discriminable. We need to know: How should sets of shapes be chosen to be easily distinguishable? Which textile properties are most suitable to make graphical shapes haptically perceivable? How can textile icons be fabricated with the necessary precision? How much can the effort and time required to distinguish the shapes be reduced?

Thereby we address shortcomings in research on haptic shape recognition.

With this thesis, we provide first insights into all of these questions. We will further address several shortcomings that we identified in the existing research corpus on haptic shape recognition/discrimination:

- Haptic shape recognition research usually considers either very simple geometric shapes (triangle, square, circle) found to be easily recognizable, or large and complex graphics found to require a lot of training. The size and complexity of textile icons lies between these two. Thus, we lack knowledge on how people explore these particular shapes and how much effort is necessary to reliably recognize them.
- Most research targets blind and/or visually impaired (blind/v.i.) people. Thus, the capabilities of sighted people are not as well understood.
- There is little research that considers the potentials and limitations of shape recognition when specifically using textile materials.

We decided to focus on the impact of varying shape properties, rather than textile properties, to keep the scope of

We focus on the impact of shape properties on haptic discriminability of textile icons.

this thesis in control. We still consider the latter an equally interesting question for future research. While we came to select a single textile property (and a second one as a baseline), we were able to derive several different fabrication variants, which in turn highlight different shape properties.

1.1 Thesis Structure

The thesis is structured as follows.

Chapter 2 presents related work on graphical icons, shape properties, textile interfaces, and haptic shape recognition. We will also have a look at non-graphical icons to identify alternative ways to encode the meaning of an icon.

Chapter 3 explains which particular textile properties, fabrication variants, and set of shapes we chose for subsequent icon sample fabrication and empirical examination. These design decisions are grounded on existing research.

Chapter 4 describes the fabrication process for the resulting 120 textile icon samples (6 fabrication variants x 20 shapes) that we created following our design decisions. In particular, we first elaborate on the exact dimensions, materials, machines, and settings that worked best based on our own exploration. Then, we share our insights on effective measures to achieve sufficient precision. Next, we explain how we created the necessary digital files and briefly discuss the scripts and software we used. Finally, we describe the production steps to turn those files into actual icon samples.

Chapter 5 focuses on the empirical study we conducted to obtain insights on the influence of shape properties and fabrication variants on haptic discriminability of textile icons.

In Chapter 6, we provide several guidelines for the design and usage of textile icons based on the findings from our empirical study.

Chapter 7 summarizes our contributions and gives some directions for future work.

Chapter 2

Related Work

The most common way to think of icons is that they are graphical and target the visual modality, usually displayed on a screen or signpost. But all of these aspects are choices: there are non-graphical icons, icons targeting other modalities, and icons displayed using other materials. Therefore, we consider it useful to initially develop a generalized definition of what icons are. This creates a basis to motivate our design choices and to organize existing research.

Icons can differ in their encoding of meaning, target modalities, and materials.

2.1 A Generalized Definition of Icons

Although numerous research in Human-Computer Interaction and beyond has investigated icons to this day, the term *icon* has rarely been defined precisely. With the aim to identify a general definition or characterization of what an icon is, we did an extensive exploration of the research landscape in suitable disciplines that self-report to address "icons", "symbols", "signs", "pictographs", or similarly named entities, and consulted relevant design literature.

The term "icon" is rarely defined precisely in the research literature.

Later sections in this chapter introduce these different types of entities, which we call *kinds of icons*. We believe that the definition as given on page 4 comes closest to subsuming all the entities we found, compared to other existing defini-

We generalize the definition given in the introduction.

tions, even though the phrasing and original context of that definition suggest it is meant to specifically target the usual *visual graphical icons*. We now develop a generalized version of this definition: the only changes we make is that the intended meaning does not have to be conveyed via graphical shape ("symbol"), and that the recommendation of an 1:1 aspect ratio only applies to certain kinds of icons. Note that the original definition does not explicitly mention the visual modality, although it might be implied by the word "read", which we also change to "recognized".

We suggest the following generalized definition of icons.

Definition: *(Generalized) Icon*

(GENERALIZED) ICON:
An icon is a spatially or temporally compact entity that represents a discrete object, action, or idea. Icons are meant to be recognized at a glance. Spatially compact icons are typically created on a square (1:1) canvas.

Icons are compact and representative. They should be easy to recognize with a clear meaning.

In detail, this definition characterizes icons as:

1. **Compact.** Icons have a small interface footprint. For some kinds of icons, including graphical icons, this refers to the *space* they occupy on the interface; for others, this may also refer to the *temporal* dimension, for instance with icons for the auditory modality.

2. **Representative.** (a) Icons represent something, i.e. they have an intended meaning that can be either an *object* or *idea*, or a (user-triggerable) *action*. (b) This meaning should be *discrete*, i.e. clear and hard to confuse with other objects, ideas, or actions that are applicable in the given context.

3. **Meant to be recognizable at a glance.** In visual perception, a *glance* is roughly defined as the first 200-500ms of perceptual processing. This phase of processing is also called the *pre-attentive stage* and occurs on a subconscious level in iconic memory, the part of sensory memory concerned with visual inputs [van der Heijden, 1996]. Similar statements can be made regarding *haptic glances* and *auditory glances*, which each use their own parts of sensory memory.

4. **Having a 1:1 aspect ratio.** This part of the characterization only makes sense for icons which are spatially compact and have at least two spatial dimensions. All spatially compact icons we found are at least 2D.

Spatially compact icons have a 1:1 aspect ratio.

In this definition, (1.), (2a.) and (4.) are mainly descriptive, whereas (2b.) and (3.) are normative. We will see that all kinds of icons that we found in related work fulfil the descriptive parts of the definition (with (4.) only applying to spatially compact icons), and many are concerned with fulfilling the normative parts.

Most of this holds for all kinds of icons.

In addition to these mostly universal properties of icons, we identified several distinguishing properties to describe the characteristics of particular kinds of icons:

Icons differ w.r.t. target group / modes, encoding of meaning and used materials.

- **Target modalities.** Which of our senses can be used to perceive the icon? All kinds of icons we found use vision, hearing, touch, or a combination of these senses. With touch, we will differenciate further between five tactual modes as explained below.
- **Encoding of meaning.** Ultimately, the intended meaning of an icon is an object, idea, or action. There are various different ways to convey, or *encode*, this meaning. We already know that graphical icons encode the intended meaning in their *graphical shape*. Other encodings include vibration patterns, sounds, or associations based on some property of the icon.
- **Materials.** Especially for graphical icons targeting touch, the available materials can facilitate or impede easy recognition of the intended meaning.
- **Dimension(s) of compactness.** We can differentiate based on whether the icon is compact in the *spatial* dimensions (and does not evolve over time) or in the *temporal* dimension (and either does not take up space at all or is not constrained in the space it takes up).

Some icons are spatially compact, some temporally. The latter are usually non-discoverable and non-interactive.

- **Discoverability and interactivity.** Some kinds of icons that we found in the literature are *non-interactive* in that they can only provide feedback or feedforward and never allow the user to trigger actions. In such

Muscle control	Perception mediated by variations in stimulation of		
	cutaneous sense	**kinesthetic sense**	**both senses**
No	tactile	passive kinesthetic	passive haptic
Yes	/	active kinesthetic	active haptic

Table 2.1: The five tactual modes according to Loomis and Lederman [1986].

cases the indended meaning of any icon cannot be an *action*. In some of these cases, icons are also *non-discoverable*, i.e. they only appear when specific events occur. Icons that are temporally compact usually are both non-interactive and non-discoverable.

- **Target group.** Especially for icons perceivable via touch, a lot of research particularly targets blind/v.i. people. On the other hand, purely visual icons are only targeted at sighted people. In general, it is helpful to consider what the target group of a particular kind of icons is.

We use terminology that differentiates five tactual modalities.

Touch can be further differentiated into tactile, kinesthetic, and haptic modalities, depending on which of the two sensory subsystems are involved: The tactile modality only involves the cutanous sense, which deals with perceiving roughness, texture, and temperature. The kinesthesic modality only involves the kinesthetic sense, which deals with perceiving pressure and limb positions [Pérez Ariza and Santís-Chaves, 2016]. If both senses are involved, this is called the haptic modality. Besides, we can differentiade whether active muscle control is used during perception (*active touch*) or not (*passive touch*).

According to Loomis and Lederman [1986], the tactile modality cannot be active: Active muscle control must involve perceiving the corresponding limb positions, thus kinesthetic perception occurs as well, which means it is the haptic modality. The authors use the term *tactual* (sic!) as an umbrella term which encompasses *tactile*, *kinesthetic*, and *haptic*, and organize all possible combinations into the five tactual modes shown in Table 2.1.

Other meanings of "tactual" and "tactile": Depending on the research area, the words "tactual" and "tactile" are also used with the more general meaning of "touchable". For instance, using our terminology, *tactile maps* should actually be called haptic maps, because they require active exploration with fingers or hands. With displays, this is sometimes further differentiated, with "tactual" implying that the system expects touch *input* while "tactile" means that information can be *perceived* via touch. In this sense, a smartphone touchscreen would be a tactual display[1], while a pin-array display would be a tactile display. We do not use this terminology in this thesis, except when explicitly referring to terms as they are used in research literature. Many authors do indeed use our chosen terminology with displays, like Tan and Pentland [2005] or Kim and Harders [2015].

Excursus: *Other meanings of "tactual" and "tactile"*

Using these distinguishing properties, *textile icons* as motivated in the introduction can be characterized as targeting the active haptic mode (as well as the visual modality), encoding their meaning via graphical shape, using textile materials like fabrics and yarns, being spatially compact and discoverable (both haptically and visually). They might also be interactive, although neither the choice of possible interactions nor the technical implementations are within the scope of this thesis. Textile icons are targeted at everyone, although people who are blind/v.i. *and* struggle with active haptic recognition of small shapes will likely be unable to use them. Fig. 2.1 visualizes this in a simplified way.

Textile icons can be characterized using the distinguishing properties we introduced.

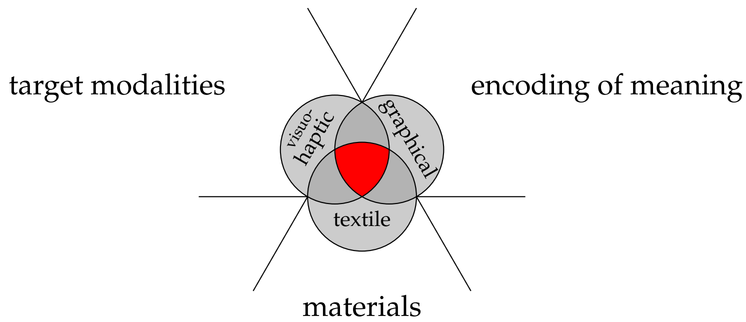


Figure 2.1: Situating textile icons (red area) among others.

[1] `https://psychologydictionary.org/tactual-display/` (accessed on June 5, 2022)

Sample Reference	Name	Target Modalities	Encoding of Meaning	Materials	Compact?	Discoverable?	Interactive?	Target Group *
uxdesign.cc[1] (2.2)	**visual graphical icons**	visual	**shape**	pixels/ink/...	spatially	when shown	can be impl.	sighted people
Harrison and Hudson [2009]	**pneumatic buttons**	visual, active haptic	**shape (2.5D, curved edges)**		spatially	when active	yes	everyone
Leo et al. [2018]	**pin-array symbols**	visual, active haptic	**shape (2.5D/3D, grid-like)**	metal/plastic pins	spatially	when active	can be impl.	everyone **
Doi et al. [2011]	**tactile map icons**	visual, active haptic	**shape (2.5D)**		spatially	yes	no	blind/v.i. people
Gual et al. [2015]	**volumetric icons**	visual, active haptic	**shape (3D)**		spatially	yes	no	blind/v.i. people
Rowland and Schweigert [1989]	**tangible symbols**	visual, active haptic	**shape (3D)**	actual objects	spatially	yes	no	blind/v.i. kids
Lebaz et al. [2012]	**raised-line drawings**	visual, active haptic	**shape (2.5D)**	swell paper	**usually no**	yes	no	blind/v.i. people
Thompson et al. [2003]	**textured pictures**	visual, active haptic	**shape (2D)**		**usually no**	yes	no	blind/v.i. people
Lawson and Bracken [2011]	**3D-printed objects**	visual, active haptic	**shape (2.5D/3D)**		**not all**	yes	no	everyone
Mlakar and Haller [2020] (2.3)	**textile symbols**	visual, active haptic	**shape (2D, via texture)**	**fabric, yarn**	spatially	yes	can be impl.	everyone
This thesis	**2D textile icons**	visual, active haptic	**shape (2D, via texture)**	**fabric, yarn**	spatially	yes	can be impl.	everyone
	2.5D textile icons	visual, active haptic	**shape (2.5D, via height)**	**fabric, yarn, MDF**	spatially	yes	can be impl.	everyone
Mlakar et al. [2021]	**tx. affordance samples**	visual, active haptic	**shape (2D/2.5D)**, texture, color	**fabric, yarn**	**not all**	yes	can be impl.	everyone
Nowak et al. [2022]	**tx. sliders and tickmarks**	visual, active haptic	**shape (2.5D)**, texture, position	**fabric, yarn**	**max. in 1D**	yes	can be impl.	everyone
Harrison et al. [2011] (2.5)	**kineticons**	visual	movement pattern	pixels	temporally	no ***	no ***	sighted people
Blattner et al. [1989]	**earcons / auditory icons**	auditory	sound		temporally	no	no	hearing people
Brewster and Brown [2004]	**tactons / tactile icons**	tactile	vibration pattern		temporally	no	no	everyone
Alotaibi et al. [2022]	**electrotactons**	tactile	electotactile stimuli pattern		temporally	no	no	everyone
Enriquez and MacLean [2003]	**hapticons / haptic icons**	passive haptic	pressure pattern		temporally	no	no	everyone
Brown et al. [2020]	**ultrahapticons**	passive/active haptic	air pressure pattern/**shape**		temp./spat.	when active	when active	everyone
Sebresos[2]	**mobile hapticons**	visual, passive haptic	association based on texture		temporally	no	no	everyone
Sebresos[3]	**textural icons**	visual, active haptic	association based on texture		spatially	yes	can be impl.	everyone
Breitschaft and Carbon [2021]	**shaped icons using AAP**	visual, active haptic	association based on shape	polycarbonate	spatially	yes	can be impl.	everyone

* As loss of the tactual modes occurs much more rarely than loss of vision or hearing, people unable to use the tactual modes are not explicitly excluded in this column. can be impl. = can be implemented

** Pin-array displays can also be used to display Braille or other tactile alphabets, which then mostly targets blind/v.i. people.

*** Kineticons can be implemented on top of visual graphical icons, which of course might very well be discoverable and interactive.

Table 2.2: The kinds of icons and other entities found during our literature review, including this thesis for comparison. We differentiate between graphical entities on non-textiles (top section), graphical entities on textiles (middle section), and non-graphical entities (bottom section). Within the top and middle sections, the top part lists kinds icons while the bottom part lists entites that disqualify as icons, mostly due to non-compactness. The bottom section only contains kinds of icons.

Structure of this Chapter

The kinds of icons that we found during our literature review are summarized in Table 2.2, together with other graphical entities that inform how people recognize shapes. The following sections of this chapter elaborate on results regarding these entities as well as further relevant research findings. The sections are organized as follows.

In the following, we elaborate on various kinds of icons and other graphical entities.

Section 2.2 introduces existing research on graphical icons and shape properties for both visual and haptic modalities. We cover guidelines for icon design, icon classification systems, salient shape features, and the influence of different kinds of 3D information on haptic recognizability.

Section 2.3 focuses on textile interfaces and recognizability of shapes on textile surfaces in particular.

Section 2.4 presents findings on how people actually haptically explore objects and shapes. We are interested in the *exploratory procedures* people use to facilitate recognition.

Finally, Section 2.5 covers non-graphical kinds of icons, i.e. icons that encode their intended meaning not via graphical shape, but in other ways.

2.2 Graphical Icons and Shape Properties

Graphical icons encode their intended meaning via *graphical shape*, which some sources also refer to as *content* [Bühler et al., 2020] or *depicted object* [Nakamura and Zeng-Treitler, 2012]. As there are multiple ways to depict the same object, to convey an intended meaning, one has to decide not only on a suitable graphical shape, but also on the particular way it should be depicted. Bühler et al. [2020] call the latter the *design of the content* and present a compilation of

For graphical icons, we differentiate between the graphical shape and its design.

[2] `http://people.artcenter.edu/~hsebresos/touch/images/hapticons.html` (accessed on June 5, 2022)

[3] `http://people.artcenter.edu/~hsebresos/touch/images/texticons.html` (accessed on June 5, 2022)

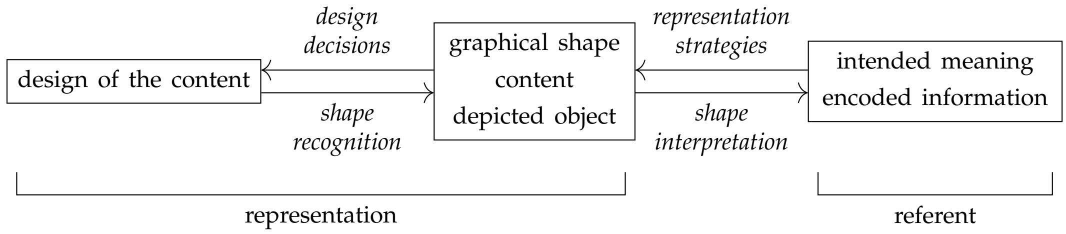


Figure 2.2: Relations between design, graphical shape, and intended meaning of a graphical icon. We included synonyms used by sources mentioned in this thesis. Left-facing arrows indicate the decision-making process when designing an icon; right-facing arrows indicate the interpretation process when encountering an icon.

We also differentiate between the graphical shape and the intended meaning, which is conveyed via representation strategies.

guidelines to inform decisions that need to be made during the design process, such that shape recognition becomes as easy as possible. As a prequisite to this, Nakamura and Zeng-Treitler [2012] characterize *representation strategies* that inform how to choose a suitable graphical shape to convey an intended meaning (which they call *referent*), such that interpreting the recognized shape becomes as easy as possible. Fig. 2.2 visualizes these relations. We further elaborate on representation strategies as part of icon classification systems in Section 2.2.2.

The same graphical shape can have multiple designs.

Fig. 2.3 shows that even for an abstract graphical shape, many different designs are possible: several 2D paths are recognizable as the same shape, and even when the path is fixed, other properties can still be varied. This set of other available properties depends on the target modalities (color is only available for vision) and materials (textile materials allow other textures than plastic).

Shape properties can be mere design choices, or be part of what constitutes an icon's meaning, or help make shapes discriminable.

Note that these properties might still be part of an icon's content, rather than part of the design of the content: in the context of emojis, for instance, hearts of different colors might convey very different intended meanings. In contrast to that, if all shapes in a set of shapes have the same color, color carries no information for the individual shapes at all, but is a mere design choice. A third option is to use color to provide additional contrast to shapes that are already discriminable. This is often done in a "natural" way: an interface with a heart icon and a star icon is more likely to have a red heart and a yellow star than the other way

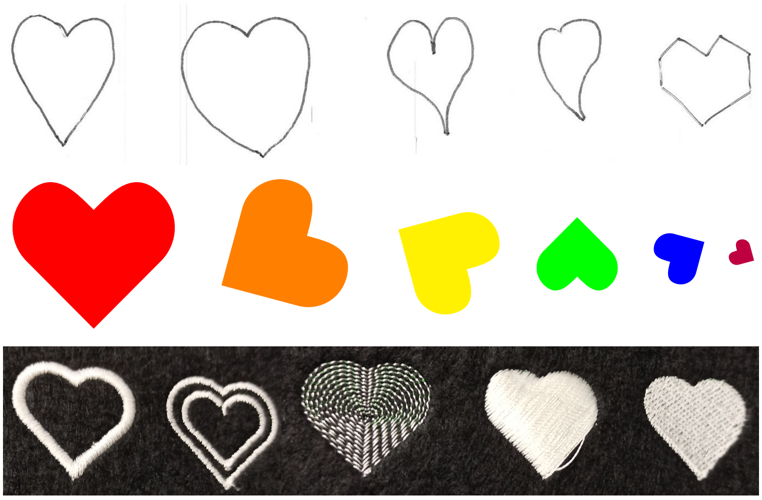


Figure 2.3: Different designs of the same content: a heart. This shape could represent, for instance, the idea of love, the action "add to favorites", or a real heart-shaped object. Varied properties are: 2D path (top row); color, size, and orientation (middle row); textile properties (bottom row).

round.[4] Each property can fall into each of these three categories, depending on the overarching design decisions that were made in a particular context.

The guidelines by Bühler et al. [2020] that inform the design of the content are derived from research on visual perception specifically. Sadly, we could not find a similarly extensive compilation for the haptic modality. We search for visual guidelines that are likely transferrable to haptics. In later subsections, we look at individual haptic properties.

Some guidelines for the design of visual icons might be transferable to haptic icons.

2.2.1 Visual Design Guidelines

Bühler et al. [2020] compiled 34 guidelines aiming at icon designs that are *universal* (targeting people of all cultures, ages, and capabilities) and *intuitive* (recognizable by automatic or partially automatic cognitive processing). Universality, however, is restricted to sighted people due to the authors' focus on visual perception. At the time of writing,

Bühler et al. provide guidelines für univeral and intuitive visual icons based on existing research.

[4]This does, indeed, correspond to *G22* in Bühler et al. [2020].

they provide the most recent and extensive literature survey on icon design. We will not elaborate on their guidelines for using color and animation, as these findings are hard to transfer to the haptic modality. Guidelines on how to project 3D objects onto 2D surfaces will be revisited in Section 2.2.4. Several guidelines are likely not transferrable to haptics due to non-sequentiality of vision or other properties unique to the visual modality. The remaining, most relevant guidelines state that icons should be designed

Icons should be symmetrical and of adequate size, show prototypical contents, and pay attention to shape features.

- "with a focus on a few invariant and distinguishing properties" (*G9*),
- "regularly and symmetrically" (*G10*),
- with "the least possible elements and must not exceed 7 ± 2 elements" (*G15*),
- with "attention to shape [features] because they may suggest unintended meanings" (*G18*),
- such that each icon is "unique and distinctive" (*G20*),
- with a size of "about 0.7° of viewing angle" (*G21*),
- and to "represent typical basic-level contents" (*G34*).

The authors note that for a viewing distance of 70cm, a viewing angle of 0.7° corresponds to an icon size of 9mm. *G9, G15, G18* and *G20* are related to the concept of salient shape features (cf. Section 2.2.3), while *G10* and *G34* inform the overall design of the content. Further ways to classify the design, content, or meaning of an icon as a whole are investigated in the next subsection.

2.2.2 Classification Systems

Survey papers on classification systems help unify the used terminology.

Numerous systems to classify graphical icons have been developed in semiotics, empirical HCI research, and visual design. A potential source of confusion is that terminology varies between sources; fortunately, three survey papers exist that organize most of the existing approaches.

Wang et al. [2007] were the first to compare existing classification systems; their compilation is quite short, but a good starting point as it includes icon samples from all presented papers. Nakamura and Zeng-Treitler [2012, Section 2] provide the most extensive survey on what they call "pictographs" as background to their investigation of the benefits of graphical icons in healthcare contexts. Finally, the most recent survey is by Korpilahti [2016]; the former two surveys are also mentioned here.

There are three such surveys; the one by Nakamura and Zeng-Treitler is most extensive.

Following Nakamura and Zeng-Treitler, we organize characteristics of visual graphical icons into four groups based on which aspects of the icon are involved:

Icon haracteristics for classification focus on different aspects of the icon.

1. **characteristics of the chosen design**
   - *complexity* (simple $\longleftrightarrow$ complex)
     "[the] amount of detail in a representation" [5]
2. **characteristics of the depicted object**
   - *concreteness* (concrete $\longleftrightarrow$ abstract)
     "the extent to which an icon represents real objects, materials, or people"
3. **characteristics of the relation between representation and referent**
   - *representation strategy* (visual similarity, semantic association, arbitrary convention)
     visual similarity: "[the icon] is created by reproducing the visual characteristics of the referent"
     semantic association: "the relation [...] is mediated as in the case of a picture of a clock used to convey the concept of 'time'"
     arbitrary convention: "the connection is established by reinforcement", "the relation [...] is established through a social contract"
   - *semantic distance* (high $\longleftrightarrow$ low)
     "how close a representation is to its referent"

[5] Nakamura and Zeng-Treitler [2012] actually do not differentiate clearly between the depicted object and its design, as considering multiple designs for the same object is not in the scope of their work. Here, they refer not merely to the depicted object, but to its particular design.

4. **characteristics of the relation between all of the former aspects and the person that interprets the shape**
   - *familiarity with the representation* (high $\longleftrightarrow$ low) "how often a given pictograph is encountered" [5]
   - *familiarity with the object being depicted*
   - *familiarity with the relationship of the depiction and its indended meaning*

There are multiple concepts of *familarity*.

We included all three different concepts of familiarity mentioned by Nakamura and Zeng-Treitler, although they are presented in different contexts (cf. page 8 and page 11) of their paper. Other authors still use different nuances of this notion, especially for icons that represent an action: Isherwood et al. [2007] differentiate between frequency of use (which they called *experience*) and familiarity with the depicted object; Sears et al. [1998] further differentiate frequency of use into *[frequency of] icon usage* and *[frequency of] function usage* ("function" in the sense of intended meaning, which in their case is always an action).

Recognizing the depicted object is the first step to understanding the meaning of an icon.

The same object can represent different meanings based on representation strategy.

Recognizing the object that the icon depicts is the first step to understanding its intended meaning. If the meaning is an object as well, the depicted object might coincide with it or not, depending on the representation strategy; if the indended meaning is an idea or action, a second step is always necessary to interpret the depicted object and infer the idea or action in question. Nakamura and Zeng-Treitler emphasize that the same depicted object can have different indended meanings by using different representation strategies: "a pictograph of a clock could be classified as visual similarity or semantic association, dependeng on whether it is intended to convey the concept 'clock' or the concept 'time', respectively."

Quantitative icon characteristics can be assessed in multiple ways.

While representation strategy is a qualitative characteristic, the other items listed above are quantitative. There are three common ways of asssessing quantitative characteristics: user ratings, user performance measures, and metrics.

There are two extensive assessments of existing icons using subsets of these characteristics. For a set of 239 icons,

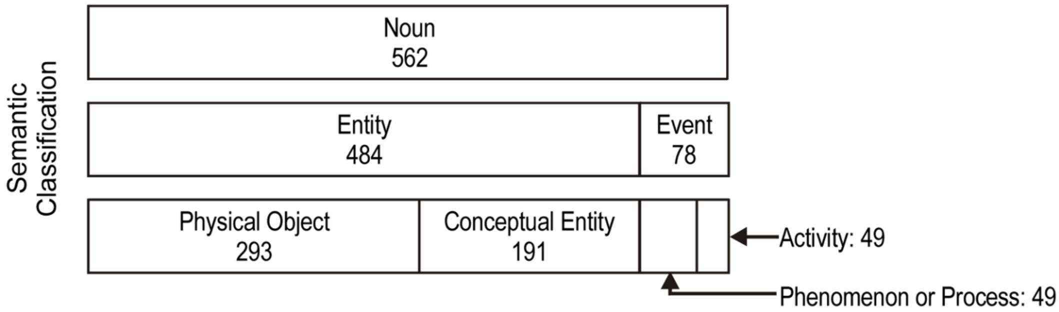


Figure 2.4: Semantic classification of 562 noun meanings; adapted from [Nakamura and Zeng-Treitler, 2012]. Classes are close to our distinction of objects, ideas, and actions.

McDougall et al. [1999] collected user ratings in the form of 5-point Likert items for complexity, concreteness, semantic distance, and familiarity (which they defined as the frequency with which a particular icon design had been encountered). Each property was rated by 40 participants that rated no other property. Participants received only requried information: for instance, only the group that rated semantic distance was told the intended meaning. A fifth group, unaware of the intended meaning, rated *meaningfulness* ("how meaningful they perceived the symbols to be") and stated what they believed the intended meaning was. From the latter, two performance measures were derived: *concept agreement* (how many participants identified the correct meaning, including related words) and *name agreement* (how many parcitipants mentioned the meaning that was stated most often). For complexity, the authors compared user ratings to a complexity metric by García et al. [1994] defined as the sum of all "horizontal, vertical, and diagonal lines, [...] closed figures, open figures, and letters present" [McDougall et al., 1999] and found a strong correlation.

McDougall et al. collected user ratings, performance measures, and metrics for quantitative characteristics of 239 icons.

The second large assessment is made by Nakamura and Zeng-Treitler [2012] themselves: They comprised a set of 846 healthcare icons to analyze their representation strategies and further differente the three basic cases. Moreover, they classified the intended meanings of these icons both lexically (most importantly, 562 icons represented nouns) and semantically (see Fig. 2.4) and identified which representation strategies were common for which classes.

Nakamura and Zeng-Treitler analyzed representation strategies for 846 icons.

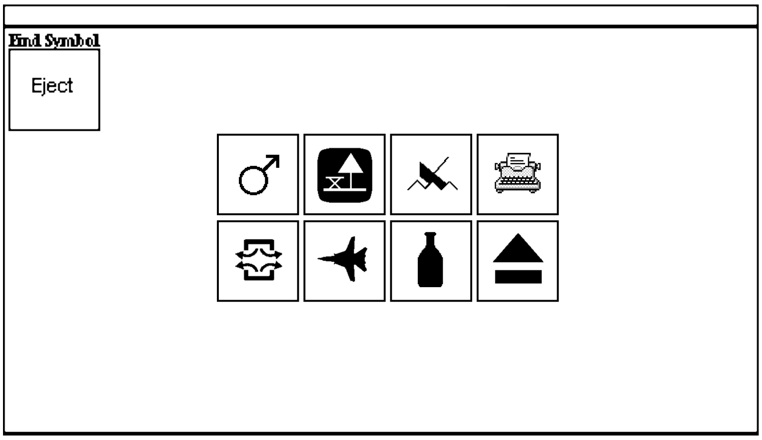


Figure 2.5: Task setup in [Isherwood et al., 2007]; image adapted from there. All icons are in the public domain.

Recognition studies can show effects of icon characteristics on the ability to understand its meaning.

User performance measures can also be obtained by experimentally varying one or more characteristics and measuring variables like recognition rate and response time. Controlled variations of the properties can be obtained either by relying on existing user ratings (for instance, Isherwood et al. [2007] use the results by McDougall et al. [1999]) or by creating multiple icons designs with the same intended meaning, as done by Pappachan and Ziefle [2008].

Isherwood et al. found that initially, low semantic distance mattered most, while with experience, high familiarity was more important.

Isherwood et al. [2007] evaluated the effect of icon characteristics (as assessed by McDougall et al.) on *accuracy* (rate of correct choice) and *response time* for 40 selected icons. Participants were given a meaning and had to match the correct icon in a set of 8 icons within 5 seconds (Fig. 2.5). They found that experience influences what characteristic best predicts fast and correct shape interpretation: initially, low semantic distance mattered most, while at the end of the experiment, participants performed best with icons with high familiarity. High concreteness also benefitted performance, but to a lesser extent, while no significant correlations existed for complexity.

Pappachan and Ziefle found that the depicted object was recognized best for concrete or familiar icons.

Pappachan and Ziefle [2008] used a set of 40 icon samples that provided all combinations of 8 intended meanings and 5 design variants (simple concrete, simple abstract, complex concrete, complex abstract, distractor; Fig. 2.6). They studied the effect of complexity, concreteness, and familiar-

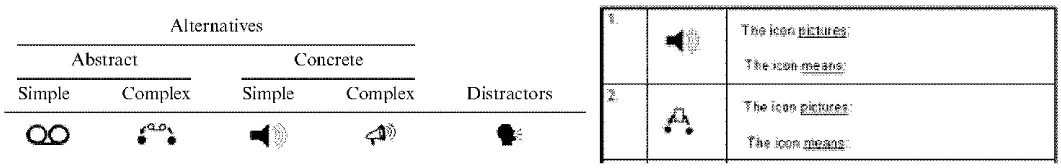


Figure 2.6: Five icon designs meaning "voice message arrived" (left) and an excerpt from the study questionnaire (right); adapted from [Pappachan and Ziefle, 2008].

ity on *pictorial transparency* (correct shape recognition) and *semantic transparency* (correct shape interpretation, similar to concept agreement). Their method of analyzing familiarity was to consider those 8 designs, one for each meaning, which had been adapted from actual mobile phone icons. They found that pictorial transparency was highest when averaging over concrete icons, followed by familiar icons. Averages for simple and complex icons were almost identical and lower than those for concrete and familiar icons. In contrast to this, semantic transparency was highest for familiar icons, although values were generally much lower than for the other characteristics. By the nature of their study design, the authors could not evaluate the effect of semantic distance.

Familiar icons gave best results regarding a correct interpretation of the depicted object.

According to Nakamura and Zeng-Treitler [2012], icon classification systems—also called pictograph taxonomies by the authors—should be seen in "synergistic relation" with recognition studies: "[A] pictograph taxonomy can enable the generalization of the findings of pictograph recognition studies. Conversely, pictograph recognition studies can be used to fine-tune the taxonomy." In contrast to this, haptic shape recognition studies usually focus on the effects of haptic design properties, instead of properties like familiarity or semantic distance. We look into these studies in the following subsections.

Classification systems and recognition studies can benefit each other.

2.2.3 Salient Shape Features

While classification systems evaluate icons as a whole, investigating individual perceptual properties is also useful. Especially interesting are properties that have a high *saliency*. This means that they are immediately perceivable

Salient features are recognizable at a glance.

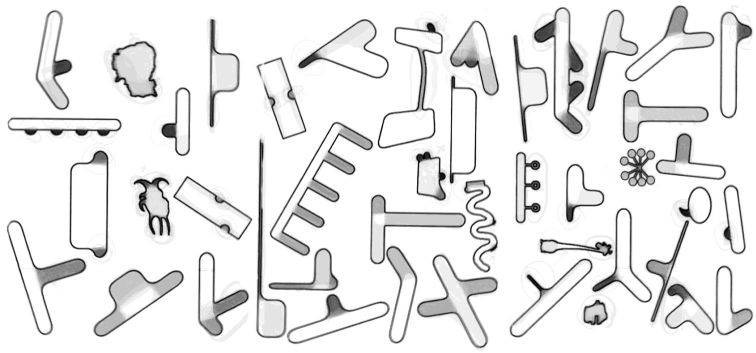


Figure 2.7: Salient features of unfamiliar 2D shapes; taken from Larsson et al. [2015]. The darker an area, the more it was considered not to be part of the main shape.

after a visual or haptic glance. Such salient features are determined via search tasks: A group of identical objects is shown that might contain one additional object that differs in a feature. If response times for determining whether such an object is present are indepentent of the total number of objects, the feature is considered salient. Haptic search tasks are usually realized via a quick swipe over a 2D surface or a quick grasp of 3D objects [Kappers and Tiest, 2015].

Roughness and the presence of edges are haptically salient shape features for 3D objects.

We are interested in haptically salient shape features, that is, properties that make the graphical shape effortlessly recognizable. Plaisier et al. [2009] found that for 3D objects, the presence of edges is a salient shape feature. This might also hold for objects mounted to a surface. Roughness was also found to haptically salient if the difference was strong enough Lederman and Klatzky [1997].

For visual 2D outlines, people conceptualize small bumps that stand out as salient.

To understand how people conceptualize salient shape features for 2D outlines, Larsson et al. [2015] showed participants a set of 44 unfamiliar closed shapes and asked them to highlight what they considered the main part of the shape. Their results show that small and irregular bumps that stood out from a large regular part of the shape are most often considered salient (Fig. 2.7).

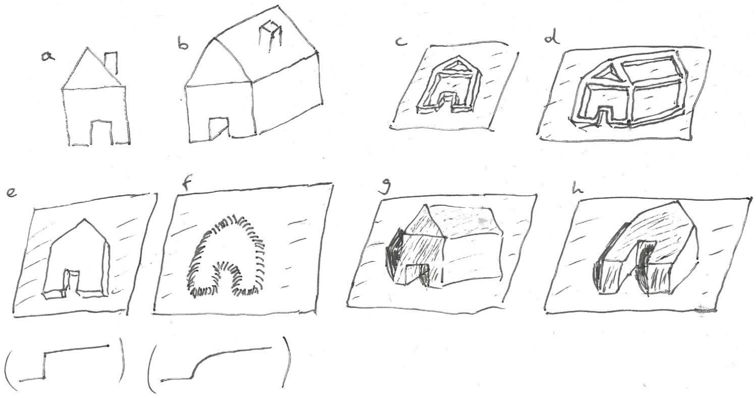


Figure 2.8: Different kinds of 3D information for a house.

GRAPHICAL AND PHYSICAL 3D INFORMATION:
In Fig. 2.8, a and b show what could be two different vector graphics depicting a house; b has graphical 3D information while a lacks it. Both can be realized, for instance, as raised-line drawings (c and d), where physical 3D information is only used to encode the outlines, but does not match the 3D information of the depicted object. Physical 3D information could also encode the filled shape instead (e and f); here, e has very sharp edges while f has some 3D curvature toward the edges. Both have different advantages.
In cases c to f, the physical 3D information is very limited (binary for c, d, e; slightly richer for f; also, the actual height difference is low). Case g shows what is called a volumetric icon on tactile maps; the physical 3D information actually matches the graphical 3D information, so we can, for instance, actually feel the slope of the roof. In case h, physical 3D information is still only used to encode the filled 2D shape, but the larger height difference allows for easier exploration of the shape.

Excursus: *Graphical and Physical 3D Information*

2.2.4 3D Information

When studying the influence of 3D information on haptic recognition of graphical shapes, it is useful to differentiate between *graphical* and *physical* 3D information. Graphical

We differentiate between graphical and physical 3D information.

3D information is any kind of 3D perspective present in a graphical depiction. Physical 3D information is any kind of height difference between the shape and the background in its physical realization.

Raised-line drawings perform poorly with sighted people.

For blind/v.i. people, haptic graphics are often realized as raised-line drawings, which are fabricated on swell paper and cause a height difference of about 0.5mm. However, it requires training to recognize these drawings. Lebaz et al. [2012] evaluated raised-line drawings with and without graphical 3D information for sighted people. They found that drawings without graphical 3D information gave better results, but mean recognition rates were still below 50% and mean response times were at 86 seconds. Thompson et al. [2003] found that drawings depicting the filled shape with a changed texture worked better even without a height difference.

Preserving 3D information of the depicted object improves recognition.

Lawson and Bracken [2011] investigated numerous ways how to apply physical 3D information to 3D-printed models of real-life objects of several centimeters in size. They found that preserving the 3D information of the objects as much as possible allows better recognition compared to models that had a constant height and only encoded the object shape in two dimensions (similar to Fig. 2.8h).

A 3D curvature can improve shape discrimination.

Harrison and Hudson [2009] created pneumatic buttons with a height difference that decreased toward the edges, such that button surfaces were curved outward or inward in the third dimension. In an attention-split study, participants executed a visually demanding task while occasionally asked to press a specific pneumatic button. The buttons had different 2D shapes and were placed outside of their field of vision. Results showed that buttons with curved surfaces needed to look away from the visual task less often than for raised buttons with a flat surface. The authors attribute this to the curvature which gives richer information on the underlying 2D shape.

Doi et al. [2011][6] compared the haptic discriminability of small circles, squares, and triangles on tactile maps when

[6] This paper is only available in Japanese, but we were able to translate it to English well enough to understand their main results.

using two different fabrication techniques: one resulted in sharp edges, the other in 3D-curved ones, similar to Harrison and Hudson [2009] but smaller. They found out that squares and triangles could be distinguished more easily with sharp edges. Interestingly, however, circles could be distinguished more easily in the 3D-curved condition. Following on this result, it might be interesting to design the height difference for more complex shapes in a way that increases and decreases 3D curvature in alignment with the curvature of the graphical shape, and investigate whether this makes haptic recognition easier.

It could be useful to combine 3D curvature along curved edges with a lack of 3D curvature along straight edges and vertices.

Gual et al. [2015] investigate *volumetric icons* on tactile maps, which make strong use of physical 3D information (similar to Fig. 2.8g). Volumetric icons are small geometric 3D objects like pyramids or cylinders that are applied to a map surface. The authors found that using these icons improved discriminability compared to raised-line icons on swell paper. They attributed this to the increased variety of possible shapes when using all three dimensions. According to the authors, however, this does not mean volumetric icons are always better than icons which are raised from the surface only slightly.

3D geometric objects improve discriminability on tactile maps.

While haptic recognition generally improves with available 3D information, the best performance is achieved in recognition studies of real-life 3D objects Klatzky et al. [1985]. This is because these objects intrinsically have a large number of varied, haptically perceivable properties and people are highly familiar with them. *Tangible symbols* [Rowland and Schweigert, 1989] use small real-life objects as 3D icons to give children with multisensory impairments an easier way of communication.

Real-life 3D objects perform best due to their high familiarity and the large number of varied properties.

2.3 Textile Interfaces

So far, there is little research on the recognizability of shapes on textile surfaces.

Seometric shapes are easily discriminable on textile surfaces, while embroidered outlines of more complex shapes are hard to recognize.

Mlakar and Haller [2020] provide the only investigation of complex textile icons existing so far. They used create four shapes (star, house, phone, heart) by embroidering their outlines on a background fabric. Recognition rates were very low: the star was best recognized (15 of 30 participants), while the phone performed worst (2 of 30 participants). For simple geometric shapes (triangles, squares, circles), the authors found that a size of 13mm is sufficient for reliable recognition if outlines or filled shapes are embroidered on the fabric. Discriminability of small interface elements (again considering triangles, squares, and circles) was found to be highest when using a height difference (of at least 1.6mm), followed by a contast in shape, with a difference in texture was most difficult to recognize.

When designing for vision and haptics, colors are useful to direct the user's attention, while shapes are useful to convey information.

Mlakar et al. [2021] looked into new kinds of affordances that are possible on textile interfaces from a design perspective. To do so, they created 30 textile samples that varied many different textile properties. They also gave insights into the role of vision in textile interfaces: For instance, they concluded that colors work well to focus the user on specific parts of an interface, for instance the interactive elements, while shapes are better suited to encode the information how to use the element or what effect it will have.

Textile sliders should be designed with a height difference. Tick marks are helpful for entering values and estimating the position, especially when individual tick mark designs are used.

Nowak et al. [2022] investigated how to design textile sliders to allow eyes-free interaction. In a user study, they compared flat, raised, and recessed slider shapes, and found that sliders creating a height difference with embroidery foam were preferred. In a follow-up study, they showed that for entering percentage values, recessed line sliders with 3 or 4 evenly spaced tick marks had higher accuracy than other tick mark alignments or shapes and were rated higher by participants regarding their confidence and enjoyment. They also evaluated tick mark designs that allow to haptically determine which tick mark is currently touched by the finger. For sliders with 3 evenly spaced tick marks, individual tick marks allowed faster estimation of the current position with less movement compared to a slider with 3 uniform tick marks. In fact, these individual tick marks also qualify as icons, as they convey a discrete position information via their shape.

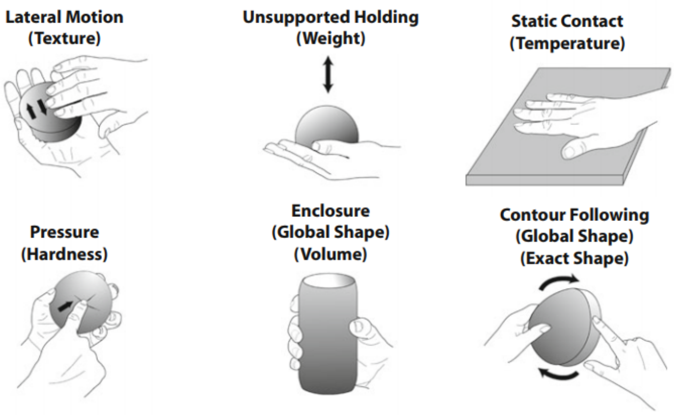


Figure 2.9: The six exploratory procedures; adapted from Lederman and Klatzky [2009].

2.4 Haptic Exploration

People use different strategies to haptically explore the shape of 2D or 3D objects. These strategies are called *exploratory procedures (EP)*. Commonly, six different procedures are differentiated [Lederman and Klatzky, 2009], as seen in Fig. 2.9. Research has shown that each of them is preferred for a particular property that people aim to explore:

People use six exploratory procedures to explore shapes haptically.

- Lateral Motion (texture)
- Pressure (softness)
- Unsupported Holding (weight)
- Enclosure (global shape, volume)
- Static Contact (temperature)
- Contour Following (global shape, exact shape)

Not all of these exploratory procedures are suitable for shapes that are mounted on surfaces, thus it is not clear whether the same procedures would apply for textile icons.

2.5 Non-Graphical Icons

There are a large assortment of icons that conform to our generalized definition without conveying their meaning via graphical shape. We conclude this chapter by briefly looking into them.

Kineticons convey meaning via motion patterns.

Harrison et al. [2011] studied *kineticons*, short or repeating movement patterns, i.e. geometric manipulations, of objects on a screen. While kineticons are often applied to visual graphical icons, and can also be applied to a window or the full desktop, they kineticon itself conveys it meaning not via shape, but via the movement pattern.

Earcons and auditory icons convey meaning via sound.

Blattner et al. [1989] introduced *earcons*, which use beeps and other artificial sounds to convey meaning. Auditory icons [Gaver, 1989] use sounds that are familiar from the real world for a similar purpose. These kinds of icons are also temporally compact. Zinck and Vogel [2022] investigate singing short melodies as an input modality. Although they focus on using melodies for menu selection, it would also be possible to directly assign meanings to melodies, which would make them icons.

Tactons convey meaning via vibration patterns.

Tactons [Brewster and Brown, 2004], also called *tactile icons*, use vibration patterns to convey their meaning. They are temporally compact, but might also be spatially compact (for instance when realized via a pin-array display). Tactile icons that are not spatially compact are found in modern smartphones that allow individual vibration patterns for different kinds of notifications. Alotaibi et al. [2022] provide first steps for the design of *electrotactons*, whichare intended to work similarly to tactons, but use electotactile stimuli instead of vibrotactile ones.

Hapticons convey meaning via force patterns.

While tactons target only the tactile mode, *hapticons* [Enriquez and MacLean, 2003], also called *haptic icons*, target the passive haptic mode. They use force patterns instead of tactile stimuli, thus providing additional kinesthetic sensory input.

Brown et al. [2020] developed *ultrahapticons*, which use ultrasonic waves to generate haptic stimuli in mid-air. They are intended for effortless eyes-free interaction in the car. Ultrahapticons can target the passive haptic mode by generating short or repeated patterns of ultrasonic stimuli on the hand, or the active haptic mode by allowing to explore virtual shapes in mid-air.

Ultrahapticons convey meaning via ultrasonic stimuli patterns or virtual shapes created by ultrasonic stimuli.

H. Sebresos investigated prototypes for two kinds of icons targeting the active haptic mode: *Mobile hapticons*[7] would change the background texture of a smartphone for a short time to convey emotions. For instance, this could be used to augment text messages with the emotional tone that was intended when writing them. The research by Hoggan et al. [2017] follows a similar direction. While mobile hapticons cover the whole underside of the smarthone and are temporally compact, *textural icons*[8] are spatially compact patches with certain textures that are also intended to convey emotions. In both cases, one goal was to explore which emotions people associate with each of the given textures.

Texture changes can be used to convey associated emotions.

Breitschaft and Carbon [2021] investigate associations of a different kind: those resulting from haptically perceivable simple geometric shapes and 3D information. Icon samples had a size of 15x15mm, 15x30mm, or 30x15mm. They explicitly follow the *Aesthetic Association Principle (AAP)*, which dates back to Gustav Theodor Fechner. It says that familiarity and experience are an essential part of perception and thus should be considered when designing haptic experiences. The difference of this approach to graphical icons is that association-based icons do not require to recognize the graphical shape as a whole, or as a nameable entity. Instead, the sensory input from haptic perception itself creates associations that can be used to convey the meaning of the icon.

Geometric shapes and 3D information also can convey meaning via common associations with the haptic stimuli.

[7] http://people.artcenter.edu/~hsebresos/touch/images/hapticons.html(accessedonJune5,2022)

[8] http://people.artcenter.edu/~hsebresos/touch/images/texticons.html(accessedonJune5,2022)

Chapter 3

Design Decisions

In Chapter 1, we motivated our first fundamental design decision: the use of *graphical shape* to convey the intended meaning of a textile icon. In this chapter, we use existing literature to further narrow down our scope of analysis.

We already decided to investigate *graphical* icons.

As we decided to mainly focus on varying shape properties and less on varying textile properties, we selected a single textile property as our main interest, and a second one as a baseline. From these, we derived six fabrication variants. In the following, we elaborate on these choices. We then explain how we selected a suitable set of shapes, characterize these shapes, and motivate our precise graphical designs.

This chapter elaborates on our further literature-based design decisions.

3.1 Choice of Textile Properties

Mlakar and Haller [2020] determined that on textile surfaces, the best way to make a small shape stand out in a group of shapes is a height difference (optimally, at least 1.6mm), compared to using a different shape or texture. In contrast to this, we are interested in finding the best textile property to make shapes easily recognizable, which implies they need to stand out *against the background*. Although we cannot be sure that the same results hold in this situation, *height difference* will be our main textile property of choice.

We choose applying a height difference as our main textile property of interest.

Applying a height difference is in itself promising because it adds some physical 3D information to the surface, and it is known that the amount of physical 3D information available positively influences ease of recognition.

Changing the texture of the filled shape might also be feasible.

Thompson et al. [2003], on the other hand, found that haptic shape recognition improved when encoding the filled shape using a different texture only, compared to encoding the outline as a raised-line drawing. It is not clear whether the better performance is due to the choice of texture rather than height, or because the filled shape was encoded rather than the outline. Filled objects with a different texture are also found to work better than raised-line drawings in modern books for blind or visually impaired children, although here these textured objects have an additional height difference [Vinter et al., 2020].

Changing the texture of the outline was already investigated for textile icons.

We choose applying a texture difference as our second textile property of interest.

We aim for a systematic exploration of available textile properties in empirical research, which is why as a start, we only inspect textile variables individually. While we identify height difference / physical 3D information as the most promising property, a change in texture is very easy to realize on textiles by using a filled embroidery pattern. Also, Mlakar and Haller [2020] provide the only empirical investigation of textile icons (that are more complex than geometric shapes) existing so far, and they chose to simply embroider the shape outlines. While any embroidery will naturally create a very slight height difference, this is the closest to only varying texture we can get using textile materials. This is why we selected *change in texture (using yarn)* as our second textile property of interest. As Mlakar and Haller report some initial findings for the case of texture encoding the shape outline, we can adopt this as a baseline in our own empirical research and compare the results.

3.2 Choice of Fabrication Variants

We cannot preserve physical 3D info, as most icons will have none.

There are numerous different ways of providing physical 3D information [Lawson and Bracken, 2011]. However, the graphical shape of an icon is likely to depict an abstract object—like a heart or a five-point star—that in itself has no

3D information. Thus, approaches that (at least partially) preserve the 3D information of the depicted object, like the *full*, *half*, and *squished* conditions by Lawson and Bracken, cannot be applied here.

As sharp vertices have been found to be salient shape properties for 3D objects [Lederman and Klatzky, 1997], we decided to go for fabrication variants that also highlight sharp vertices of the graphical shape, instead of variants that height depending on the position on the shape to create 3D curvature (similar to [Harrison and Hudson, 2009]). As we use abstract shapes (see Section 3.3) with little physical 3D information, the most straightforward way to highlight sharp vertices is by raising the filled shape uniformly compared to the background. We call this variant *RaisedFill*. Another approach is to highlight sharp concave vertices, i.e. angles between 270° and 360°. This can be achieved by recessing the filled shape uniformly compared to the background. We call this variant *RecessedFill*.

We aim to highlight sharp vertices of the icon shape.

We include variants that uniformly raise or recess the filled shape.

Further height-based variants we consider interesting for further inspection are those that only raise or recess the outline instead of the filled shape. For one, this allows comparisons to existing literature on raised-line drawings. In addition, a raised outline can give the user more haptic information, as it is similar to *RaisedFill* when approached from the outside, but similar to *RecessedFill* when explored from the inside. We call this variant *RaisedOutline*. Similarly, recessing the outline might feel similar to *RecessedFill* when approached from the outside and similar to *RaisedFill* when explored from the inside. We call this variant *RecessedOutline*. We are interested in whether this richer information benefits recognition or is a source of confusion for users.

We also include variants that uniformly raise or recess the outline.

In addition to these four height-based variants, we include two texture-based variants. Similarly to how we organized the height-based variants, we include one variant that uniformly changes the texture of the filled shape using a yarn embroidery pattern (*FlatFill*) and one for which we only use yarn for the shape outline (*FlatOutline*). The former is similar to [Thompson et al., 2003], but on textiles and with smaller shapes, while the latter is aimed to be close to the textile symbols investigated by [Mlakar and Haller, 2020].

In a similar way, we include variants that uniformly change the texture of the filled shape or the outline using yarn.

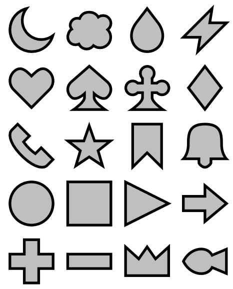


Figure 3.1: Our chosen set of 20 shapes for the fabrication of texile icon samples. **Cloud**, **Spade**, **Club**, and **Diamond** had to be removed for the empirical study of Chapter 5, while **Crown** and **Fish** were chosen as test shapes due to their assumed lower familiarity.

3.3 Choice of Shapes

We brainstormed a set visually familiar shapes and narrowed it down using selection criteria.

To be able to use visual discoverability of textile icons to our advantage, we aim to investigate shapes that are visually familiar to users. To decide on a suitable set of shapes, we did an initial brainstorming of icon shapes that we considered visually common on mobile devices, desktop computers, and social media platforms. We then used the followng selection criteria to further narrow down the shape set:

- Shapes should consist of a single closed outline (and thus, have a single filled area).
- No inner contours (as, e.g., an envelope shape)
- No lines that lead away from the closed outline (as, e.g., a sun shape)
- No holes in the shape (as, e.g., a gear shape)
- Shapes should not require a high level of detail to depict (as, e.g., a castle shape)

We ensured that shapes could be realized in all variants.

These criteria were chosen for two purposes: On the one hand, they ensured that shapes could be realized in all six variants unambiguously, without having to make further assumptions on how to represent inner contours or lines in the different variants. On the the other hand, they make haptic exploration easier, especially when users try to trace the shape contours: There will always be only one way to go. Applying these criteria ultimately resulted in the set of 20 shapes as shown in Fig. 3.1.

3.4 Choice of Graphical Designs

From Bühler et al. [2020], we know that visual graphical icons should be designed "regularly and symmetrically" *(G10)* and to "represent typical basic-level contents" *(G34)*. We argue that this is likely even more true for haptic icons: due to the sequentiality of haptic exploration, any breaks of symmetry and complex shape features can not be understood at a glance, and thus users will likely believe them to be an essential aspect of the shape. This is why our designs are very simple (Fig. 3.1). Moreover, in alignment with our definition of spatially compact icons, we created the designs on a square canvas.

We designed the shapes on a square canvas and made them as simple as possible.

Shapes have been designed to highlight their shape features as much as possible, especially if the shape has a lot of detail. For instance, the concave vertex of **Heart** and the clapper of **Bell** have been made rather prominent compared to alternative design options.

Shape features were highlighted as much as possible.

We have included a few shapes that could also be realized as simple lines instead of closed shapes: **Lightning**, **Plus**, and **Minus**. We chose the closed-shape design due to our criteria for choosing shapes, thus ensuring that we could fabricate the corresponding icon samples in all variants. It is still possible that the outlined variants might be confusing for users as they might expect a simpler haptic representation as lines.

A few shapes could be designed as lines instead of filled shapes.

The level of detail in our shape designs is also influenced by limitations imposed by the fabrication process. While we developed our fabrication process, some designs had to be slightly adjusted to conform to these limitations. The shape designs shown here are the final designs.

Shape designs were adjusted slightly to be suitable for our fabrication process.

3.5 Further Characterization of Shapes

We present possible intended meanings for each shape.

Our shapes and shape designs cover a large range of complexity, familiarity, domains, and kinds of (supposed) intended meanings. The actual intended meanings of the icons are not of interest for us in any way, as we are only focusing on shape recognition. However, it is still a characteristic of a shape if it has a commonly attributed meaning, which is why we include these here. Regarding familiarity, we believed that **Crown** and **Fish** stood out because, while being common shapes in themselves, they are rarely encountered on interfaces. Due to this assumed low familiarity, we chose them as test shapes for our empirical study.

We aimed to use familar shapes. On interfaces, Crown and Fish are least familiar.

We organize our shapes via domains.

Our shapes could roughly be classified into the following domains: nature, smartphone, card games, social media, geometry, and music player. Several shapes belonged to multiple of these domains, while **Crown** arguably belongs to none of them. Table 3.1 shows these domains and possible familiar intended meanings. We do not aim at providing a complete list of possible meanings, but rather at illustrating what associations people are likely to have with these shapes. We also include our assessment of the complexity metric by García et al. [1994] for these shapes, which in our case simplifies to the number of lines in the shape due to our choice of single closed shapes. As additional metrics, we include the number of convex vertices and the number of and concave vertices.

We calculate three shape metrics.

We include visually similar shapes to investigate in which variants they are discriminable.

The set of shapes deliberately includes pairs of shapes that we consider rather similar (for instance, **Moon** and **Phone** or **Raindrop** and **Circle**). This allows to investigate whether such shapes will still be discriminable or, to be more precise, which fabrication variants will highlight the salient shape features that need to be recognized to tell the shapes apart.

In the next chapter, we demonstrate how we fabricated the actual textile icon samples for our chosen set of shapes.

	metrics	domains	familiar intended meanings
Moon	2/2/0	nature, smartphone	moon (object), night (idea), activate dark mode (action)
Cloud	6/0/6	nature, smartphone	cloud (object), access cloud service (action)
Raindrop	1/1/0	nature	raindrop, teardrop (objects), water (idea)
Lightning	6/4/2	nature, smartphone	moon (object), night (idea), activate dark mode (action)
Heart	2/1/1	card games, social media	heart (object), love, Hearts (ideas), like (action)
Spade	4/3/2	card games	Spades (idea)
Club	6/2/4	card games	Clubs (idea)
Diamond	4/4/0	card games	Diamonds (idea)
Phone	6/4/2	smartphone	call (action)
Star	10/5/5	nature, social media	star (object), favorite (action)
Bookmark	5/4/1	social media	add to bookmarks (action)
Bell	4/2/2	smartphone, social media	bell (object), allow notifications (action)
Circle	1/0/0	geometry, music player	circle (object), record (action)
Square	4/4/0	geometry, music player	square (object), stop (action)
Triangle	3/3/0	geometry, music player	triangle (object), play (action)
Arrow	7/5/2	geometry	right (idea)
Plus	12/8/4	geometry, music player	plus, cross (objects), increase volume (action)
Minus	4/4/0	geometry, music player	minus, rectangle (objects), decrease volume (action)
Crown	7/5/2	/	crown (object)
Fish	5/3/2	nature	fish (object)

Table 3.1: Characterizations of the 20 chosen shapes. Metrics are complexity (left), number of convex vertices (middle), and number of concave vertices (right).

Chapter 4

A Fabrication Process for Textile Icon Samples

Textile icon samples were fabricated for each combination of our chosen 20 shapes and 6 variants. Even with these choices already made, the process of turning them into physical samples with sufficient quality and precision is difficult. For instance, Nowak et al. [2022] state that their textile sliders varied in length by up to 2mm due to the fabrication process. Due to the higher complexity of textile icons, it is even more important to control fabrication imprecisions, especially as textile icons should be small. In this chapter, we explain how we achieved to produce our textile icon samples with high quality.

Our fabrication process aims at achieving high quality and precision for all variants.

4.1 Fine-Tuning Dimensions, Materials, and Machine Settings

As fabric for the background, we chose a soft polyester fabric[1] that was 1−2mm thick (depending on the pressure applied) and had only very slight stretchability. This fabric was reminiscent of the armrest of a sofa, which is one likely

We used a background fabric that resembles the armrest of a sofa.

[1]https://www.stoffe-hemmers.de/moebelstoff-rolando-grau

use case for textile icons. It is the same fabric that has been used by Nowak et al. [2022] for their textile sliders.

Realizing height difference by cutting fabric into shape was ineffective.

We first attempted to realize height differences by cutting a second fabric layer into shape and glueing it on onto the background layer. This was ineffective: Manual cutting could not achieve the necessary precision and created fringes at the edges that would cause confusion during haptic recognition. Lasercutting, while believed to give better results due to burned—and thus, sealed—edges, was not viable in our case as some components in our fabric had the risk of giving off toxic fumes when heated. Moreover, due to the softness of the fabric, outlines created by a second fabric layer were generally hard to recognize. Thus, we chose a different approach to realize height differences: putting some other material on top of the background layer and placing a second fabric layer above it.

Instead, we place another material between two fabric layers.

Lasercuttable materials were suitable for highlighting sharp vertices. Plywood was safe, but only available in rather high thicknesses.

We tested different materials and thicknesses. We found that using embroidery foam was not viable because it would get compressed strongly toward the edges, creating 3D curvature and thus making sharp vertices hard to recognize. As described in the previous chapter, we intend to create a uniform height difference to make sharp vertices stand out. Next, we switched to lasercuttable materials, which would be glued onto the background layer, before the second fabric layer would be fixated above by embroidering an outline around the lasercut object. Plywood was the first such material we tested. It worked better, but was only available in 3mm and 4mm (and higher) thicknesses, which made it difficult to fixate the second fabric layer as the fabric would get stretched strongly. However, one advantage of the softness of Plywood was that it increased safety in the fabrication process: when mistakes were made during the fixation of the second layer, the needle of the embroidery machine could go through the material without getting damaged.

We did not investigate acrylic. Cardboard made icons susceptible to folding.

We did not try acrylic as alternative to Plywood for safety reasons. We tested cardboard of 1mm and 2mm thickness and found that while the 2mm thickness seemed suitable, resulting icons were highly susceptible to folding. Especially in the following user study, the risk of damaging an icon sample during placement or removal would have been high. Thus, we did not consider it an option.

The best material that we could find was MDF. These sheets were even a bit stiffer than Plywood and available with lower thicknesses, while still a lot safer to use than acrylic and producing no toxic fumes during lasercutting like our sofa fabric. A side effect of using MDF, however, is that we do not only create a height difference, but also a difference in softness, as only the raised parts of a sample would have the MDF sheet below the fabric layer. From our own exploration of the materials, we believe that for height-based textile icons, decreasing softness is a necessity when aiming at clearly recognizable sharp vertices.

We identified MDF as the best material.

To highlight sharp vertices, it is necessary to decrease softness.

In the end, we chose MDF sheets of 1.6mm thickness. This is for three reasons: First, our tests with Plywood had already shown that a thickness of 3mm or more makes fabrication difficult as the second fabric layer gets stretched strongly. Secondly, Mlakar and Haller [2020] identified a height difference of 1.6mm as sufficient for easy discrimination of shapes. While it is not clear whether this holds as well for recognizing shapes against a background, it is a strong indication. Thirdly, we consider 1.6−2mm as good ergonomic choice based on our own tests: While 1mm cardboard was hard to recognize and 3mm Plywood felt like a barrier that the finger would run against during haptic exploration, materials with 1.6mm or 2mm thickness seemed both well recognizable (regarding the height difference itself) and comfortably explorable.

We chose a thickness of 1.6mm for reasons of fabrication, existing research, and ergonomics.

The embroidery steps were done on a BERNINA 880 embroidery machine. We chose a yarn that was unobtrusive enough (haptically) when embroidering the shape outlines for the height-based variants such that it would not cause additional confusion, but still well recognizable on the flat variants using suitable stitch types. While we used a single stitch for all embroidery on height-based variants, we tested different stich types for the variants *FlatOutline* and *FlatFill*. We found a triple stitch to work best for *FlatOutline*, as a satin stitch would create confusion on edges and narrow curves of a shape. We also found a step fill to work best for *FlatFill*, as a filled satin stitch would not result in a not-

We identified the best stitch types for variants that change texture using yarn.

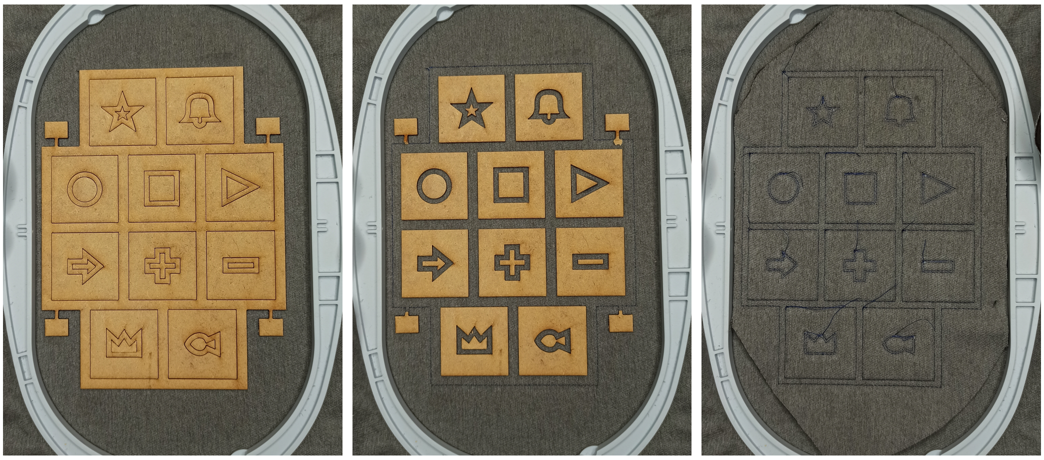


Figure 4.1: Fabrication steps for 10 textile icon samples of variant *RecessedOutline*.

icable texture change and could feel very different depending on whether the direction of finger movement aligned with the direction of the yarn.

Samples consisted of icons sitting in the middle of a larger square.

We designed the samples in such a way that the shape would sit in the middle of a larger square. For *RaisedFill* and *RaisedOutline*, the MDF cutouts were just the filled or outlined shapes, which were placed in the middle of the square before the second fabric layer way was placed on top and fixated with embroidery outlines. For *RecessedFill* and *RecessedOutline*, the MDF cutouts were squares with a hole in the middle that had the corresponding shape. For *RecessedOutline*, a second, smaller cutout of the shape was then placed in the middle of the hole. For *FlatFill* and *FlatOutline*, only a single layer of fabric was used. We tested using two layers such that the background would have the same height as for the raised variants, but this caused the embroidery to create height differences as the two layers were more compressible than a single layer.

4.2 Achieving Sufficient Precision

From our initial tests to the final fabrication process, we identified several factors that had strong influence on the precision of fabrication that could be achieved.

Figure 4.2: Different amounts of removed material depending on lasercutter settings. From left to right, power was successively decreased, while speed was increased.

Initially, we tried to achieve a precise alignment of the MDF cutouts by embroidering individual shape outlines on the background layer. Due to the slight loss of material during lasercutting, it was possible to align the shapes in such a way that the embroidered outlines were visible on all sides. However, we found that results were still quite imprecise.

Manually aligning the MDF cutouts was quite imprecise.

We recommend using a different approach: using the remaining lasercut parts as *fitting aids* (Fig. 4.1). We created an additional MDF frame around the samples that was glued to the background layer only on 4 small flaps. Then the actual parts of the icon would be fully glued to the background layer. After the glue had dried, the glue flaps could be broken off from the rest of the fitting aid with a little care, allowing to remove the fitting aid. For *RecessedOutline*, we used the MDF parts representing the shape outline as another fitting aid for glueing the middle parts. Fig. 4.1 (left) shows all parts in place; glue is applied only to the elements that are still visible in Fig. 4.1 (middle), the state after removing all fitting aids. Finally, Fig. 4.1 (right) shows the state after applying the second fabric layer.

We discovered that precision is increased highly by using fitting aids.

As we use the lasercut parts as fitting aids, it is very important to use suitable lasercutter settings. In particular, settings need to be fine-tuned such that as little material as possible is lost due to the heat of the laser. The leftmost icon in Fig. 4.2 has much more spacing between the outline fitting aid and the middle part than the rightmost icon. Although the difference is only a fraction of a millimeter, this spacing creates more potential for imprecision when using the fitting aids. We also noticed that with such precise choice of settings, the result can depend strongly on the placement of the MDF sheet within the lasercutter, so it might be advisable to not use the whole area at once.

To make fitting aids as precise as possible, Lasercutter settings should be adjusted such that as little material as possible is removed.

We recommend not to use very large embroidery hoops.

We also decided against using the largest hoop for embroidery, although it would have allowed us to create all 20 samples of one variant at once. In such a large hoop, the background layer cannot be held in place as tightly as in the standard medium-sized hoop, which impacts precision negatively.

We aimed at an average shape size of 18x18mm.

We aimed at creating the textile icon shapes with an average size as small as 18x18mm. This is still larger than fingertip size, but still a very small size considering that working with height differences on textile materials is necessarily less delicate than, for instance, glueing the MDF cutouts to a smooth surface directly. It is also the same size that Mlakar and Haller [2020] used for their textile symbols of higher complexity.

Fabrication requires that outlines used for lasercutting and embroidery must be offset by a small amount.

Note that we call these dimensions an average size. While the source vector graphics for each icon were fitted exactly in an 18x18mm canvas, all outlines that are either lasercut or embroidered need to be offset from this reference shape by a small amount. This is because the fabric of the second layer needs a bit of room to wrap around the MDF cutouts. We found that outsetting and insetting the outlines gave better results than scaling the shapes, because the former ensures that the distance of the two outlines stays constant over the whole shape. We did further tests to fine-tune the correct offsets. For *RaisedFill* and *RecessedFill*, outlines for lasercutter and embroidery were offset by 0.5mm in opposite directions, thus giving the fabric 1mm of space. Thus, the actual outline is still perceived at about the original position, as the soft top fabric fills up what was removed “too much” from the MDF cutouts.

For filled variants, offsets of 0.5mm in opposite directions were used.

Outlined variants required additional offsets, which made shapes a bit larger.

For *RaisedOutline* and *RecessedOutline*, we initially were unsure how to proceed, because applying further offsets would increase the overall shape size by a few millimeters. On the other hand, this could only be counteracted by rescaling the icons, and it was not clear how this should be done, as the new bounding boxes of the offset vector shapes differ depending on the actual shape. In the end, we decided to still simply apply offsets centered around the original 18x18mm outline: For the MDF cutouts of *RaisedOutline*, we offset the original outline by 0.5mm in opposite directions, which resulted in a lasercut outline piece with 1mm width. We checked that this was still stable enough; even thinner MDF outlines became unstable. For the embroidered outlines of the same variant, we offset the original outline by 1.5mm in opposite directions, which again gave the fabric 1mm of space to wrap around the MDF cutouts—only this time on both the outside and the inside. For *RecessedOutline*, we did it the other way round: The MDF cutouts (as seen in Fig. 4.1) used 1.5mm offsets in opposite directions, while the embroidered outlines used 0.5mm offsets.

For outlined variants, 0.5mm offsets were used for the inner outlines and 1.5mm offsets were used for the outer ones.

Even though the resulting bounding boxes of *RaisedOutline* and *RecessedOutline* icon samples are larger than 18x18mm, we still believe this is the best way to compare the variants: While approaching the shapes from the outside might give the feeling of a slightly larger shape, the shape will feel smaller when touching the inside. The center of the outline is still at the same position for all variants, which is why we call 18x18mm the average size.

Whether outlined variants feel a bit larger or smaller than filled variants depends on the way they are explored.

A final step to increase precision was to choose the right upper thread tension. We found that using a higher tension made the second fabric layer wrap around sharp vertices more tightly, but when it was too high it would hinder precise fabrication, as the yarn would pull too much on the second fabric layer. For our setup, setting the BERNINA to a value of 2.75 appeared to be the best compromise. For *FlatOutline* and *FlatFill*, however, we found that a low tension of 1 gave the best results. For the height-based variants, we increased the effect of highlighting sharp vertices by using rounded corners for the embroidery outlines, which would wrap around vertices even more tightly. This was not possible for *RecessedOutline*, as the embroidery outlines needed to fit tightly between the two MDF cutouts.

A upper thread tension of 2.75 and rounded vertices for embroidered outlines allowed the second fabric layer to tightly wrap around sharp vertices.

4.3 Creating the Necessary Files

In this section, we will explain how we created the offset outlines and the files necessary for the actual production of the textile icon samples.

We used a combination of SVG, XSLT, the Inkscape command-line, and Bash scripts to automate the generation of files as much as possible.

We created several assisting scripts. Vector paths were created as SVG files and then placed into a custom XML file. We also created XSLT stylesheets which placed these paths into SVG templates for different hoop sizes. This way, we could flexibly choose which shapes we would like to produce in which variants for each of the "sample squares" individually. This was very useful in the testing phase. Offsets were done using the command-line features of Inkscape, and Bash scripts were used to automate the whole process for the final production. In the end, a few more adjustments needed to be made to create the files that the BERNINA and the lasercutter could actually work with.

The final process consisted of the following steps:

- Given the XML file `icons.xml`, which contained the original 18x18mm SVG paths in a condensed form, all necessary offset paths could be created by calling the script `generate-icon-variants.bash`. These offset paths would be written to the new file `icon-variants.xml`.
- Using this new file and two additional files `conditionsX.xml` (which defines which outline variants constitute which fabrication variant) and `icon-choices.xml` (which defines the shapes that should currently be used), the SVG files to use with the BERNINA and the lasercutter could be assembled by calling the script `generate-conditions3cX.bash`. Due to a technical issue, we had to actually use PNG files of sufficiently high resolution as source for the BERNINA software; this script creates these as well.
- The lasercutter SVG files could be directly imported into Affinity Designer; all objects would be lasercut in the correct order.
- The BERNINA PNG files were imported into the BERNINA software and traced to get back the vector outlines. Then the order of the shapes had to be manually adjusted, before exporting the actual BERNINA files to use with the embroidery machine.

4.4 Producing the Actual Icon Samples

The following steps were taken to fabricate the actual icon samples from the generated files. After creating the files, the process of creating a set of 120 textile icon samples requires about $1-1.5$ work days when done efficiently.

We present the steps to fabricate the icon samples from generated files.

- The fabric was cut into patches of predetermined sizes that were suitable for the background (12 patches) and second layers (8 patches). The background patches were larger as they needed to fit into the embroidery hoop.
- The patches were ironed to make sure that no wrinkles had formed that could impact haptic perception.
- All necessary lasercutter parts were created. To remove fitting aids and insides without losing pieces, we applied adhesive tape to the top of the outermost fitting aids before removing them.
- For each set of 10 icon samples, the following steps were executed:
  1. A background patch was placed into the medium-sized hoop.
  2. For *FlatOutline* and *FlatFill* samples, the corresponding BERNINA file was opened and the shapes were embroidered directly.
  3. Otherwise, the outline of the outermost fitting aid was embroidered onto the background layer. Then, the hoop was removed from the machine and the lasercut fitting aid (still holding all inner parts with in place with adhesive tape) was glued precisely inside the embroidered outline using the four flaps.
  4. After the glue had dried, the adhesive tape was carefully removed. Depending on the variant, the corresponding inner parts were glued onto the background layer within the fitting aid. (Fig. 4.1 left)

5. After the glue had dried once more, the outer fitting aid was carefully removed by breaking off the flaps. If present, inner fitting aids were removed as well. (Fig. 4.1 middle)
6. The hoop was placed back into the embroidery machine, and a patch for the second layer was placed loosely on top of the hoop.
7. The second layer was embroidered using the corresponding BERNINA file. (Fig. 4.1 right)
8. The connected layers, were removed from the hoop. Any loose thread ends were cut, and the individual samples were cut out.
9. In the end, the "loop side" of a hook and loop fastener was applied to the underside of each sample as a preparation for the empirical study.

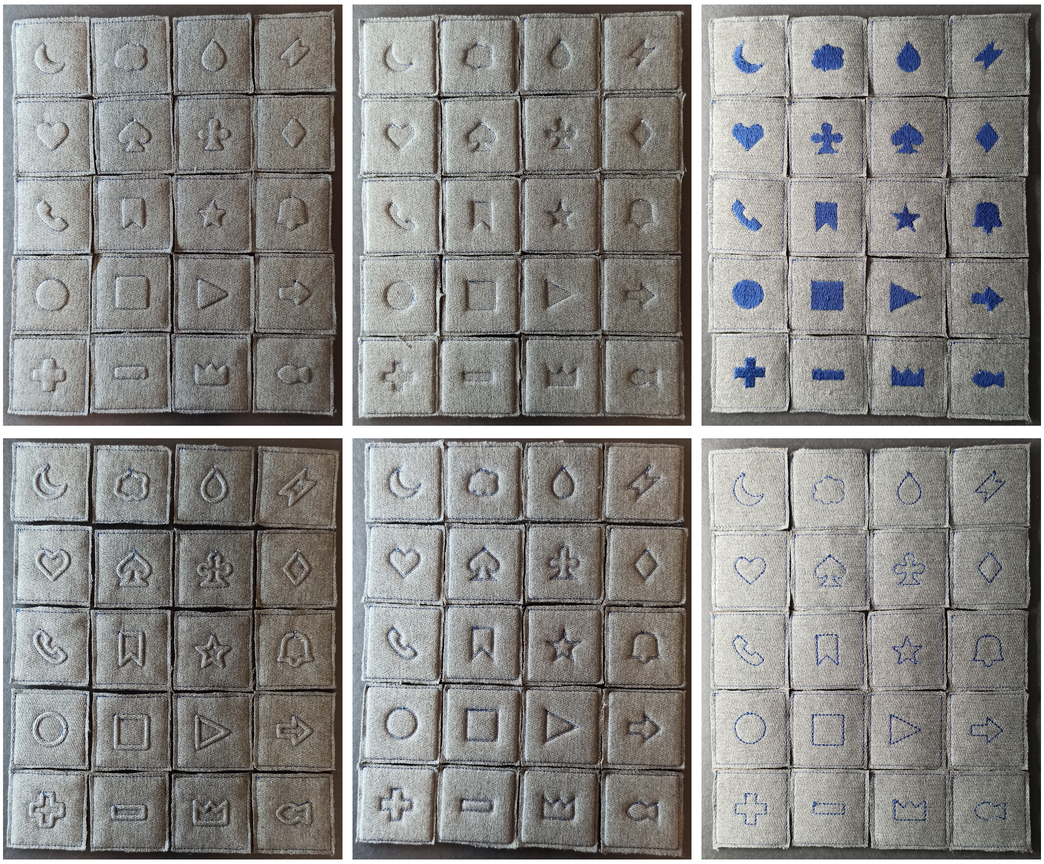


Figure 4.3: The full set of 120 icon samples created with our fabrication process.

Chapter 5

Empirical Study on the Impact of Shape Properties on Haptic Discriminability

We conducted a user study to evaluate the textile icon samples that we created as described in Chapter 4.

We use a combination of experimental and exploratory research.

Our basic research question is how to make textile icons easily distinguishable. Distinguishability depends on both the actual icon designs and the set of shapes that appear on an interface. Due to a lack of existing research on haptic graphical icons for sighted people, we will only be able to formulate few explicit hypotheses backed by literature. This is why we opted for a combination of experimental and exploratory research using both quantitative and qualitative methods. Our study has multiple immediate goals:

1. We hope to find that height difference improves haptic shape discrimination in comparison to embroidered outlines as presented in Mlakar and Haller [2020], and in comparison to filled textured icons.

2. We hope to determine which variants of achieving a height difference—out of the four ways we chose to investigate—work best.

3. We hope to determine which shapes are most easily recognizable, and which shapes are likely to confused with one another—at least for our set of shapes.

4. We hope to get an understanding of which shape properties have the most impact on recognizability for which variants.

5. We hope to get an understanding of the way people explore textile icons haptically without vision.

6. We hope to gain insights on how users perceive the process of interacting with textile icons.

7. We hope to show that height-based variants overall allow for sufficiently reliable, fast, and effortless haptic shape discrimination.

Subsequent goals are the derivation of design guidelines, as well as the development of new hypotheses for confirmatory analysis and follow-up research questions.

5.1 Approaches to Each of the Study Goals

We will calculate four performance measures: the number of times replies were given in time / correctly, and mean response times for replies given in time / correctly.

Our measures for each trial are the shape referred to via the uttered name, as well as the response time. As we explain further below, we had to include a timeout after 30 seconds for each trial to keep the duration of our study procedure in control. As a result, response times are capped at 30 seconds and are missing for trials that ended with a timeout. Thus, we are not able to use individual trial response times, or response times averaged over all trials. Instead, for each participant and variant, we calculate the following four measures: number of in-time responses *(InTime)*, number of correct responses *(Correct)*, response time averaged over all in-time trials *(ResTime)*, and response time averaged over all correct trials *(CorResTime)*. This choice of measures was inspired by the approach for measuring user performance for raised-line drawings chosen by Lebaz et al. [2012].

For (1.)—(2.), we provide the following hypotheses:

We hypothesize that the variant has an effect of all four measures.

- The variant influences *InTime (H1)*.
- The variant influences *Correct (H2)*.
- The variant influences *ResTime (H3)*.
- The variant influences *CorResTime (H4)*.

To allow a clean analysis, we chose to not include further assumptions about which variants work better than others, and instead aimed for a large sample size to increase the statistical power of post-hoc tests.

We compare the results for *InTime* and *Correct*, as well as for *ResTime* and *CorResTime*, to get at least some information on the validity of our chosen measures. When interpreting the results, we focus on the measures *Correct* and *CorResTime*.

To understand which shapes are confusable, we create confusion matrices.

For (3.), we do not calculate similar measures per participant and shape, as performance measures for shapes will be strongly confounded by the chosen set of shapes, and particularly by the number of similar shapes present. As we know little about what makes shapes haptically similar and confusable—in fact, we aim to identify such groups of shapes with this study—we cannot control this confounding variable. Instead, we provide confusion matrices for each variant as well as an overall matrix, and use an algorithm to determine subsets of shapes that are haptically similar and confusable. We also calculate error scores for each shape. We then interpret these results and reason how they might be generalized.

We study how shape metrics correlate with recognizability.

For (4.), we study the influence of three shape metrics—complexity as defined by García et al. [1994] *(Complexity)*, number of convex vertices *(ConvexV)*, and number of concave vertices *(ConcaveV)*—on the error scores for the corresponding shape. We have already characterized our shape set with regards to these metrics in Section 3.5.

We create video recordings of how participants explore icons.

For (5.), we create video recordings of the participants' hands as they explore the textile icons, allowing to analyze

Figure 5.1: The 6 textile icon samples for shape ☾ **Moon**. Top row (from left to right): *RaisedFill, RecessedFill, FlatFill.* Bottom row: *RaisedOutline, RecessedOutline, FlatOutline.*

which exploratory procedures were used by participants with which variants and shapes.

We collect comments and self-reported data from participants.

For (6.), we collect verbal comments made by participants during the study, observations made by the principal investigator, as well as Likert items, easiest and most difficult shapes, rankings, and free-text replies given by participants in two kinds of questionnaires: a post-task questionnaire was given to them after each of the six variants, and a post-test questionnaire was given to them at the end of the study (see Appendix A).

We end with a general discussion.

For (7.), we look for accordances and discrepancies in the results for the prior goals, as we give a general discussion of our findings.

We present the study protocol in the usual order for experimental studies, while Section 5.9 considers each of the seven goals individually.

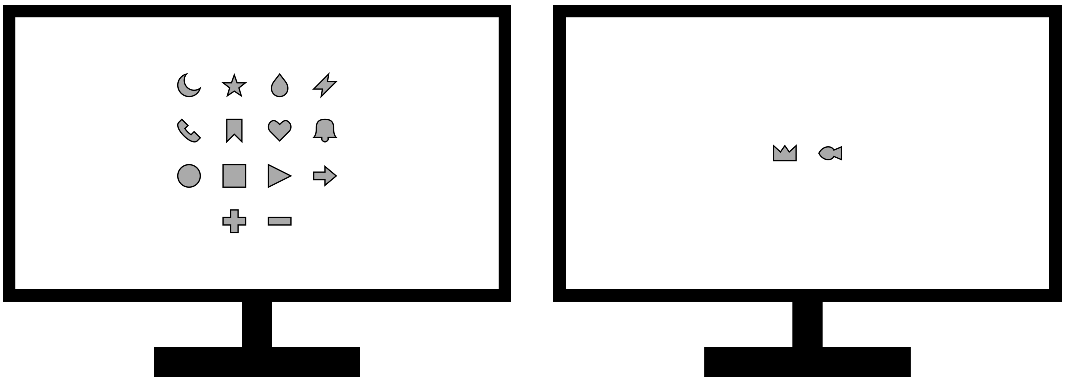


Figure 5.2: Screen image of the 14 possible values of the independent variable *shape*, as it appeared during the study (left); screen image of the 2 test shapes (right).

5.2 Independent Variables

By the nature of a shape recognition study, the independent variables are determined by the samples that are used. In our case, we have two independent variables, with one textile icon sample for each possible combination.

Independent variables are variant and shape.

Each sample used in this study is fabricated via one of the 6 *fabrication variants*, or *variants* for short, that we chose for the fabrication of textile icon samples as described in Section 3.2 (Fig. 5.1).

Each sample used in this study depicts one of 14 *shapes*, which are a subset of the 20 shapes that we chose for the fabrication of textile icon samples as described in Section 3.3 (Fig. 5.2 left). The shapes that were removed altogether are **Cloud**, **Spade**, **Club**, and **Diamond**, whereas **Crown** and **Fish** are not measured, but serve as test shapes instead (Fig. 5.2 right).

We originally considered doing multiple trials per icon sample, such that we could also evaluate experience as an independent variable. However, as we needed to keep our study procedure reasonably short, we could not include this in our study design.

We could not include repetition as independent variable.

5.3 Experimental Design

Combining the two factors results in a 14 *shapes* × 6 *variants* study design. We were able to keep both factors as within-subjects factors, resulting in 84 trials per participant. For (1.)—(2.), we only consider *variant* as a factor, as we sum and average over the shapes, giving a one-factor design.

5.4 Participants

After a pilot phase with two participants, we had to make changes to shorten the study.

The study contained a pilot phase that consisted of an incomplete run with one of the thesis advisors as participant, as well as 2 participants who each completed a full run (1 non-binary, 0 women, 1 man). They were 24 and 26 years old, both right-handed and students, and both rarely pursued design-related activities. One participant often pursued crafting-related activities, while the other never did. Both participants chose German as the language that was easier for them.

These two participants were originally intended to be part of our main convenience sample; however, as they needed 150 and 180 minutes to complete the study, we had to adjust our study design to allow completion within the desired time period of 90 to 120 minutes. Due to these adjustments, they are not included in the final sample.

In the end, 42 persons participated in our study. Demographical data included age, gender and handedness.

Our final convenience sample consists of 42 participants (5 non-binary, 14 women, 22 men, 1 n/a) that were between 18 and 42 years old (M = 24.73 years, SD = 4.48 years). Two participants were much older than the rest (Fig. 5.3). 37 participants self-reported as right-handed, 3 as left-landed, 2 as ambidextrous. Upon questioning, both ambidextrous participants reported that they would draw using their right hand, which is why we treated them like right-handed participants during the study.

32 participants were students and/or student assistants, many of which had a background in computer science or Human-Computer Interaction; 6 participants reported jobs

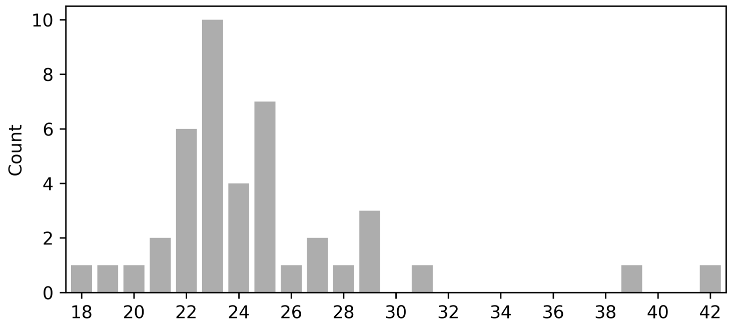


Figure 5.3: Histogram for the demographic variable *Age*.

related to computer science. Remaining self-reports regarding occupation consisted of 1 research assistant, 1 Business Intelligence Consultant, 1 office worker, and 1 currently unemployed participant. 33 participants reported to at least rarely pursue design-related activities (12 of these often), while 31 participants reported to at least rarely pursue crafting-related activities (10 of these often). 34 participants chose German as the language that was easier for them, 8 chose English.

Demographical data also included occupation, frequency of pursuing design- and crafting-related tasks, and prefered language for the study.

While all participants came to our lab for the study, for the last 2 participants (as well as the initial incomplete pilot run) we had to use a different room at the lab. Images of the study setup variants in both rooms and for both right- and left-handed participants can be found in Appendix B.

The study took place in two different rooms.

Altogether, our convenience sample contains 3528 trials: 14 shapes $\times$ 6 variants $\times$ 42 participants.

5.5 Apparatus

As the means required for the fabrication of our icon samples have already been explained in detail, for this section, we assume that the icon samples are already present.

In the following, we first describe the study setup from the participant's view, followed by the conductor's view. We then provide details on specific parts of the apparatus.

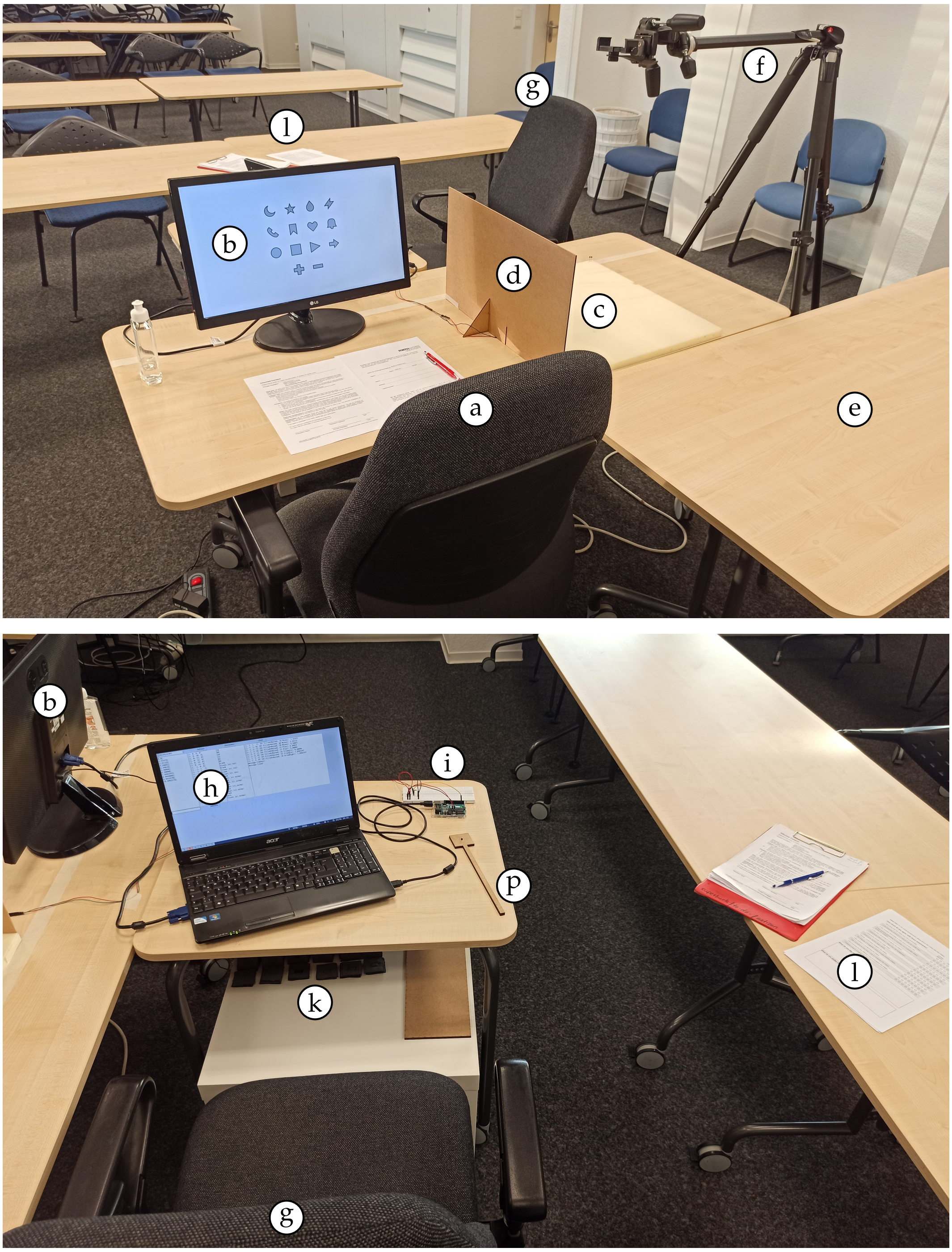


Figure 5.4: Study setup from participant's (top) and conductor's view (bottom). (a) participant's chair, (b) participant's screen, (c) foam layer, (d) visual cover, (e) optional elbow rest, (f) camera stand, (g) conductor's chair, (h) conductor's laptop, (i) Arduino Uno, (k) secret area with prepared icon samples, (l) conductor's notes and questionnaires, (p) paddle. The left-handed setup is mirrored.

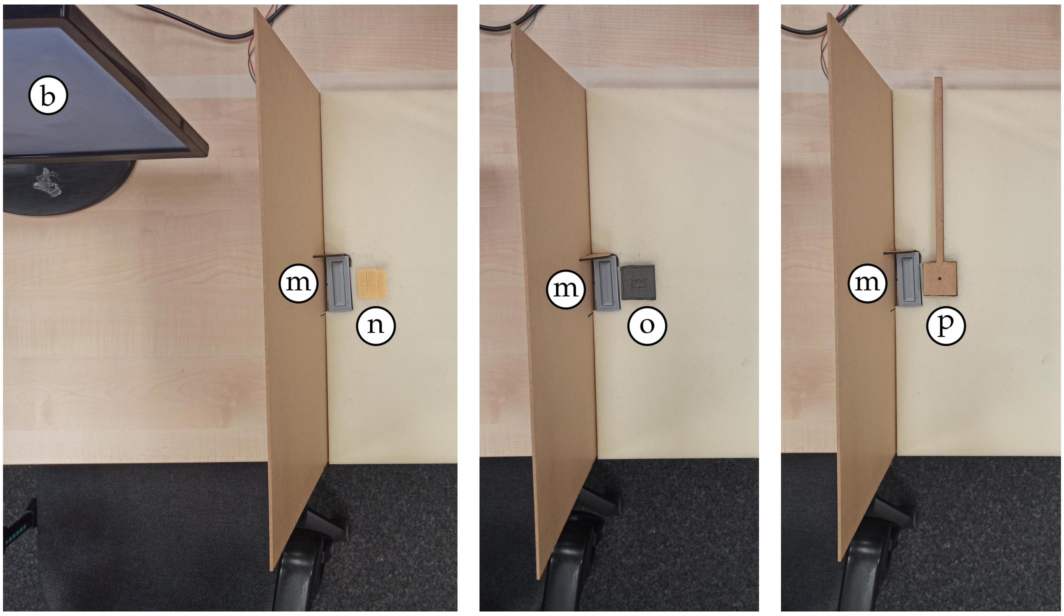


Figure 5.5: The area behind the visual cover. (b) participant's screen, (m) button, (n) icon placement area, (o) textile icon sample, (p) paddle.

5.5.1 Study Setup Overview

Fig. 5.4 gives an overview of the study setup from both perspectives for a right-handed participant. The participant would sit down on a chair (a) in front of a 21-inch Full HD monitor (b) that is placed on a desk at a comfortable viewing distance. To the right, a thick foam layer (c) was taped onto the desk, which serves as a comfortable surface for participants to rest their hand and wrist. We used foam to resemble the feeling of placing the hand on the armrest of a sofa. The layer was wider than needed as we used the same desk-with-foam that was also used by Nowak et al. [2022] for both of their user studies.

The participant was seated in front of a screen.

The leftmost part of the foam layer was hidden from the participant's view using a visual cover (d). We ensured its dimensions were sufficient for all participants. Participants could optionally use a second desk as an elbow rest (e) if this felt more comfortable. A camera stand (f) was placed in such a way that a smartphone could record video of what happened behind the visual cover from a bird's-eye view.

A visual cover blocked their view on the area where icons would be placed.

The conductor was seated digonally opposite to the participant.

The experiment conductor, on the other side, would sit down on a chair diagonally opposite and to the right of the participant (g). While we do assume that this position is more comfortable to the participant than a position directly opposed to or next to them, it is also a necessity for this study: the conductor needs direct access to the area behind the visual cover. The conductor's laptop (h) was placed on a smaller table in front of them, at such an angle that the participant could not see the screen. The laptop ran a software that allowed the conducter to control the steps of the study, to take notes, and to measure a participant's response times via a connected Arduino Uno (i).

The conductor could prepare icon samples on a desk hidden from the participant's view.

Below the conductor's table, an even lower white table provided a secret area (k) for preparing the upcoming icon samples and placing those that had already been used. The whole setup was arranged in such a way that the participant could never see the white table. To the right of the conductor, further tables provided space to place notes and questionnaires (l) without distracting the participant.

Next to the icon sample, a button allowed participants to start and stop the timing.

The area behind the visual cover (Fig. 5.5) held a button (m) to start and stop the response time measurements, and an icon placement area (n) that containted the "hook side" of a hook-and-loop fastener, taped directly on the foam. The corresponding "loop sides" had already been taped to the underside of the icon samples as part of the fabrication process (see Section 4.4). This way, an icon sample (o) could be conveniently fixated on the icon placement area. The paddle (p) could be used by the conductor to hide the icon sample from "haptic view" until the participant pressed the button to start the timing.

5.5.2 Paddle

A paddle was created using lasercutting and a pin.

The paddle was created by lasercutting a 50x50mm square shape with a tiny hole in its center and a long "arm" on one side out of an 1.6mm thick MDF sheet *twice*. We broke a pin apart about 2-3mm below its head, applied glue to its end and to one side of each MDF cutout, glued the cutouts together, pressed the pin into the tiny hole, and let it all dry.

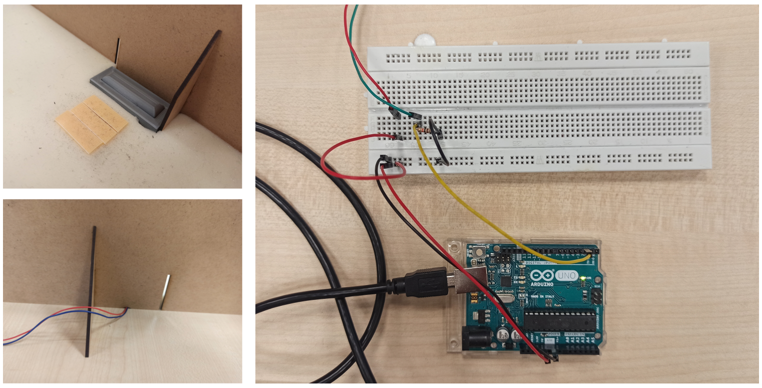


Figure 5.6: Arduino Uno circuitry and button connection.

5.5.3 Button

A push-button of comfortable height was used to allow comfortable switching between icon sample and button.

Pettirsch [2022] created the button (called "homing button" in their work) for a user study. Thankfully, they let us use the button afterwards. It consists of a small electronic DTS61K push-button that is fixated on a wooden foundation. Two 3D-printed parts constitute the outer frame and the depressable button surface. Two wires are soldered to the legs of the small push-button to allow connection with a circuit. We cut out a small part of the foam layer to make just enough room for the button, as visible in Fig. 5.5. When an icon sample is placed next to the button, the button surface is only slightly above the sample; when the paddle is placed on top of the icon sample, the button surface is only slightly below the paddle. This allows comfortable back-and-forth switching between the icon placement area and the button, which is an essential part of the study task.

5.5.4 Arduino Uno

Response times were measured using an Arduino Uno.

The Arduino Uno was used to measure a participant's response times. It connected to the button (Fig. 5.6) using very simple circuitry and code from the Arduino example "State Change Detection for push-buttons"[1], whose code

[1] `https://www.arduino.cc/en/Tutorial/BuiltInExamples/StateChangeDetection` (accessed on August 7, 2022)

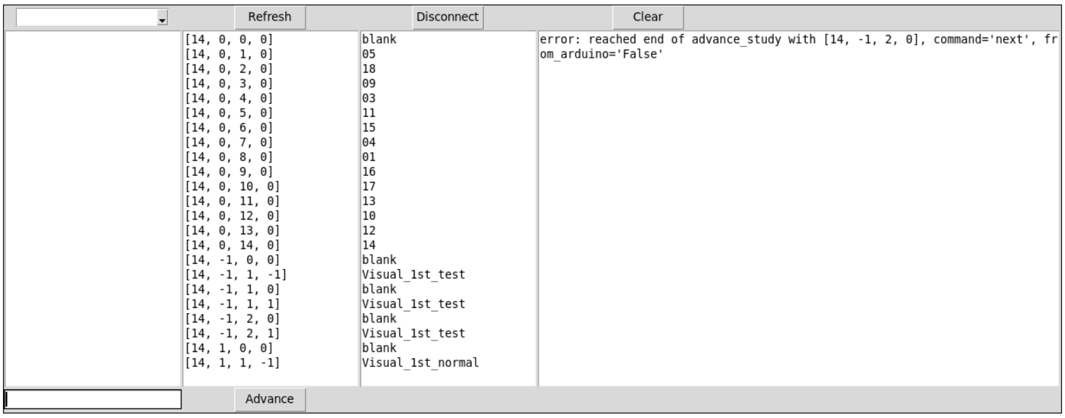


Figure 5.7: Screenshot of the `study-software` application that was running on the conductor's laptop.

is in the public domain, and connected to the conductor's laptop via its USB serial driver. To measure response times, we modified the code to start a timer right after the upload to the Arduino Uno had completed. Thus, every time the button was depressed, it sent the current state of the timer (in milliseconds) together with the state of an increasing counter to the conductor's laptop. After a button press, 500 milliseconds would have to pass before another button press would be accepted. We implemented this to stabilize our setup for cases in which a single button press would generate multiple signals. The rest of the application logic was implemented in the software that ran on the laptop.

study-software-arduino.ino[a]

[a] `https://git.rwth-aachen.de/i10/thesis-lovis-suchmann-textile-icons/-/tree/main/study-software/arduino/study-software-arduino.ino`

5.5.5 Conductor's Laptop

The conductor controled the study using a software on their laptop.

On the conductor's laptop, the `study-software` application was running to control the steps of the study, take notes, and log response time measurements. It is written in Python and uses Tkinter to create a (rather rudimentary) graphical user interface (Fig. 5.7). We built upon some code by Pettirsch [2022] for GUI and serial connection setup.

To control the steps of the study, we chose a state machine software architecture. Each state over the course of the study was represented in the application as a certain 4-tuple of integers (second column from the left). The state representation alone determined which image was shown on the participant's screen (indicated to the conductor by its filename in the third column from the left), whether and how button presses were logged (raw data from the Arduino Uno was displayed in the leftmost column, and the log created by the application was displayed in the rightmost column), and whether a timeout should occur after remaining in the state for 30 seconds.

The software used a state machine architecture.

State changes could be triggered by the participant via button presses, by the software via timeouts, and by the conductor via written commands entered in the bottom left text field, which needed to be confirmed with the Enter key or clicking the "Advance" GUI button. Logs were saved as plain text files on the laptop.

Logs were saved as plain text on the computer.

study-software.py[a]

[a] `https://git.rwth-aachen.de/i10/thesis-lovis-suchmann-textile-icons/-/tree/main/study-software/study-software.py`

5.5.6 Participant's Screen

The participant's screen was connected to the laptop via a VGA cable. Depending on the application state, the screen displayed one of six different kinds of images: the set of 14 possible shapes (Fig. 5.2 left), the set of 2 test shapes (Fig. 5.2 right), a blank white screen, a message that the button worked, a blank black screen, or a single shape (or test shape) at the center of the screen.

The participant's screen showed different sets of icons.

A blank black screen was only shown when a timeout occurred; at the same time, a short jingle was played back from the laptop's loudspeakers to give the participant both visual and auditory feedback.

A black screen and sound cue indicated a timeout.

5.6 Study Procedure

After being greeted, the participant sat down on the participant's chair, facing the participant's screen, which initially was blank white. On the desk in front of the screen, the participant could find an Informed Consent form (see Appendix A), a contact tracing form due to the COVID-19 pandemic, and a pen. They were asked to fill out the contact tracing form first. After that, the conductor explained to them the contents of the Informed Consent form, particularly that snacks and drinks were available (not visible in Fig. 5.4 because they were placed on another desk behind the participant's chair) and that breaks were always possible when needed.

An initial visual recognition task allowed participants to familiarize with the shape set and to define shape names.

After giving informed consent, the participant had to do an initial visual recognition task. On the screen, each of the 16 shapes appeared one after the other (first the 2 test shapes, then the rest in a randomized order). The participant was asked to state what they would intuitively name the respective shape. This visual task served three purposes:

1. It should help the participant to remember the shapes over the rest of the study.
2. It allowed us to verify our assumption that the shapes were visually familiar to the participant.
3. It enabled the participant and the conductor to agree on unambiguous shape names based on the participant's own most familiar shape interpretations.

All shape names that implied a correct recognition of the depicted object were accepted.

The participant was only corrected if they chose a shape name that could also refer to another shape (for instance, "rectangle" could refer to both **Minus** and **Square**) or if their chosen name indicated that they misunderstood the depicted object (for instance, one participant initially believed **Lightning** to depict a "razor blade"). They were not corrected if, for instance, they called **Square** "stop" or **Lightning** "power", as these words are common intended meanings for square and lightning shapes, implying that the participant understood the shape.

Following the visual recognition task, the participant had to do one haptic discrimination task for each of the 6 variants. These are discrimination tasks because the participant had built up at least some knowledge of the existing shapes via the visual recognition task, and was further assisted in remembering them using the screen (as explained below).

Six haptic discrimination tasks followed, one for each variant.

At the beginning of each haptic discrimination task, the participant did a "mini version" of the task using the 2 test shapes as the set of possible shapes. After the participant indicated they were ready, the task proceeded as follows:

Each task started with a "mini version" with 2 test shapes, after which the actual task began.

1. The conductor changed the application state such that an image showing all possible shapes appeared on the participant's screen (Fig. 5.2 right for the "mini version" of the task, left for the actual task).
2. The conductor held the first icon sample to the underside of the paddle and placed them together on the icon placement area (Fig. 5.5 right).
3. The conductor started the video recording.
4. The participant placed their hand on the foam layer (and, optionally, their arm on the elbow rest) such that they could reach both the pin tip of the paddle and the button comfortably.
5. The participant touched the pin tip of the paddle.
6. At a time of their choice, the participant moved their hand to the button and depressed it to start the timing. The participant could verify that the button press was registered by the screen turning blank white. At the same time, the conductor moved away the paddle by pulling it towards them.
7. The participant moved their hand back to the position where the pin tip had been, and started to explore the icon sample.
8. Once they were certain which of the possible shapes it was, the participant pressed the button again (stopping the timing and making the screen image reappear) and then moved their hand away such that they could not further explore the sample.

9. The participant named the shape verbally. They were allowed to take time if they had forgotten the word, and if an ambiguous name was given, the conductor would ask the participant to clarify what they meant. As we used the button presses for response time measurements, they were not impacted by this. The participant was disallowed, however, to search for a suitable shape on the screen after the second button press. No feedback was given if the reply was correct.

8a., 9a. If a timeout occured before the participant finished exploring the shape, the screen turned black and a short jingle was played. The participant could still provide a guess which shape they thought it might be, or reply "I don't know". No feedback was given. The conductor then made the screen image reappear.

10. The conductor removed the sample, held the next one to the underside of the paddle and placed them together on the icon placement area (Fig. 5.5 right).

Steps (5.)—(10.) were then repeated until all samples from the given set and variant had been explored.

To save time, the conductor already held the next sample to the underside of the paddle while the participant explored a sample. When the participant arrived at the last sample, the conductor would still do this with an arbitrary sample to give no indication that the task was nearly complete.

The "mini version" tasks differed slightly from the actual tasks.

Apart from the set of shapes, the "mini version" differed from the actual task in that no video recordings were made and no measurements were logged, and participants were told whether they replied correctly or not. Due to an error in the software, timeouts could still occur during the "mini version", but participants were told to ignore them.

We ensured that the participant understood the variant correctly.

The "mini version" tasks served the purpose of haptically familiarizing the participant with the given variant. (The first such task was also used to explain and practice the task procedure.) After each "mini version", the participant was asked to describe what approach was used to make the shapes haptically perceivable. This was done

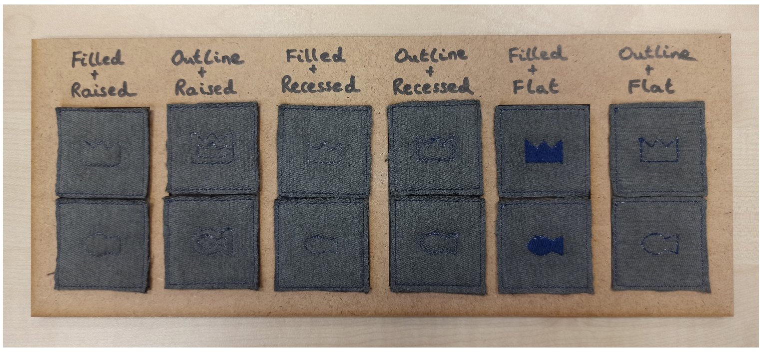


Figure 5.8: The test shapes of all 6 variants as presented to the participant at the end of the study.

to ensure the participant understood that the fill/outline was raised/recessed/embroidered. If a wrong or incomplete description was given, the conductor explained the approach. In both cases, the participant was allowed to further explore test shapes of their choice until they felt confident. Once they indicated this, the conductor started the actual task for the given variant.

The participant was asked to fill out post-task questionnaire after each variant.

After each actual haptic discrimination task was completed, the participant was asked to fill out a post-task questionnaire (Appendix A). During this step, the screen still showed all icons (Fig. 5.2 left). Participants could also give verbal feedback over the whole study, which the conductor logged using a note-taking feature of the laptop application. This feature was also used to log incorrect responses by the participant. The conductor delayed the point of note-taking arbitrarily to give no indication whether a reply was correct.

The participant was asked to fill out a post-test questionnaire at the end of the study.

At the end of the study, the participant was asked to fill out a post-test questionnaire (Appendix A). Here, they should first complete the front before turning the page. For the back of the page, the participant was shown actual icon samples for all variants to get a visual impression. Due to space limitations, only the two test shapes were presented (Fig. 5.8), but the participant was allowed to ask for additional samples. After completing the back and filling out a short demographics questionnaire (Appendix A), the conductor thanked the participant and dismissed them.

		order of variants					
		1	2	3	4	5	6
order of partcipants	1	**A**	**B**	**F**	**C**	**E**	**D**
	2	**B**	**C**	**A**	**D**	**F**	**E**
	3	**C**	**D**	**B**	**E**	**A**	**F**
	4	**D**	**E**	**C**	**F**	**B**	**A**
	5	**E**	**F**	**D**	**A**	**C**	**B**
	6	**F**	**A**	**E**	**B**	**D**	**C**

A	RaisedFill
B	RecessedOutline
C	FlatFill
D	RaisedOutline
E	RecessedFill
F	FlatOutline

Figure 5.9: The Latin Square for counterbalancing *variant*.

5.6.1 Controlling Order Effecs and Mental Load

We ensured that the study time was acceptable and encouraged the participant to take breaks.

We estimated the final procedure to take 90 to 120 minutes, which was deemed acceptable. Although we did not keep track of this precisely, we remember that the fastest participant took about 80 minutes and the slowest one took about 140 minutes to complete the study. Due to the length of the study, we included a mandatory break of at least 3 minutes after the first three variants, and encouraged participants to ask for additional breaks as needed. Slower participants usually also had more and/or longer breaks.

The Latin Square for the variants also helped to reduce frustration.

The order of shapes within a variant was randomized. The order of the 6 variants was counterbalanced using the Latin Square shown in Fig. 5.9. This particular Latin Square was chosen because it is one that puts as much overall distance between *FlatFill* and *FlatOutline*, the variants that we assume to perform worst, as possible. We believe this contributed to reducing frustration levels.

We attempted to simulate the effects of visual and haptic discoverability in our study procedure.

Using visually familiar shapes, showing images of all possible icons, doing "mini version" tasks, and letting participants use their own shape names were steps we took to simulate the effects that visual and haptic discoverability would have over time for a real-world textile interface (see Chapter 1). This way we created as much knowledge in the head as possible, reducing the mental load while still being able to evaluate more than the 7 ± 2 objects that humans can keep in mind at the same time accoding to Miller [1956]. Another step to reduce mental load was that we explicitly asked participants which of the two offered languages (German or English) was easier for them, and conducted the study in that language.

5.7 Changes Compared to Pilot Phase

This study procedure includes a few changes that had to be made in comparison to the pilot phase: Originally, we included 18 shapes (all except test shapes **Crown** and **Fish**) as possible values of the IV *shape*. Besides, we originally did not use timeouts, but gave participants as much time as they felt they needed, while also being allowed to respond "I don't know" at any time. Even so, participants spent a lot of time trying to recognize difficult shapes, often more than a minute, which raised frustration levels. Timeouts shortened the study time and also seemed to cause less frustration. In total, the study time could be reduced from the 150 and 180 minutes taken by the pilot phase participants to a more reasonable 90 to 120 minutes.

We removed four shapes and added timeouts to reduce study time.

Another cause of frustration in the original study procedure was the choice of Latin Square. Originally, by the design of the square, *FlatFill* and *FlatOutline* would always appear one after the other, which ptentially created a long continuous phase of frustration within the study. As we had assumed from the start that these variants would perform worst, this was an oversight on our side. We gladly took the chance to correct this when it became clear that adjusting the study procedure was inevitable.

The pilot phase used a different Latin Square that caused more frustration.

Moreover, we had made sure that for the visual recognition task, the order of shapes was such that **Club** always appeared before **Plus**. This was to avoid that German-speaking participants called the latter "Kreuz" and had to be corrected as this name had to be reserved for **Club** (which has no other alternative shape names). As the final set of icons did not contain **Club**, we could remove this complexity. No other changes were made compared to the pilot study procedure.

We could remove complexity added for the pilot phase to avoid ambiguous naming of shapes.

5.8 Data Preparation

We rounded response times to tenths of seconds. Data was analyzed with Python.

Logs created by the `study-software` application were converted into CSV files using a semi-automated process. Response times were rounded from milliseconds to tenths of seconds to avoid conveying a false impression of precision. We then used JupyterLab[2] to further transform and analyze the data with Python.

5.9 Results

Results will be presented individually for each of the seven study goals introduced at the beginning of the chapter.

5.9.1 Description of Measures *InTime, Correct, ResTime, CorResTime*

We log-transformed response times using base 2.

For *ResTime* and *CorResTime*, we had decided in advance to apply a log transform to the response times of individual trials, as is usual for measures of time. The choice of logarithm base does not matter for such transformations; against convention, we chose base 2 because it gave us a better intuition on what the log-tranformed values meant.

We found that *InTime* and *Correct* were not normally distributed, likely due to a ceiling effect (Fig. 5.10 top). *ResTime* and *CorResTime* were log-normally distributed, which we confirmed using Shapiro-Wilk tests, with approximately equal variances (Fig. 5.10 middle). For comparison, we studied the distributions when calculating *ResTime* and *CorResTime* using non-transformed trial data (Fig. 5.10 bottom). In this case, three Shapiro-Wilk tests indicate non-normality (*ResTime*: *RaisedFill*; *CorResTime*: *RaisedFill, RaisedOutline*) and violin plots clearly show strong variations of variances. We will not inspect the non-transformed measures further in this thesis. Means and standard deviations for all four measures are shown in Table 5.1.

[2] `https://jupyter.org/try-jupyter/lab/`

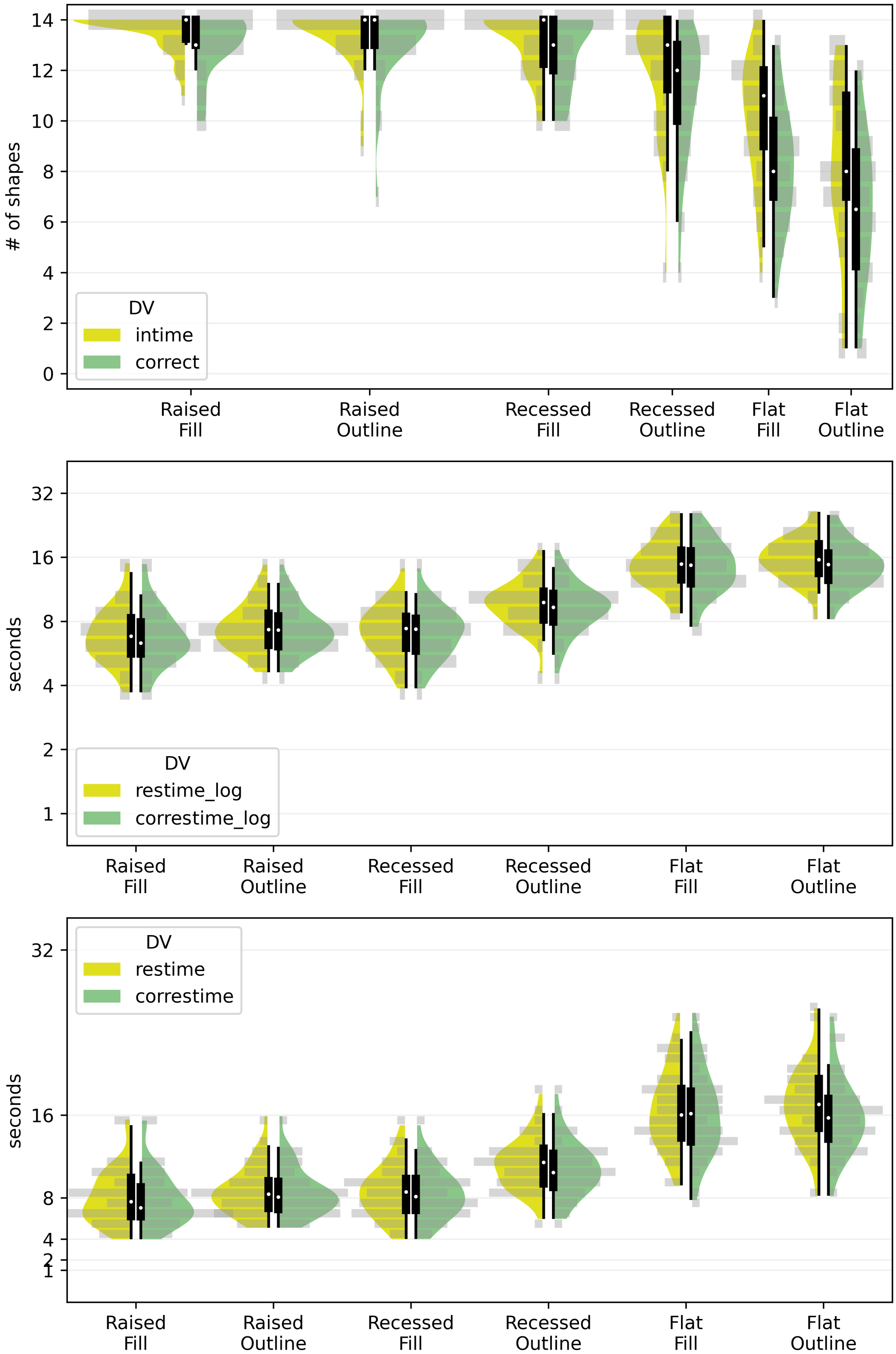


Figure 5.10: Violin plots for *InTime* and *Correct* (top), *ResTime* and *CorResTime* (middle, log-transformed). Black boxplots show medians and the 2.5th, 25th, 75th, and 97.5th percentiles. Yellow and green curves ("violins") show kernel density plots cut off at minimum and maximum values. Transparent overlays are histrograms. Plots for non-transformed *ResTime* and *CorResTime* (bottom) for comparison only.

	InTime		*Correct*		*ResTime*		*CorResTime*	
variant	M	SD	M	SD	M[3]	SD[3]	M[3]	SD[3]
RaisedFill	13.62	$\pm$ 0.73	13.00	$\pm$ 1.21	6.87 s	$\cdot\ 1.35^{\pm1}$	6.76 s	$\cdot\ 1.35^{\pm1}$
RaisedOutline	13.43	$\pm$ 1.09	13.12	$\pm$ 1.42	7.46 s	$\cdot\ 1.30^{\pm1}$	7.36 s	$\cdot\ 1.30^{\pm1}$
RecessedFill	13.19	$\pm$ 1.17	12.69	$\pm$ 1.46	7.19 s	$\cdot\ 1.33^{\pm1}$	7.07 s	$\cdot\ 1.32^{\pm1}$
RecessedOutline	12.14	$\pm$ 2.19	11.10	$\pm$ 2.41	9.69 s	$\cdot\ 1.28^{\pm1}$	9.25 s	$\cdot\ 1.31^{\pm1}$
FlatFill	10.21	$\pm$ 2.48	8.24	$\pm$ 2.37	14.97 s	$\cdot\ 1.29^{\pm1}$	14.48 s	$\cdot\ 1.33^{\pm1}$
FlatOutline	8.57	$\pm$ 3.32	6.50	$\pm$ 2.88	15.65 s	$\cdot\ 1.26^{\pm1}$	14.64 s	$\cdot\ 1.27^{\pm1}$

Table 5.1: Means and standard deviations for *InTime*, *Correct*, *ResTime*, *CorResTime*.

As *InTime* and *Correct* were not normally distributed, we chose non-parametric tests. Friedman tests revealed significant effects of the *variant* on both *InTime* ($\chi^2(5)=137.393$, $p<0.001$) and *Correct* ($\chi^2(5)=153.473$, $p<0.001$). For post-hoc pairwise comparisons, we conducted Wilcoxon Signed-Rank tests with continuity correction. Holm's method was used to counteract the multiple comparisons problem.

ResTime and *CorResTime* were log-normally distributed with equal variances. We conducted one-factor repeated-measures ANOVA, which revealed significant effects of the *variant* on both *ResTime* ($F(5,205)=219.038$, $p<0.001$) and *CorResTime* ($F(5,205)=172.462$, $p<0.001$). For post-hoc pairwise comparisons, we conducted paired-samples t-tests. Holm's method was used to counteract the multiple comparisons problem.

For each of the four measures, Table 5.2 visualizes the significantly different pairs with corresponding significance levels. Overall, we were able to accept all four hypotheses *(H1)*—*(H4)*. For *Correct* and *CorResTime*, we now interpret the results and provide effect sizes.

[3]Due to the log-transformed values, geometric means and standard deviations are presented.

	InTime	*Correct*	*ResTime*	*CorResTime*
variant	Significance	Significance	Significance	Significance
RaisedFill				
RaisedOutline				
RecessedFill				
RecessedOutline				
FlatFill				
FlatOutline				

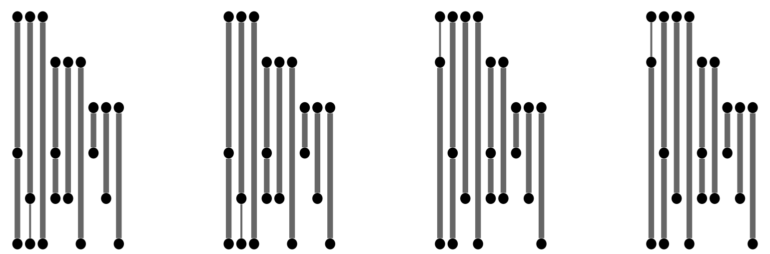


Table 5.2: Significance levels for post-hoc pairwise comparisons for *InTime, Correct, ResTime, CorResTime*. Thick lines indicate p<0.001, thin lines p<0.01. Note that *InTime* and *Correct* have the same graphic, as well as *ResTime* and *CorResTime*.

5.9.2 Interpreting Results for *Correct, CorResTime*

RaisedFill, RaisedOutline, and *RecessedFill* enabled participants to recognize more than 90% of shapes.

In the *RaisedFill, RaisedOutline,* and *RecessedFill* variants, participants could on average recognize more than 90% of the shapes. For *RaisedFill* and *RecessedFill*, every participant recognized at least 10 shapes, while for *RaisedOutline* all but one (who recognized only 7) did. Differences in the number of correctly recognized shapes (*Correct*) were not significant between these three variants. With *RecessedOutline*, significantly less shapes could be recognized compared to all three initially mentioned variants (79% on average). The yarn variants, *FlatFill* and *FlatOutline*, had the worst recognition with less than 60% on average. They were significantly worse than all other variants, with *FlatOutline* also significantly worse than *FlatFill*. We note that for variants with lower recognizability, the variance of *Correct* increases. We think this can be explained by the known large differences in haptic perception capabilities between humans, which would become better noticable with harder tasks.

In these variants, average recognition times were around 7 seconds.

Regarding *CorResTime*, the three best variants were also *RaisedFill, RaisedOutline,* and *RecessedFill*, whose corresponding geometric means were all below 7.5 seconds. Here, however, *RaisedFill* gave significantly better results than *RaisedOutline*, with *RecessedFill* in between the two (and not significantly different compared to any of the two).

	Moon	Star	Drop	Lightning	Phone	Bookmark	Heart	Bell	Circle	Square	Triangle	Arrow	Cross	Minus	/
Moon	**224**	1	2	2	6			1							16
Star	1	**186**		3	1	1		2			1	4	2		51
Drop	3		**205**			2		2	4	1	4		1		30
Lightning		15	1	**176**				1			1	4	5		49
Phone	14			3	**200**		2							1	32
Bookmark		2	1	2	1	**198**		2		6					40
Heart	3			2			**190**	1	1			9	1		45
Bell	2	3		1		13	1	**175**	3	2	3	1			48
Circle	1	1	7				2	9	**198**			1			33
Square										**232**	1	1			18
Triangle				2			2	1			**214**				33
Arrow		7		22		1		3				**142**	5	1	71
Cross	1	30		9		1		4				2	**146**		59
Minus				3	1					1		4		**228**	15

Figure 5.11: Confusion matrix for all variants altogether. Row headers show the actual shape, Column headers show what shape participants believed it to be. The last column denotes how often timeouts occurred with this shape. For instance, **Moon** was recognized correctly in 224 trials, mistaken for **Phone** in 6 trials, and had 16 timeouts. Each row contains 242 trials (6 variants $\times$ 42 participants) Colors indicate sets of potentially confusable shapes.

RecessedOutline was significantly slower than all of these with 9.25 seconds as geometric average. Again, the yarn variants had the worst results, requiring more than 14 seconds on average and thus being significantly slower than all other variants. However, there was no significant difference between the two yarn variants *FlatFill* and *FlatOutline*.

5.9.3 Confusion Matrices and Error Scores

We created confusing matrices and derived sets of confusable shapes.

To understand which shapes easily distinguishable within our set of chosen shapes, we created confusion matrices for individual variants (Appendix C) as well as an overall confusion matrix (Fig. 5.11). We aimed at identifying subsets of our shape set that are potentially confusing. To derive these from the overall confusion matrix, we used the following simple algorithm:

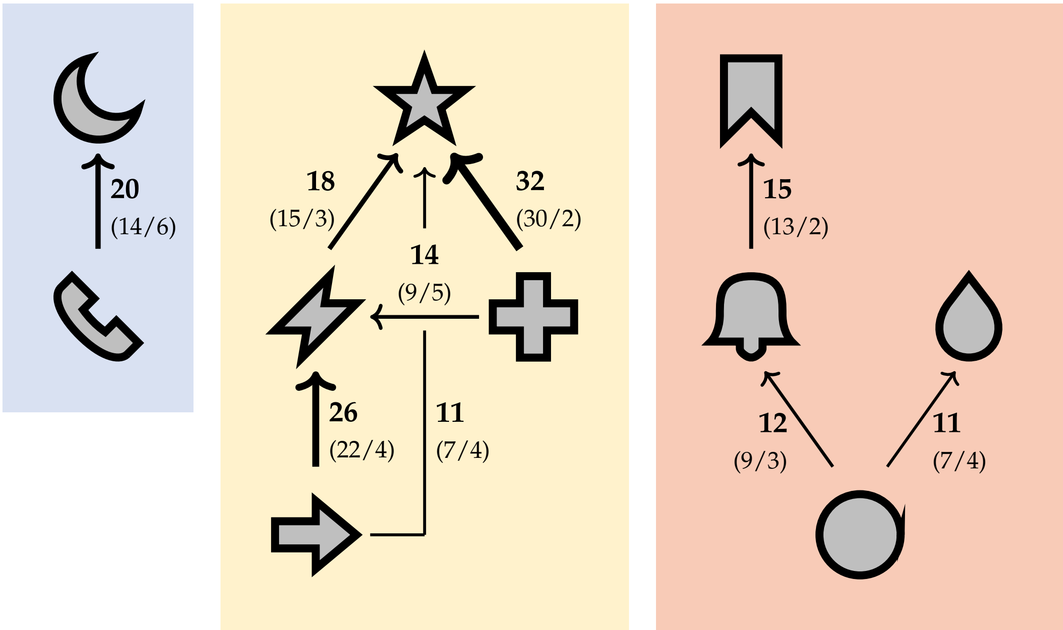


Figure 5.12: Sets of potentially confusable shapes. Edge labels denote the number of trials that one of the two adjacent shapes has been confused for the other; parenthesized numbers are those in the same/opposite diretion as the edge. For instance, **Moon** and **Phone** were confused in 20 trials overall; in 14 trials, **Phone** was mistaken for **Moon**, and in 6 trials, **Moon** was mistaken for **Phone**. Edges are only drawn for shape pairs that were confused in at least 11 trials.

1. For each pair of shapes, we added the values of the two corresponding table cells (representing two directions of confusion).
2. Iterating though the resulting values by size, starting with the largest value, we put the two corresponding shapes in a subset. If one of the shapes already was part of a subset, we added the other shape. If both shapes already were part of subsets, we merged them.
3. This process was terminated once the next value fell below a certain threshold.

The threshold was defined post-hoc via inspecting the confusion matrix: A high threshold results in only few shapes that are identified as confusing, while a low threshold makes most shapes end up in the same subset. We found a threshold of 11 to give the clearest insights (Fig. 5.12), although they will of course be biased by this choice.

We found three sets of confusable shapes. Moon and Phone are visually similar.

The three determined subsets of confusable shapes have very different characteristics. **Moon** and **Phone** from the blue subset have a very similar curved form. Thus, discriminating between the two required that the tips could be recognized as either pointy or rectangular, which might have been difficult. For each of the *RaisedFill*, *RaisedOutline*, *RecessedFill*, and—interestingly—*FlatFill* variants, this confusion happened in only two or less trials, which suggests that this difficulty might be resolvable by using a suiltable variant.

Shapes with high numbers of sharp convex and sharp concave vertices are confusable.

The yellow subset consists of the shapes which have high numbers of both vertices with angles $\leq 90°$ *and* vertices with angles $\geq 270°$. This indicates that participants likely had a hard time to precisely distinguish the arrangment of these shape features, which might have been due to properties of haptic perception like sequentiality and low resolution. Some of these shapes were still confused in 4 or more trials even in the well-performing variants; this suggests that more caution should be exercised when deciding to use textile icons with "pointy shapes" in an interface.

Shapes are confusable if participants draw incorrect conclusions from shape features.

The orange subset contains a more varied assortment of shapes. From our observations when conducting the study, as well as comments made by the participants, we suggest two reasons for these errors: For **Bookmark** and **Bell**, in most cases, participants confused them after they had explored the concave edge of **Bookmark** or one of the two concave edges of **Bell**. They might have regarded this shape feature as a salient one and not consider which other shapes might have a similar feature. For the other two confusable pairs, we assume that participants were able to identify the rough shape as somewhat round, but became confused when looking for detailed shape features. Cases in which they took **Circle** for a more complex shape mostly occured in *FlatOutline* and *FlatFill*, which suggests that the reason might lie in irregularities of the textured outline or fill.

If in doubt, simpler or more familiar shapes might be the preferred choice.

We also notice that most of these confusable pairs have a "preferred direction": For instance, **Plus** was mistaken for **Star** in 30 trials, while **Star** was mistaken for **Plus** in only two trials. Based on the preferred direc-

Metric	Error scores for	Corr. coeff.	Significance
Complexity	*RaisedFill*	0.757	p<0.05
Complexity	*RecessedFill*	0.765	p<0.05
Complexity	*RecessedOutline*	0.749	p<0.05
ConcaveV	Overall	0.806	p<0.01
ConcaveV	*RaisedFill*	0.916	p<0.001
ConcaveV	*RecessedFill*	0.724	p<0.05
ConcaveV	*RecessedOutline*	0.810	p<0.01
ConcaveV	*FlatOutline*	0.810	p<0.01

Table 5.3: Significant results from linear regression tests for shape metrics and error scores.

tions as shown in Fig. 5.12, this might indicate that when in doubt, participants would rather assume the simpler or more familiar shape (except for confusions due to haptic irregularities).

In additon to the confusion matrices, for each shape we calculated what we call *error scores*: The error score of an individual shape is the sum of the number of trials it was mistaken for a different shape, the number of trials a different shape was mistaken for it, and the number of timeout trials for the shape. We calculated both overall error scores and scores per individual variant. Rankings of the shapes based on these error scores can be found in Table 5.4.

We ranked shapes based on how often they were confused with other shapes.

5.9.4 Effect of Shape Metrics on Error Scores

To find out whether our three shape metrics influence the error scores, we did linear regression tests for all combinations of metric (*Complexity, ConvexV, ConcaveV*) and error scores (both overall and for individual variants). Holm's method was used to counteract the multiple comparisons problem. Combinations for which significant correlations were found are listed in Table 5.4.

Overall	Individual variants					
	RaisedFill	*RaisedOutline*	*RecessedFill*	*RecessedOutline*	*FlatFill*	*FlatOutline*
26 (9/2/15)	**0** (0/0/0)	**0** (0/0/0)	**0** (0/0/0)	**1** (0/0/1)	**3** (1/0/2)	**9** (0/4/5)
30 (2/10/18)	**0** (0/0/0)	**0** (0/0/0)	**0** (0/0/0)	**3** (0/1/2)	**7** (1/4/2)	**14** (2/4/8)
48 (5/10/33)	**1** (0/0/1)	**1** (0/1/0)	**0** (0/0/0)	**3** (0/1/2)	**8** (1/2/5)	**19** (5/2/12)
53 (12/25/16)	**1** (0/1/0)	**1** (1/0/0)	**1** (0/1/0)	**5** (2/3/0)	**17** (2/4/11)	**23** (4/5/14)
58 (17/11/30)	**1** (0/1/0)	**2** (0/2/0)	**1** (0/0/1)	**6** (0/1/5)	**20** (11/4/5)	**24** (10/2/12)
61 (20/9/32)	**2** (2/0/0)	**2** (2/0/0)	**1** (0/0/1)	**6** (1/0/5)	**23** (9/1/13)	**25** (2/8/15)
62 (21/8/33)	**4** (0/3/1)	**3** (0/2/1)	**2** (2/0/0)	**6** (2/2/2)	**26** (10/3/13)	**29** (7/4/18)
69 (17/7/45)	**4** (3/0/1)	**3** (0/1/2)	**3** (0/1/2)	**11** (2/8/1)	**27** (3/14/10)	**29** (9/9/11)
72 (14/18/40)	**5** (0/5/0)	**3** (0/1/2)	**3** (1/0/2)	**11** (4/0/7)	**28** (3/15/10)	**30** (5/3/22)
103 (29/26/48)	**7** (5/0/2)	**3** (0/0/3)	**3** (1/0/2)	**15** (7/3/5)	**30** (9/0/21)	**35** (8/7/20)
120 (47/14/59)	**8** (3/0/5)	**4** (2/0/2)	**12** (2/7/3)	**22** (10/1/11)	**30** (3/4/23)	**36** (9/14/13)
125 (15/59/51)	**10** (3/3/4)	**7** (0/4/3)	**15** (5/1/9)	**25** (3/12/10)	**32** (9/7/16)	**43** (7/10/26)
125 (27/49/49)	**11** (10/0/1)	**8** (4/0/4)	**16** (4/5/7)	**26** (6/8/12)	**35** (9/13/13)	**43** (8/4/31)
136 (39/26/71)	**14** (0/13/1)	**13** (4/2/7)	**19** (6/6/7)	**26** (7/4/15)	**39** (12/12/15)	**44** (11/11/22)

Table 5.4: Rankings of our shape set based on overall and variant-specific error scores. The parenthesized numbers are: the number of trials this shape was mistaken for another shape (left), the number of trials another shape was mistaken for this shape (middle), and the number of timeout trials for this shape (right).

The number of convex vertices was never found to significantly correlate with error scores. Regarding the number of concave vertices, *RaisedFill* correlated the strongest. As this was also one of the best performing variants, this might indicate that there are few other reasons for errors left, other than a difficulty of haptically understanding shapes with many concave vertices. Interestingly, there was no significant correlation for *RaisedOutline*, although this variant also was one of the best performing variants. This might indicate that raised outlines make it easier to understand concave vertices than a raised fill.

Concave vertices might increase the difficulty of recognition. Raised outlines might reduce this difficulty.

RecessedFill was the only variant that had a higher correlation coefficient with *Complexity* than with *ConcaveV*. This might indicate that in this variant, the concave vertices had a lesser part in making shapes difficult to recognize. This would make sense considering that concave edges in *RecessedFill* feel like convex edges in *RaisedFill* and thus are easier to detect.

The correlation is not as strong for recessed fills, likely because they make concave vertices easier to recognize.

5.9.5 Haptic Exploration of Textile Icons

We provide video recordings of 98% of all trials. 2% of all trials (73 out of $6 \times 14 \times 42 = 3528$ trials) were not recorded due to technical issues. For reasons of data protection, the recordings only include video, but no sound. The recordings are only made available to researchers of the Chair.

We provide a large corpus of video recordings.

By inspecting the videos, we can confirm that participants indeed used different exploratory procedures, like contour tracing, lateral movement, pressure, and—for *RaisedFill*—enclosure. Enclosure, in this case, meant that participants applied sideways pressure from the outside with multiple fingers, as it was not possible to hold the full shape in the hand.

Participants did use multiple exploratory procedures.

We recommend that future research should include a detailed video analysis to understand even better with which variants and shapes people would use which exploratory procedures.

A detailed analysis should be conducted as future research.

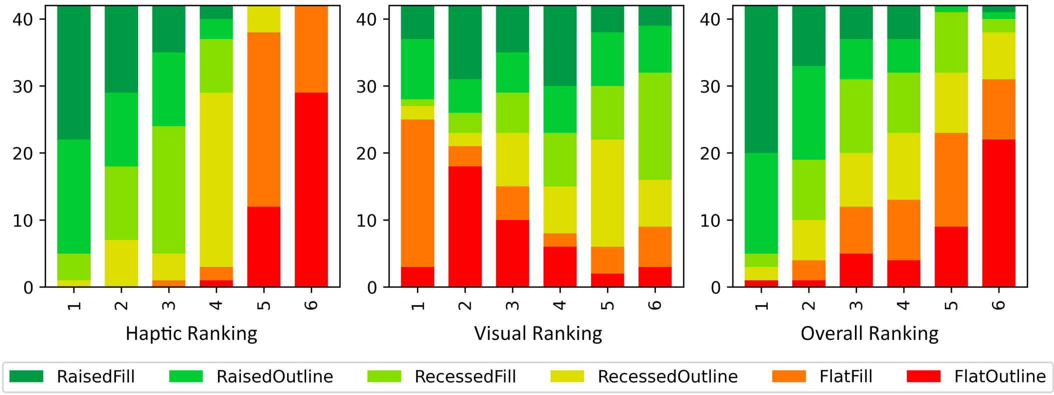


Figure 5.13: Results for the three rankings we obtained from participants.

5.9.6 Participant Ratings

We provide analyses for rankings, Likert items, and self-reported easiest and most difficult shapes. Observations by the study conductor as well as verbal comments and replies to the free-text questions by all participants are available for future analysis.

Rankings

We collected three rankings of variants from participants: one for their haptic experience over the study, one for the visual appeal they attributed to the variants, and one overall ranking. The visual and overall rankings were obtained at the end of the study, after participants were allowed to see and interact with the test shapes (Fig. 5.8) and, upon request, other textile samples. For the overall ranking, participants were told that they did not have to give a ranking that lied between the other two, but should rank based on their individual preference. Results are shown in Fig. 5.13.

Haptically, raised variants were favored.

Haptically, nearly half of the participants gave each of *RaisedFill* and *RaisedOutline* the rank 1, the few remaining participants prefering recessed variants. Raised variants occured only on ranks 1 to 4, with decreasing rate as ranks increase, but always almost equally partitioned. In contrast to this, flat variants nearly exclusively occured on ranks 5 and 6, with only 4 instances of a flat variant on ranks 3 or 4. *FlatOutline* received rank 6 more often than *FlatFill*. The recessed were more prominent in the middle ranks, with a larger portion of *RecessedOutline* on rank 4.

Visually, participants show a different and less clear trend. More than half of the participants ranked *FlatFill* on rank 1 or 2, with about half the participants choosing rank 1; nearly half of the participants ranked *FlatOutline* on rank 1 or 2, with most of these choosing rank 2. Most rankings for flat variants have ranks 1 to 4, but also most rankings for *RaisedFill* do. While *RaisedOutline* is spread out almost equally over the ranks, recessed variants mostly occur on ranks 3 to 6.

Visually, flat variants were favored, followed by *RaisedFill*.

In the overall ranking, tendencies are still similar to the haptic ranking, although they are not as strong. Still, about half of the participants gave each of *RaisedFill* and *RaisedOutline* the rank 1. Flat variants were ranked better than in the haptic ranking, but were still mostly given ranks 3 to 6. Apart from flat variants, nearly all other attributions to ranks 5 and 6 are for recessed variants. While haptically, *RecessedOutline* mostly was placed on rank 4 while *RecessedFill* was ranked better, in the overall ranking, there are relatively equally distributed.

Overall, raised variants were still favored.

The high placement of flat variants in the visual ranking is likely due to the more prominent use of yarn, and thus, of color. This indicates it might be feasible to investigate variants that combine a raised fill or outline with a coloring of the raised parts.

Visual preference of flat variants is likely due to the use of color.

Likert Items

We collected 14 seven-point Likert items from participants for each variant. We are aware of the ongoing dispute on whether data collected from Likert items should be treated as ordinal or interval data. For this thesis, we treat them as interval data. Our data was not normally distributed, thus we chose non-parametric tests. Friedman tests revealed sig-

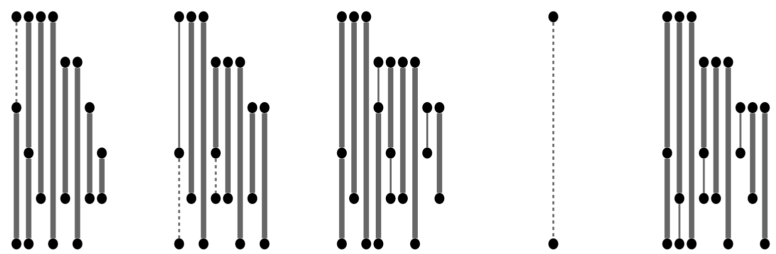
	Comfort		*PDemand*		*MDemand*		*MRememb*		*TDemand*	
variant	M	SD	M	SD	M	SD	M	SD	M	SD
RaisedFill	6.19	±0.77	1.93	±0.89	2.90	±1.46	3.36	±1.59	2.60	±1.34
RaisedOutline	5.81	±0.99	1.96	±0.91	2.95	±1.71	3.48	±1.88	2.90	±1.61
RecessedFill	5.62	±1.23	2.33	±1.20	3.67	±1.59	3.64	±1.86	3.24	±1.59
RecessedOutline	5.07	±1.47	2.88	±1.58	5.05	±1.19	3.90	±1.78	4.71	±1.44
FlatFill	3.64	±1.74	3.74	±2.04	6.05	±1.03	4.33	±1.71	6.05	±1.06
FlatOutline	3.33	±1.66	3.74	±1.95	6.33	±0.75	4.43	±1.81	6.64	±1.66

	SBackgr		*SRough*		*SDetail*		*SOverall*		*DiffVar*	
variant	M	SD	M	SD	M	SD	M	SD	M	SD
RaisedFill	6.60	±0.86	6.43	±0.83	5.24	±1.30	5.83	±1.12	3.83	±1.90
RaisedOutline	6.43	±0.97	5.81	±1.17	5.26	±1.50	5.45	±1.35	3.71	±1.74
RecessedFill	6.12	±1.38	5.95	±1.32	4.26	±1.69	5.02	±1.54	4.86	±1.68
RecessedOutline	4.50	±1.92	4.76	±1.68	3.26	±1.48	3.98	±1.39	5.36	±1.19
FlatFill	2.93	±1.72	2.93	±1.39	1.98	±1.33	2.21	±1.14	4.19	±1.64
FlatOutline	1.90	±1.34	2.21	±1.14	1.62	±0.91	1.62	±0.85	3.38	±1.55

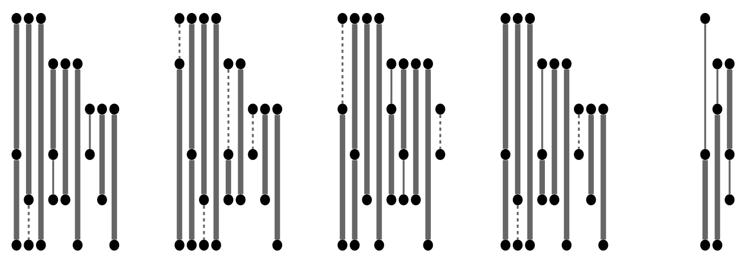
	Confidence		*TFrust*		*MFrust*		*Enjoyment*	
variant	M	SD	M	SD	M	SD	M	SD
RaisedFill	5.69	±1.16	1.88	±0.97	1.76	±0.96	5.93	±0.95
RaisedOutline	5.74	±1.21	2.02	±1.44	2.07	±1.49	5.52	±1.09
RecessedFill	5.17	±1.43	2.36	±1.43	2.67	±1.65	5.55	±1.27
RecessedOutline	3.81	±1.50	3.64	±1.65	3.79	±1.70	4.55	±1.64
FlatFill	2.33	±1.26	4.83	±1.75	5.14	±1.83	3.40	±1.67
FlatOutline	1.60	±0.73	5.14	±1.72	5.45	±1.48	3.33	±1.71

Table 5.5: Means and standard deviations for the 14 Likert items on the post-task questionnaires.

	Comfort	*PDemand*	*MDemand*	*MRememb*	*TDemand*
variant	Significance	Significance	Significance	Significance	Significance
RaisedFill					
RaisedOutline					
RecessedFill					
RecessedOutline					
FlatFill					
FlatOutline					



	SBackgr	*SRough*	*SDetail*	*SOverall*	*DiffVar*
variant	Significance	Significance	Significance	Significance	Significance
RaisedFill					
RaisedOutline					
RecessedFill					
RecessedOutline					
FlatFill					
FlatOutline					



	Confidence	*TFrust*	*MFrust*	*Enjoyment*
variant	Significance	Significance	Significance	Significance
RaisedFill				
RaisedOutline				
RecessedFill				
RecessedOutline				
FlatFill				
FlatOutline				

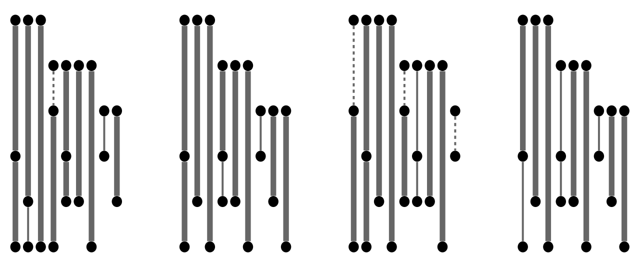


Table 5.6: Significance levels for post-hoc pairwise comparisons for the 14 Likert items. Thick lines indicate p<0.001, thin lines p<0.01, and dashed lines p<0.05.

nificant effects of the *variant* on each of the 14 items ($p<0.05$ for *MRememb*, $p<0.001$ for all other items). For post-hoc pairwise comparisons, we conducted Wilcoxon Signed-Rank tests with continuity correction. Holm's method was used to counteract the multiple comparisons problem.

Table 5.5 shows means and standard deviations for the 14 Likert items. Table 5.6 visualizes the significantly different pairs with corresponding significance levels. The items are listed in the same order as they appear on the post-task questionnaire (Appendix A).

For most items, *RaisedFill*, *RaisedOutline*, and *RecessedFill* received better ratings.

For most items, there was a clear trend of *RaisedFill*, *RaisedOutline*, and *RecessedFill* having significantly better (higher or lower, depending on the phrasing of the question) results than the other variants, with *RecessedOutline* significantly better than *FlatFill* and *FlatOutline*, and *FlatFill* in turn significantly better than *FlatOutline*. In the following, we refer to these variants as the "top three" and "bottom three" variants, respectively. The two largest exceptions to this are *MRememb*, the perceived mental effort required to remember the 14 possible shapes, which was only significantly better for *RaisedFill* compared to *FlatOutline*, and *DiffVar*, the perceived amount of variation in the difficulty of shapes, which was highest for *RecessedOutline* and significantly higher than all raised and flat variants. For other items, the set significant pairs might also differ slightly, but in no other cases there was a significant difference in a direction that goes against our initial statement.

Flat variants had especially low confidence and high frustration levels.

Comfort and *Enjoyment* levels were high for the top three variants and medium for the bottom three variants. *Confidence* had a larger range with about 5.7 on average for raised variants and only 1.6 on average for *FlatOutline*. Both frustration-related items behaved similar to *Confidence* but in the oppposite direction, with about 1.8 on average for *RaisedFill* and an average above 5 for *FlatOutline*.

Mental and temporal demand were higher than physical demand

Both mental and temporal demand were rated higher than physical demand: *MDemand* had an average of 2.9 for *RaisedFill* and one of 6.3 for *FlatOutline*, with similar values for *TDemand* (2.6 and 6.6). Means for *PDemand* ranged only between 1.9 for *RaisedFill* and 3.7 for *FlatOutline*.

Participants reported shape details as harder to recognize than the rough shape: Means for *SRough* ranged from 6.4 to 2.2, while means for *SDetail* ranged from 5.3 to 1.6. *SOverall* lies between the two for all variants. Recognizing the background had a larger range compared to the other three items: Means for *SBackgr* ranged from 6.6 to 1.9.

The rough shape was easier to identify than shape details.

Easiest and Most Difficult Shapes

For each variant, participant could specify up to 3 easiest and up to 3 most difficult shapes. On the post-test questionnaire, participants could specify the same for all variants altogether. In the post-task case, participants were also allowed to instead specify combinations of variant and shape that they considered most easy or difficult overall. Only one participant did this for one difficult combination: ☆ **Star** in the *RecessedFill* variant. We removed this data point for the following analysis.

For each of the seven cases (6 variants and overall), we calculated the number of times each shape was mentioned as especially easy or difficult, and subtracted the number of difficult mentions from the number of easy mentions. Based on the resulting values, we created another set of shape rankings that is shown in Table 5.7. We also included the ranking that resulted from summing up the values for individual variants for each shape.

5.9.7 Overall Discussion

The performance measures (*Correct* and *CorResTime*), haptic and overall rankings, and Likert items all largely agree that *RaisedFill*, *RaisedOutline* and *RecessedFill* are the preferable variants, while *FlatFill* and *FlatOutline* are the least preferable. Performance measures for *RecessedOutline* are worse than for the other height-based variants, but the differences are smaller than when comparing *RecessedOutline* with flat variants. Recognition rates of more than 90% for the top three variants suggest it is indeed viable to use these variants in textile interfaces. Even so, the mean response times

RaisedFill, *RaisedOutline*, and *RecessedFill* gave best results overall, followed by *RecessedOutline*.

Overall	Sum	Individual variants					
		RaisedFill	*RaisedOutline*	*RecessedFill*	*RecessedOutline*	*FlatFill*	*FlatOutline*
■ **30** (30/0)	■ **127** (135/8)	☾ **17** (20/3)	■ **20** (22/2)	● **29** (31/2)	■ **24** (25/1)	● **24** (24/0)	■ **30** (30/0)
● **29** (29/0)	● **104** (113/9)	▬ **13** (15/2)	● **14** (18/4)	■ **20** (22/2)	● **8** (10/2)	■ **23** (23/0)	● **25** (25/0)
▶ **17** (19/2)	▬ **64** (69/5)	■ **10** (13/3)	☾ **11** (14/3)	▬ **10** (12/2)	▶ **8** (9/1)	▬ **15** (15/0)	▶ **17** (18/1)
▬ **16** (16/0)	▶ **51** (60/9)	● **4** (5/1)	♡ **10** (12/2)	💧 **4** (7/3)	▬ **3** (3/0)	▶ **13** (14/1)	▬ **14** (14/0)
☾ **6** (10/4)	☾ **26** (54/28)	💧 **3** (5/2)	▶ **10** (10/0)	▶ **3** (7/4)	💧 **3** (6/3)	💧 **7** (7/0)	♡ **5** (6/1)
♡ **2** (5/3)	💧 **21** (37/16)	✚ **1** (5/4)	▬ **9** (10/1)	🔖 **2** (5/3)	🔖 **1** (3/2)	♡ **5** (7/2)	💧 **1** (6/5)
💧 **2** (5/3)	♡ **16** (30/14)	▶ **0** (2/2)	🔖 **3** (6/3)	☾ **1** (5/4)	☾ **0** (3/3)	☾ **1** (7/6)	🔖 **-3** (2/5)
✚ **-2** (1/3)	🔖 **-3** (22/25)	☆ **-1** (7/8)	💧 **3** (6/3)	♡ **0** (3/3)	♡ **-1** (1/2)	🔖 **-1** (6/7)	✚ **-3** (2/5)
🔖 **-3** (1/4)	✚ **-24** (18/42)	⇨ **-3** (3/6)	✚ **-3** (6/9)	✆ **-3** (4/7)	✆ **-2** (2/4)	⇨ **-8** (1/9)	☾ **-4** (5/9)
🔔 **-11** (0/11)	✆ **-43** (15/58)	♡ **-3** (1/4)	⇨ **-6** (0/6)	✚ **-5** (3/8)	✚ **-5** (0/5)	🔔 **-9** (1/10)	🔔 **-6** (1/7)
✆ **-11** (4/15)	⇨ **-45** (4/49)	✆ **-3** (4/7)	☆ **-7** (7/14)	🔔 **-8** (3/11)	⇨ **-6** (0/6)	✚ **-9** (2/11)	⇨ **-10** (0/10)
☆ **-13** (1/14)	🔔 **-47** (9/56)	🔖 **-5** (0/5)	🔔 **-8** (0/8)	⇨ **-12** (0/12)	🔔 **-7** (2/9)	✆ **-13** (0/13)	✆ **-14** (2/16)
⇨ **-21** (0/21)	☆ **-65** (20/85)	⚡ **-7** (3/10)	✆ **-8** (3/11)	☆ **-17** (3/20)	☆ **-10** (2/12)	☆ **-14** (0/14)	☆ **-16** (1/17)
⚡ **-31** (0/31)	⚡ **-90** (5/95)	🔔 **-9** (2/11)	⚡ **-15** (1/16)	⚡ **-20** (1/21)	⚡ **-11** (0/11)	⚡ **-20** (0/20)	⚡ **-17** (0/17)

Table 5.7: Rankings of our shape set based on participants' judgements which shapes they consider especially easy or difficult.. The parenthesized numbers are the number of times the shape was mentioned as one of the easiest (left) or one of the most difficult (right). Shapes are ranked based on the difference of these two numbers. The "Sum" column considers the sum of the statements for the individual variants from the post-task questionnaire, while the "Overall" column considers the statements from the post-test questionnaire.

for correctly recognized shapes are still quite high for the top three variants, namely around 7 seconds, meaning this recognition does not happen "at a glance", as it would in the visual modality. Mean participant ratings for mental effort are also rather high even for the top three variants, with 2.9 for *RaisedFill* as the best mean value for a seven-point Likert item. Further work is required to understand whether these results qualify the top three variants for secondary tasks as envisioned in Chapter 1.

Participants prefered *RaisedFill*, followed by *RaisedOutline*, followed by *RecessedFill*.

Out of the top three variants, participants prefered *RaisedFill* over *RaisedOutline* and *RaisedOutline* over *RecessedFill*, which is also reflected in those Likert items that show any significance differences within the top three variants at all. This slightly deviates from results for *CorResTime*, which places *RecessedFill* between *RaisedFill* and *RecessedOutline*, while only the difference between *RaisedFill* and *RecessedOutline* is significant (in favor of *RaisedFill*). However, this difference should be interpreted with caution: by the nature of the measure, *CorResTime* "depends" on *Correct*, which gave *RaisedOutline* the best result (albeit not significantly better than the other two) and thus more trials contributed to calculating the value of *CorResTime* for *RaisedOutline*.

Simpler shapes were easier to recognize, while shapes with a high number of sharp convex and sharp concave vertices are especially confusable.

In all variants, simpler shapes had better results both regarding error scores (how often a shape was actually confused with others) and participants' judgements of easiest and most difficult shapes. One subset of shapes that were often confused with each other consisted of precisely those shapes that had a large number of sharp convex and sharp concave vertices. It is possible that complex shapes are still generally suitable for textile interfaces if the number of shapes with this property is restricted.

5.10 Limitations of the Study

There are several limitations of the way this study was conducted that might impede the ability to transfer its findings to the general population and real-life scenarios:

- Nearly all participants in our convenience sample were students or people affiliated with the field of computer science. Nearly all of our participants were in their twenties. Thus, it is very much possible that other parts of the population perform very differently.
- The study setting was very artificial. We could neither provide a real living room setting nor a proper textile interface with multiple elements. Thus, it is not clear how well our textile icons would still perform in such an environment.

There were also some minor issues during the study conduction that we believe do not influence the ability to transfer our findings:

- When placing samples on the icon placement area, their rotational alignments would slightly differ, due to natural imprecisions in the act of placing. We believe that this does not impact our results as this happend without any pattern. Also we did not control the exact hand and arm positions of participants, which will in themselves create slight differences in the perceived rotational alignments.
- Due to our way of cutting the fabric when creating the icon samples, the very fine pattern on the fabric was not oriented in the same direction for all samples. Similarly, due to the way the step fill embroidery pattern worked for the *FlatFill* variant, orientations of the individual yarn threads would change. A few participants actually noticed and communicated this. We should avoid this for the background fabric in the future, but are are convinced that the step fill was still the best option available.
- Participants used different strategies to switch between the icon sample and the button. Some would move their index finger back and forth, some would rest their thumb on the button and index or middle finger on the icon or paddle, some used even different strategies. We chose to not predefine the way of movement as we believed this might prime participants to explore shapes only using their index fingers.

The strategies had no relevant effect on the time people needed to switch between the sample and the button. However, we had to adjust one piece of our experiment protocol due to this observation: Originally we defined that trials should be repeated if participants touched the paddle in any way after the first button press. When using the thumb for the button press, participants sometimes still touched the pin tip on paddle with their index finger as they pressed the button. In nearly all such cases, the paddle could still be moved away without the participants touching any other parts of the paddle. In such cases, we decided to not repeat trials.

- With two participants, we could clearly see that they misunderstood the orientation of the Likert items on one questionnaire. We reached out to these participants right after the study and were able to correct this data. One of these participants also had made an error in one of the rankings, which they were able to correct confidently. A few participants provided ambiguous names like "rectangle" as easy or difficult shapes; they were also able to correct their data.
- In a few cases, participants looked at one of the test shapes although having been told not to do so. We only strictly prohibited looking at test shapes after the end of the "mini version" of the task because we did not want their post-test haptic rankings to be influenced by their visual impressions. If this happened, it did only once for the very first variant, thus we assumed that its influence on the ranking was marginal and took no further action except emphasizing once more that they should not look at the shapes. This never happened for non-test shapes.

Chapter 6

Guidelines for Textile Icon Design

We use the findings from our study to provide six initial guidelines for the design and usage of textile icons on textile interfaces. We assume that a process similar to ours is used for the fabrication of variants with height differences.

01. Prefer a height difference over embroidering shapes with yarn.

Our results have clearly shown that icon samples of all variants that use a height difference perform better and are rated better than yarn-based variants.

02. Prefer raised fills over raised outlines, raised outlines over recessed fills, and recessed fills over recessed outlines. Recessed outlines should be used very sparingly.

While performance measures can be considered equal for the first three variants, participants' rankings and Likert item ratings indicate that preferences are ordered in this way. Recessed outlines also perform worse, but we imagine they could be useful to show that one icon has a different kind of purpose on the interface or (if used as a button) should be triggered with caution, similar to some buttons on remote controls.

03. Do not use complex textile icons in scenarios where a very fast eyes-free discrimination of shapes is required or desired.

In our study, even for the best variants, mean recognition times were around 7 seconds. This might be acceptible when one desires to trigger an action on a textile interface at their own pace without vision. However, when fast reactions are necessary, for instance if a textile icon is used as a button to open pop-up notifications on a Smart TV, users might become frustrated if they do not manage to identify the correct icon in time.

04. Avoid using multiple shapes that have large numbers of both sharp convex and sharp concave vertices.

Such icons, like **Plus**, **Lightning**, **Star**, and **Arrow**, are confusable even in the best variants. We recommend using only one such icon together with differently-shaped icons in an interface, if possible.

05. When using visually similar icons, make sure their distinct features are easily discriminable in the variant of your choice.

As an example, whether **Moon** and **Phone** are easily discriminable depends on the variant: In our study, they were never confused when realized as raised outlines or recessed fills, while in the other cases they were sometimes confused. It appears that both raised outlines and recessed fills highlight the different "tips" of these two shapes more strongly than other variants.

06. If possible without influencing the texture, color the insides or outlines of textile icons with height differences.

Participants clearly visually preferred textile icons that strongly used color. However, we cannot recommend using yarn to achieve this—as far as we know, any changed texture, especially if it is not uniform, should be avoided.

Chapter 7

Conclusion

With this theses, we give a first detailed investigation of textile icons. Based on our initial decisions to investigate *graphical* icons with either a *height difference* or a *texture difference using yarn*, we explored how to optimize their design and fabrication for reliable, fast, and easy recognition. In a user study, we showed that height-based textile icons fabricated with our process have potential for practical use, and gained insights on choosing suitable sets of shapes.

7.1 Contributions

This thesis provides several contributions:

1. We gave insights into sub-millimeter-precise fabrication of textile icons using common fab lab machinery.
2. We created a collection of scripts to largely automate the generation of files necessary for fabrication.
3. We provided a set of 120 (6 fabrication variants $\times$ 20 shapes) textile icon samples as artifacts that may be used in further user studies.
4. We presented results from a shape discrimination user study with 42 participants, from which initial

guidelines for the design and use of texile icons have been derived.

5. We made available a large video corpus from the aforementioned study, allowing future more detailed analyses of the ways people recognize small graphical shapes haptically.

7.2 Future Work

There are many ways to further unlock the potential of textile icons.

Our investigation was limited to two textile properties, height and texture, that were not combined. Due to the large number of textile properties available, we consider the potential of textile icons to be even higher than our results indicate, but this potential is still largely unexplored.

There are several directions to expand the research scope for textile icons:

- investigating the effects of other textile properties or combinations of textile properties
- exploring how to represent other kinds of shapes, for instance shapes with holes or inner contours, or 3D objects
- examining how texile icons can and should actually be used as part of a large textile interface
- conducting different kinds of studies, especially split-attention studies to investigate the potential of textile icons for secondary tasks, and studies in the field
- conducting studies with different kinds of population samples, especially including older people
- looking into the exploratory procedures that people use with textile icons, for instance using our video corpus
- determining whether non-graphical icons could be an option, especially association-based icons

Especially textile icons using the *Aesthetic Association Principle (AAP)*, similar to those presented by Breitschaft and Carbon [2021], could be a promising new approach to make the process of interpreting icons more natural—again due to the large number of textile properties potentially allowing to convey a large number of intended associations, if designed in the right way. Associations could also be used to augment graphical textile icons: A raised heart shape with a soft and warm texture and a raised star shape with a hard and cool texture might be more intuitively discriminable than the other way round.

We believe that association-based icons are also suitable for textile icons.

Other types of non-graphical icons might also be useful to either improve recognition or provide additional information: Adding vibration or force patterns to individual textile icons, similar to tactons and hapticons, could make shapes more immersive, for instance by adding a heartbeat to a heart shape. It could also provide additional information, like beating faster or slower to communicate different states. If a way is found to move textile icons on the surface, a haptic version of kineticons could also be realized.

Textile icons could be augmented by non-graphical kinds of icons.

We are convinced that future research will unlock the potential of textile icons even more and are excited to find out what the future will hold for textile interfaces.

Appendix A

Informed Consent and Questionnaires

In this appendix, we present the consent form and questionnaires that were used in our empirical study. Both German and English versions were created for all documents.

The documents are presented in the following order:

1. Figures A.1—A.2:
   Informed consent form (1 page)
2. Figures A.3—A.6:
   Post-task questionnaire (2 pages, 6 per study)
3. Figures A.7—A.10:
   Post-test questionnaire (2 pages, 1 per study)
4. Figures A.11—A.12:
   Demographics questionnaire (1/3 page)

Informierte Zustimmung (engl. “Informed Consent”)

Experimentelle Studie zur haptischen Erkennbarkeit von Formen für textile Icons

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Studienziel: Ziel dieser Studie ist, zu verstehen, wie Icons auf textilen Interfaces gestaltet sein sollten, um eine einfache und schnelle haptische Erkennung und eine angenehme Nutzungserfahrung zu ermöglichen. Ein weiteres Ziel ist es, zu verstehen, wie Menschen Icons auf Texilien haptisch erkunden, wenn sie nicht in der Lage sind, diese Icons zu sehen. In dieser Studie bezeichnet der Begriff „Icon“ ein kleines Interface-Element mit einer Form, mit welcher der*die Nutzer*in bereits visuell vertraut ist.

Erhobene Daten: Die folgenden Daten werden während der Studie erhoben und anonym unter Verwendung von Identifikationsnummern gespeichert. Sie werden nur dem*der Versuchsleiter*in und dem Personal der Media Computing Group verfügbar gemacht.

- Erkennungszeiten und Erkennungsraten der Formen für die texilen Icons
- Notizen, die von dem*der Versuchsleiter*in von Hand und an deren Computer angefertigt werden
  (Sie können diese Notizen gerne am Ende der Studie einsehen, um sicherzustellen, dass keine Informationen über Sie bekannt werden)
- Video-Aufzeichnungen Ihrer Hand
  (Die Soundspur wird nicht aufgezeichnet)
- Jegliche Informationen, die Sie über die Fragebögen zur Verfügung stellen

Verfahren: Die Studie wird aus vier Phasen bestehen.

1. Sie werden die möglichen Formen visuell kennenlernen und lernen, den Versuchsaufbau zu benutzen.
2. Als nächstes werden Sie versuchen, Formen in drei Varianten textiler Icon-Sets zu erkennen. Nach jedem Icon-Set werden Sie gebeten einen Fragebogen auszufüllen.
3. Nach einer kurzen Pause werden Sie versuchen, Formen in drei weiteren Varianten textiler Icon-Sets zu erkennen. Nach jedem Icon-Set werden Sie gebeten einen Fragebogen auszufüllen.
4. Abschließend werden Sie gebeten einen weiteren Frageboten auszufüllen und demographische Informationen anzugeben.

Risiken: Es ist möglich, dass geistige oder körperliche Ermüdungserscheinungen während der Studienteilnahme auftreten. Sie werden Gelegenheiten zur Pause bekommen, zwischen den Icon-Sets und zwischen den Studienphasen, wann immer Sie diese benötigen. Nach Phase Zwei wird eine Pause von mindestens drei Minuten stattfinden, bevor die Studie fortgesetzt wird. Sollten Sie sich während der Studie unwohl fühlen, haben Sie die Möglichkeit, die Studie jederzeit zu unterbrechen oder zu beenden. Sollte irgendein Teil der Studie eine Belastung für Sie werden, wird die Studie sofort abgebrochen.

Kosten und Entschädigung: Die Teilnahme an der Studie ist für Sie kostenlos. Der*die Versuchsleiter*in wird Ihnen während und nach der Studie Snacks und Getränke zur Verfügung stellen.

Vertraulichkeit: Alle während der Studie erhobenen Daten werden streng vertraulich behandelt. Sie werden über Identifikationsnummern identifiziert. Die Daten werden Veröffentlichungen oder Berichte (z.B. Masterarbeit, Konferenz-Paper) verwendet werden. Dabei wird sichergestellt werden, dass diese keine Informationen beinhalten, die Rückschlüsse auf die Teilnehmer*innen erlauben.

Wenn Sie sich mit der Teilnahme an dieser Studie einverstanden erklären, unterschreiben Sie bitte im Folgenden.

☐ Ich habe die Informationen auf diesem Formular gelesen und verstanden.

☐ Ich habe mir die Informationen auf diesem Formular erklären lassen.

Name der teilnehmenden Person	Unterschrift der teilnehmenden Person	Datum
	Unterschrift Versuchsleiter*in	Datum

Auf Wunsch ist es möglich, eine Kopie dieses Dokuments zu erhalten. Falls Sie Fragen zu dieser Studie haben, wenden Sie sich dazu bitte an Lovis Suchmann unter lovis.suchmann@rwth-aachen.de

Figure A.1: Informed consent form, German version.

Informed Consent

Experimental study on haptic recognizability of shapes for textile icons

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Study goal: The goal of this study is to understand how icons on textile interfaces should be designed to allow easy and fast haptic recognition and a pleasurable user experience. An additional goal is to understand how people haptically explore icons on textiles when being unable to see these icons. In this study, the term "icon" refers to a small interface element having a shape that the user is already familiar with visually.

Collected Data: The following data is collected during the study and stored anonymously by using identification numbers. It will only be made available to the principal investigator and the personnel of Media Computing Group.

- Shape recognition times and recognition rates for the textile icons
- Notes taken by the principal investigator by hand and on their computer
  (You are welcome to review these notes at the end of the study to ensure no information about you is revealed)
- Video recordings of your hand
  (Sound will not be recorded)
- Any information which you provide in the questionnaires

Procedure: The study will consist of four phases.

1. You will visually get to know the possible shapes and learn how to use the study setup.
2. Next, you will try to recognize shapes in three variants of textile icon sets. After each icon set, you will be asked to fill out a questionnaire.
3. After a short break, you will try to recognize shapes in three more variants of textile icon sets. After each icon set, you will be asked to fill out a questionnaire.
4. Finally, you will be asked to fill out an additional questionnaire and provide demographic information.

Risks: You might experience mental or physical fatigue while participating in the study. You will have opportunities to rest between icon sets and between phases whenever you need them. After phase two, a break of at least three minutes will take place before continuing with the study. If you feel uncomfortable during the study, you will be able to pause or end the study at any time. Should any part of the study become distressing to you, it will be terminated immediately. Hand sanitizer will be available for you to use at any point during the study.

Costs and Compensations: Participation in this study will involve no costs to you. The principal investigator will provide snacks and drinks for you during and after the study.

Confidentiality: All data collected during the study will be kept strictly confidential. You will be identified via identification numbers. The data is going to be used for publications or reports (e.g., master thesis, conference paper). Thereby will be is ensured that no identifying information about the participants will be contained in them.

If you agree to participate in this study, please sign your name below.

☐ I have read and understood the information on this form.

☐ I have had the information on this form explained to me.

Participant's Name	Participant's Signature	Date
	Principal Investigator	Date

Upon request, it is possible to receive a copy of this document. If you have any questions regarding this study, please contact Lovis Suchmann at lovis.suchmann@rwth-aachen.de

Figure A.2: Informed consent form, English version.

ID: _____

Hinweis: Bitte ignorieren Sie für den gesamten Fragebogen die Formen Krone und Fisch.

Wie sehr stimmen Sie den folgenden Aussagen zu?	*stimme gar nicht zu*			*neutral*			*stimme voll zu*
Mit den textilen Icons zu interagieren, fühlte sich angenehm an.	○	○	○	○	○	○	○
Es war körperlich anstrengend, mit den textilen Icons zu interagieren.	○	○	○	○	○	○	○
Es war geistig fordernd, aus dem, was ich fühlte, schlau zu werden.	○	○	○	○	○	○	○
Es war geistig fordernd, während dieses Durchgangs die 14 möglichen Formen im Kopf zu behalten.	○	○	○	○	○	○	○
Es war zeitaufwendig, die Formen zu erkennen.	○	○	○	○	○	○	○
Ich konnte leicht eine Form vom Hintergrund unterscheiden.	○	○	○	○	○	○	○
Ich konnte leicht die grobe Form identifizieren.	○	○	○	○	○	○	○
Ich konnte leicht Formen-Details identifizieren.	○	○	○	○	○	○	○
Insgesamt konnte ich die Formen leicht erkennen.	○	○	○	○	○	○	○
Die Erkennungsschwierigkeit unterschied sich stark zwischen Formen.	○	○	○	○	○	○	○
Ich fühlte mich sicher, die Formen erkennen zu können.	○	○	○	○	○	○	○
Ich war frustriert davon, wie lange es dauerte, die Formen zu erkennen.	○	○	○	○	○	○	○
Ich war frustriert davon, wie schwierig es war, die Formen zu erkennen.	○	○	○	○	○	○	○
Es hat mir Spaß gemacht, zu versuchen, die Formen zu erkennen.	○	○	○	○	○	○	○

Was mögen Sie an dieser Variante?

Was mögen Sie an dieser Variante nicht?

Figure A.3: Post-task questionnaire, page 1/2 of German version.

ID: _____

Please note: For this whole questionnaire, please ignore the Crown and Fish shapes.

How much do you agree with these statements?	*strongly disagree*			*neutral*			*strongly agree*
Interacting with the textile icons felt comfortable.	○	○	○	○	○	○	○
It was physically strenuous to interact with the textile icons.	○	○	○	○	○	○	○
It was mentally demanding to make sense of what I felt.	○	○	○	○	○	○	○
It was mentally demanding to remember the 14 possible shapes during this condition.	○	○	○	○	○	○	○
It was time consuming to recognize the shapes.	○	○	○	○	○	○	○
I could easily differentiate a shape from the background.	○	○	○	○	○	○	○
I could easily identify the rough shape.	○	○	○	○	○	○	○
I could easily identify shape details.	○	○	○	○	○	○	○
Overall, I could easily recognize the shapes.	○	○	○	○	○	○	○
The difficulty of recognition varied strongly between shapes.	○	○	○	○	○	○	○
I felt confident in recognizing the shapes.	○	○	○	○	○	○	○
I was frustrated by how long it took to recognize the shapes.	○	○	○	○	○	○	○
I was frustrated by how difficult it was to recognize the shapes.	○	○	○	○	○	○	○
I enjoyed trying to recognize the shapes.	○	○	○	○	○	○	○

What do you like about this variant?

What do you dislike about this variant?

Figure A.4: Post-task questionnaire, page 1/2 of English version.

Hinweis: Bitte ignorieren Sie für den gesamten Fragebogen die Formen Krone und Fisch.

Wie könnte diese Variante verbessert werden?

Nennen Sie bis zu 3 Formen, die am leichtesten zu erkennen waren:

Was machte diese für Sie leicht zu erkennen?

Nennen Sie bis zu 3 Formen, die am schwersten zu erkennen waren:

Was machte diese für Sie schwer zu erkennnen?

Falls Sie weitere Anmerkungen haben, ergänzen Sie diese bitte hier:

Figure A.5: Post-task questionnaire, page 2/2 of German version.

Please note: For this whole questionnaire, please ignore the Crown and Fish shapes.

How could this variant be improved?

Name up to 3 shapes that were easiest to recognize:

What made them easy for you to recognize?

Name up to 3 shapes that were most difficult to recognize:

What made them difficult for you to recognize?

If you have any further remarks, please add them here:

Figure A.6: Post-task questionnaire, page 2/2 of English version.

ID: _____

Hinweis: Bitte ignorieren Sie für den gesamten Fragebogen die Formen Krone und Fisch.

Nennen Sie bis zu 3 Formen, die insgesamt am leichtesten zu erkennen waren:

Was machte diese für Sie leicht zu erkennen?

Nennen Sie bis zu 3 Formen, die insgesamt am schwersten zu erkennen waren:

Was machte diese für Sie schwer zu erkennnen?

Welche Strategien haben Sie genutzt, um die Formen zu erkennnen?

Bitte ordnen Sie die 6 Varianten an: 1 ist am besten, 6 ist am schlechtesten. Bitte vergeben Sie jede Zahl nur einmal.

Bewerten Sie ihre Haptik.

Filled + Raised	
Outline + Raised	
Filled + Recessed	
Outline + Recessed	
Filled + Flat	
Outline + Flat	

Figure A.7: Post-test questionnaire, page 1/2 of German version.

ID: _____

Please note: For this whole questionnaire, please ignore the Crown and Fish shapes.

Name up to 3 shapes that were <u>easiest</u> to recognize overall:

What made them <u>easy</u> for you to recognize?

Name up to 3 shapes that were <u>most difficult</u> to recognize overall:

What made them <u>difficult</u> for you to recognize?

What strategies did you use to recognize the shapes?

Please rank the six variants: <u>1 is best, 6 is worst.</u> Use each number once.

	Rank them by their haptics.
Filled + Raised	
Outline + Raised	
Filled + Recessed	
Outline + Recessed	
Filled + Flat	
Outline + Flat	

Figure A.8: Post-test questionnaire, page 1/2 of English version.

Hinweis: Bitte ignorieren Sie für den gesamten Fragebogen die Formen Krone und Fisch.

Bitte ordnen Sie die 6 Varianten an: 1 ist am besten, 6 ist am schlechtesten. Bitte vergeben Sie jede Zahl nur einmal.

	Bewerten Sie ihre visuelle Attraktivität.	**Bewerten Sie sie insgesamt.**
Filled + Raised		
Outline + Raised		
Filled + Recessed		
Outline + Recessed		
Filled + Flat		
Outline + Flat		

Stellen Sie sich nun bitte vor, Sie könnten Ihr eigenes textiles Icon-Set erschaffen.

Wie würde es sich anfühlen?

Wie würde es aussehen?

Falls Sie weitere Anmerkungen haben, ergänzen Sie diese bitte hier:

Figure A.9: Post-test questionnaire, page 2/2 of German version.

Please note: For this whole questionnaire, please ignore the Crown and Fish shapes.

Please rank the six variants: 1 is best, 6 is worst. Use each number once.

	Rank them by their visual appeal.	**Rank them overall.**
Filled + Raised		
Outline + Raised		
Filled + Recessed		
Outline + Recessed		
Filled + Flat		
Outline + Flat		

Now, please imagine you could create your own textile icon set.

What would it feel like?

What would it look like?

If you have any further remarks, please add them here:

Figure A.10: Post-test questionnaire, page 2/2 of English version.

ID: _____

Alter: ______________________________

Geschlecht: ______________________________

Händigkeit: ○ Linkshändig ○ Rechtshändig ○ Beidhändig

Beruf: ______________________________

Gehen Sie oft Aktivitäten im Bereich Visuelles Design oder Grafikdesign nach?

○ Ja, oft ○ Nur selten ○ Nie

Gehen Sie oft Aktivitäten im Bereich Basteln, Handarbeiten usw. nach?

○ Ja, oft ○ Nur selten ○ Nie

Figure A.11: Demographics questionnaire, German version.

ID: _____

Age: ______________________________

Gender: ______________________________

Handedness: ○ Left-handed ○ Right-handed ○ Ambidextrous

Occupation: ______________________________

Do you often pursue activities related to visual design or graphic design?

○ Yes, often ○ Only rarely ○ Never

Do you often pursue activities related to crafting, needlework or similar?

○ Yes, often ○ Only rarely ○ Never

Figure A.12: Demographics questionnaire, English version.

Appendix B

Study Setups by Room and Handedness

During the empirical study, we had to move our study setup multiple times, either when changing the room or when adjusting for a participant with different handedness. Here, we present detailed photographs of these study setups to demonstrate that they were sufficiently similar.

We show the following four setups:

1. Seminar Room, right-handed
2. Seminar Room, left-handed
3. Media Space, right-handed
4. Media Space, left-handed

On the following pages, the top image always shows the Seminar Room, while the bottom image always shows the Media Space.

Figure B.1: Conductor's perspective from afar, left-handed.

Figure B.2: Conductor's perspective from afar, right-handed.

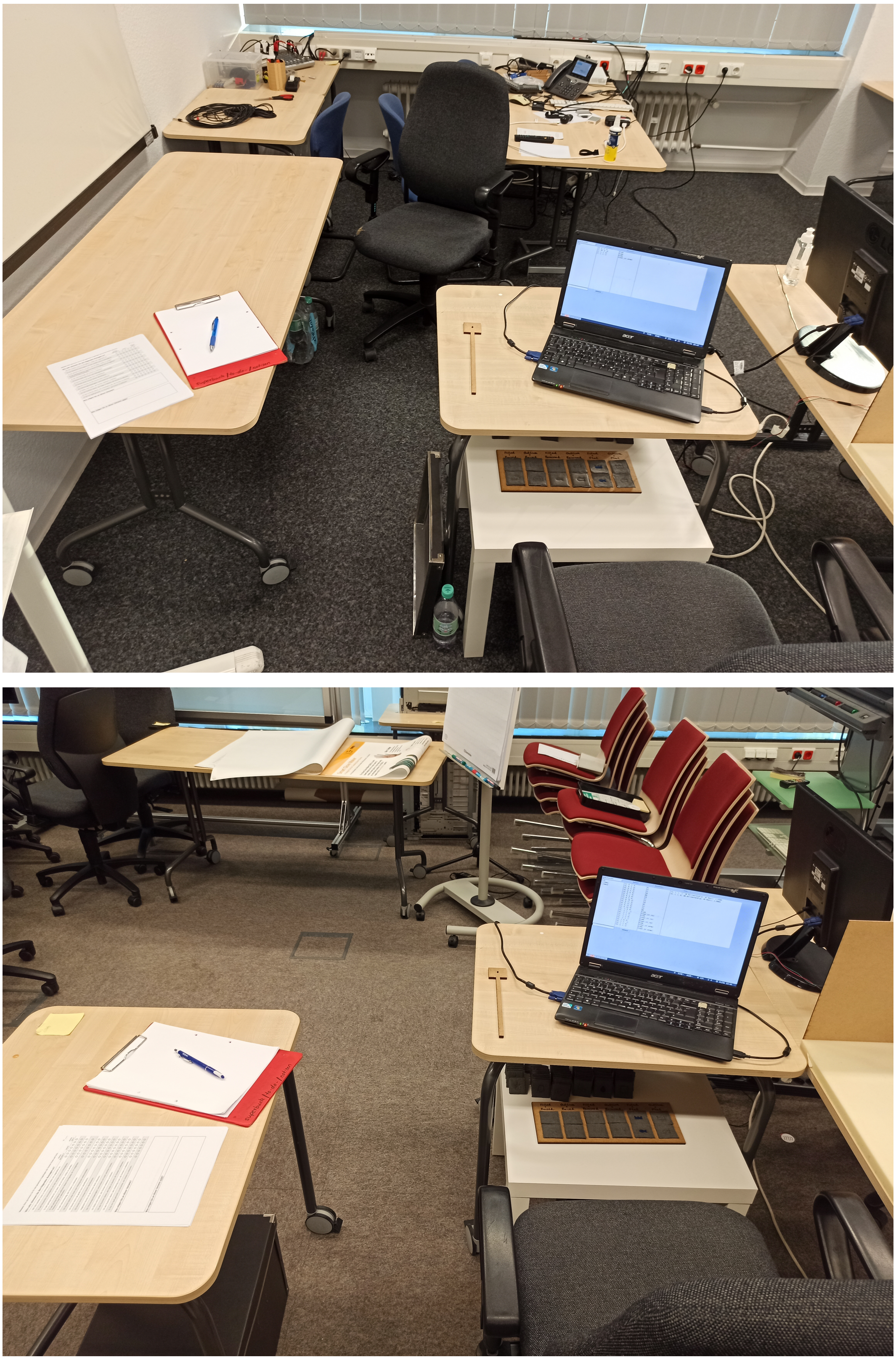

Figure B.3: Conductor's perspective, close-up, left-handed.

Figure B.4: Conductor's perspective, close-up, right-handed.

Figure B.5: Participant's perspective from afar, left-handed.

Figure B.6: Participant's perspective from afar, right-handed.

Figure B.7: Participant's perspective, close-up, left-handed.

Figure B.8: Participant's perspective, close-up, right-handed.

Appendix C

Confusion Matrices for Individual Variants

We present confusion matrices for individual fabrication variants similiar to Fig. 5.11. Colored row and column headers indicate sets of potentially confusable shapes. For the algorithm, we chose a threshold of 3 trials.

	☾	☆	💧	⚡	✆	🔖	♡	🔔	○	□	▷	⇨	✚	▭	/
☾	**41**														1
☆		**41**													1
💧			**40**						1		1				
⚡		3		**35**											4
✆	3				**38**										1
🔖						**42**									
♡							**41**								1
🔔						5		**35**							2
○									**42**						
□										**42**					
▷											**42**				
⇨		1		2								**34**			5
✚		9		1									**31**		1
▭														**42**	

Figure C.1: Confusion matrix for variant *RaisedFill*.

	☾	☆	💧	⚡	✆	🔖	♡	🔔	○	□	▷	⇨	✚	▭	/
☾	**42**														
☆		**41**													1
💧			**40**						2						
⚡				**39**											3
✆	1				**38**		1								2
🔖						**39**									3
♡							**40**								2
🔔								**40**							2
○									**42**						
□										**42**					
▷											**42**				
⇨				4								**31**			7
✚		2						1				1	**34**		4
▭												1		**41**	

Figure C.2: Confusion matrix for variant *RaisedOutline*.

	☾	☆	💧	⚡	✆	🔖	♡	🔔	○	□	▷	⇨	✚	▭	/
☾	**41**														1
☆		**37**		1									1		3
💧			**42**												
⚡		3		**29**								1	2		7
✆					**41**										1
🔖				1		**39**									2
♡				1			**39**								2
🔔								**40**							2
○									**42**						
□										**42**					
▷											**42**				
⇨				2				1				**28**	2		9
✚		4											**31**		7
▭				1						1				**40**	

Figure C.3: Confusion matrix for variant *RecessedFill*.

	☾	☆	💧	⚡	✆	🔖	♡	🔔	○	□	▷	⇨	✚	▭	
☾	**39**				2										1
☆		**29**			1							2			10
💧	1		**38**						1						2
⚡		3		**24**							1	1	1		12
✆	7				**30**										5
🔖						**37**									5
♡				1			**36**								5
🔔						1		**31**	2	1					7
○			2						**40**						
□										**40**					2
▷											**40**				2
⇨		1		6								**20**			15
✚		8		1								1	**21**		11
▭														**41**	1

Figure C.4: Confusion matrix for variant *RecessedOutline*.

	☾	☆	💧	⚡	✆	🔖	♡	🔔	○	□	▷	⇨	✚	▭	/
☾	**39**				1										2
☆	1	**29**						1					1		10
💧	2		**20**			2		2		1	2				13
⚡		2		**29**				1							10
✆	1				**36**										5
🔖		2	1	1	1	**17**		1		3					16
♡							**19**					9	1		13
🔔		3		1		4		**20**			1				13
○							2	6	**12**			1			21
□										**29**	1	1			11
▷				2			1				**16**				23
⇨		4		5				1				**15**	2		15
✚		4		5		1		1					**26**		5
▭												1		**39**	2

Figure C.5: Confusion matrix for variant *FlatFill*.

	☾	☆	💧	⚡	✆	🔖	♡	🔔	○	□	▷	⇨	✚	▭	/
☾	**22**	1	2	2	3			1							11
☆		**9**		2		1		1			1	2			26
💧			**25**								1		1		15
⚡		4	1	**20**								2	2		13
✆	2			3	**17**		1							1	18
🔖						**24**		1		3					14
♡	3						**15**	1	1						22
🔔	2					3	1	**9**	1	1	2	1			22
○	1	1	5					3	**20**						12
□										**37**					5
▷							1	1			**32**				8
⇨		1		3		1		1				**14**	1	1	20
✚	1	3		2				2					**3**		31
▭				2	1							2		**25**	12

Figure C.6: Confusion matrix for variant *FlatOutline*.

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