

# Investigating Pointing Performance for Tangible Surfaces with Physical 3D Targets

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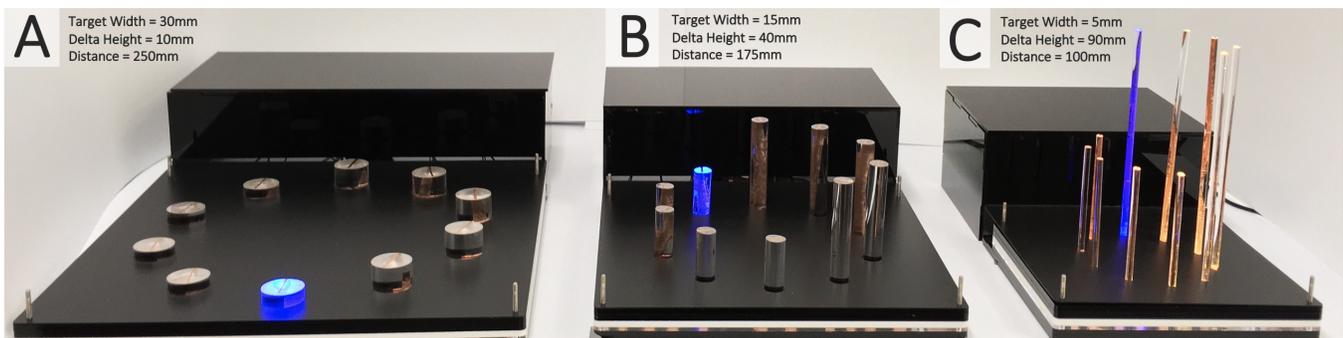


Figure 1: Experimental setup with varied target widths, delta heights (e.g., height different between two targets), and distances.

## ABSTRACT

One of the most fundamental interactions –pointing– is well understood on flat surfaces. However, pointing performance on tangible surfaces with physical targets is still limited for Tangible User Interfaces (TUIs). We investigate the effect of a target’s physical width, height, and distance on user pointing performance. We conducted a study using a reciprocal tapping task ( $n = 19$ ) with physical rods arranged in a circle. We compared our data with five conventional interaction models designed for 2D/3D tasks rather than tangible targets. We show that variance in the movement times was only satisfactorily explained by a model established for volumetric displays ( $r^2 = 0.954$ ). Analysis shows that movement direction and height should be included as parameters to this model to generalize for 3D tangible targets. Qualitative feedback from participants suggests that pointing at physical targets involves additional human factors (e.g., perception of sharpness or robustness) that need to be investigated further to understand how performance with tangible objects is affected.

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## CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **Empirical studies in HCI**.

## KEYWORDS

Tangible Surfaces; Pointing Interaction; Tangible User Interfaces

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## 1 INTRODUCTION

As we move toward more physical user interfaces and surfaces (e.g., tangible or shape-changing interfaces), there is an increasing need to understand the effect of form factor on user performance. Currently, a vast number of studies investigate pointing on GUIs [21, 44, 57] and touchscreens [2, 19, 68], focusing on how the target index of difficulty affects pointing performance. However, pointing on 3D physical targets is under-explored, and thus designers lack an understanding of how form factors affect user performance. We predict that pointing at physical 3D targets is fundamentally different than 2D ones. Studies in 3D virtual environments [60, 70] already demonstrate that the size of targets in three dimensions, and the angle of movement affect pointing performance. Additionally, touch accuracy is impacted by physical aspects such as the

topology (convex or concave) of the surface touched [53] and the size of the contact area created when the finger touches the surface [28]. To establish an initial understanding of fundamental user performance with physical interfaces, we conducted an empirical study to investigate how height, width and distance of physical targets affect pointing time. A reciprocal tapping task [44] was used and adapted to physical touch-sensitive rods of various heights and widths. To achieve this, we built an experimentation platform using capacitive sensing and variously sized Perspex rods as targets.

We compared our data with five conventional interaction models (Fitts') designed for 2D/3D tasks rather than tangible targets. Our results show that our data fits well with a volumetric display variation by Grossman and Balakrishnan [20] ( $r^2 = 0.954$ ). To further understand how Fitts' Law can be modeled for physical environments, we analyzed how the factors in our experiment affected pointing performance. The results demonstrate that movement direction and height should be added as parameters to existing pointing models in order to generalize them to physical 3D targets. Additional qualitative feedback from participants suggests that pointing at physical targets involves additional human factors compared to pointing at virtual ones. For example, the perception of the object's sharpness, or its apparent fragility may slow down the users in reaching the target. We discuss how this work opens new directions to further investigate how those physical factors alter pointing performance.

We believe our results will be of particular interest to communities within the HCI fields developing tangible user interfaces, organic user interfaces or shape-changing interfaces, which are all looking to further the development and design of physical interfaces. We discuss how having such insights could in turn help designers and researchers with new design considerations in a similar manner to more conventional devices. Our work aims to encourage the community to adopt similar techniques to further understanding of how physical design variables that affect user performance with tangible user interfaces (TUIs).

## 1.1 Contributions

Our contributions can be summarized as: (1) An empirical evaluation that shows that the pointing model for volumetric displays [20] can be both **generalizable and extended** to pointing on physical objects. (2) **Design considerations** derived from our findings that show additional complexities need to be taken into consideration, such as materiality and affordance. (3) Our **testing platform** and set-up can be easily reproduced in order to support others in developing new **directions for future work** on establishing interaction models specifically for tangible user interfaces.

Note that studying tangible interaction opens up an exponential design space to examine, and thus a dilemma on what factors to study initially occurs. Interaction with traditional GUIs (e.g., desktop+mouse) is relatively well understood because as we have over 40 years of studies covering a myriad of usage scenarios and interaction modeling. We wish to invite the community to further support more empirical studies with new forms of interactive systems (e.g., TUIs and shape-changing interfaces). Nevertheless, such explorations are difficult to implement given the exponential nature of the design space. At the end of this paper, we offer our position on this issue and how we potentially can overcome it.

## 2 RELATED WORK

We review work on the physicalization of interfaces and associated studies. We then discuss existing pointing performance models that is, Fitts' Law and its variations.

### 2.1 Physical Interfaces

Tangible [29, 30, 32, 56], organic [27, 67] and shape changing interfaces [3, 15, 50, 52] are areas that push toward the physicalization of data and interfaces, either by using static, malleable or dynamic physical devices. Tangible User Interfaces (TUIs) utilize physical modalities for enhanced interactive user experience and give physical form to digital data and information [64]. The field has progressed significantly by presenting a range of models and prototypes for TUI implementation [30, 48, 49, 63]. Similarly, Organic User Interfaces allow users to interact with a non-flat display that can be manually deformed if required [27, 67].

Shape-changing displays [50] add dynamic interactive capabilities to tangible interfaces. This enables dynamic datasets to be physically encoded [58]. Such interfaces have been used to represent a wide range of information [18, 41] as well as enhance communication capabilities [40]. These physically deformable displays can be utilized in diverse new application areas, such as dynamic landscape and topographical modelling [14], architectural design [16], physical telepresence [18] and object manipulation [31]. However, there is still limited low-level understanding of how physical modalities affect interaction [33, 56].

Current shape-changing displays enable input by touching and pressing into the surface as well as gestural interactions [16, 41, 42]. These inputs enable tangible and shape-changing displays to offer tactile interaction capabilities that go beyond that of 2D touchscreens. Recent work has focused on the design of new interaction styles [16, 42, 59], however, little empirical performance data is presented. Similarly, recent reviews of the state-of-the-art, on both tangible and shape-changing user interfaces, such as Jansen et al. [33] and Rasmussen et al. [50], highlight the need to develop fundamental understanding of basic user interactions for those interfaces. Jansen et al. [33] emphasizes the need to better support interaction with physical forms in terms of affordances and haptics. One of the motivations for our work is to encourage the community to gather more empirical data about how physical features impact user performance.

### 2.2 Pointing Studies on Physical Interfaces

Recent work on interaction with non-flat surfaces focuses predominantly on curved or deformable displays. BendDesk [71] begins to investigate user performance for dragging gestures across a curved hybrid interface. Their findings suggest that motor control across a curved surface is more complex than a flat plane, and therefore takes longer. Voelker et al. [69] also investigate flicking gestures with a similar set-up. They find flicking gestures on curved surfaces are mostly influenced by the motor execution stage of the gesture rather than the visual perception stage. We presume as similar motor control effect could be observed with tangible targets of different height, though these studies are not focused on pointing but rather continuous gestures.

Empirical studies for pointing on deformable displays begin to look at user performance in terms of accuracy. Bacim et al. [5] evaluate how surface deformation affects touch interactions for selection accuracy on flat and hemispherical deformable displays. They find that users rely heavily on visual feedback for precision on deformable surfaces. Preliminary work also begins to build an understanding of form factors affect the design of deformable interfaces. Lee et al. [39] show that the device size is an important factor to consider when designing mobile deformable devices. Though these studies are looking at user interaction, they focus on touch accuracy and not pointing performance.

Fitts' Law work that closely relates to our setup and explores touch input either looks at 'edge of a table' user performance [36] or barrier pointing on flat screens [19]. Though the exploration of surface edges is applicable to our setup, as our targets also have edges, both of these studies focus on utilizing flat surfaces and displays rather than tangible targets. The closest relatable work explores touch input on curved surfaces by Roudaut et al. [53], where they evaluate how participants acquire targets on non-flat surfaces with different curvature and at locations of different slope. While our work also focuses on non-flat surfaces, we explore tangible targets that protrude from a flat surface directly (e.g., straight rods), without slopes or curved contours.

## 2.3 Pointing Models

Fitts' Law [17] provides an established model to profile users' motor skills by relating the movement time ( $MT$ ) to reach and touch a target. This is calculated using a target's size ( $W$ ) and distance ( $D$ ) from an origin. The logarithmic element of the equation is known as the "Index of Difficulty" ( $ID$ ). This law has been used in a large variety of contexts and has seen many variations. Soukoreff and MacKenzie provide a thorough review [57]. Despite being originally conducted in the (flat) tangible world, Fitts' Law has not been investigated with physical 3D targets. Below is the Shannon formulation [45] used to calculate  $ID$ s for factor analysis in this study:

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

*Shannon Formulation*

**2.3.1 Extending Fitts' Law for 3D Applications.** A number of proposed models have extended Fitts' Law for 3D movements to real-world targets [12, 62] well as stereoscopic target objects and display environments [7, 10]. However, there is limited work examining the applicability of these models specifically for tangible user interfaces. Ha and Woo [22] evaluate user performance for 3D object manipulation in a tangible augmented reality environment but only using virtual hand techniques. Additionally, Barrera and Stuerzlinger [7] evaluated 3D pointing with physical targets for two directions but using a stereo display. More recent work in Fitts' Law begins to explore interaction for 3D applications but these new 3D extensions still focus on traditional displays and interfaces such as touchscreens [65], comparisons between AR and VR performance [8, 9], or applications solely in Virtual Reality (VR) environments [13, 55, 74]. Triantafyllidis and Li [62] begin to explore the challenges in modeling human-performance in 3D space with Fitts' Law. However, unlike current 3D models for Fitts' Law, that are

grounded in virtual environments, the key motivation of this paper is to understand how interaction performance is affected with tangible user interfaces in real physical environments.

**2.3.2 Rational Behind Model Selection.** There is a large number of Fitts' Law models for a large range of contexts and apparatus (e.g. [23, 34, 38, 57, 66]). Our goal was to select a subset of these models of interest either based on established models or that are closely related to the scope of our paper. We first choose the original Fitts' [17] as a baseline comparison. Next, we looked at the most compared and established models in 1D/2D, choosing MacKenzie's and Welford's models. There is certainly work into extending 1D Fitts' to 2D tasks (e.g. MacKenzie and Buxton [45] for 2D rectangular targets) but a smaller amount of work going from 2D to 3D in the tangible world.

We choose Murata's model [47] as it extends Fitts 2D to 3D, although not fully, as their apparatus involves a touch surface moving up and down. The other closest model is Grossman et al.'s [20]. While it does use a pointing apparatus rather than touch, the targets are on a volumetric display, which is close to our work on real world physical targets. There have also been attempts to go from 2D to 3D in virtual environments [11, 12, 35, 60, 61]. We did not add a model from the VR literature because the most recent and established works [11, 60] use the original Fitts' model which we have already included.

### 2.3.3 Pointing Models of Interest.

- (1) The original **Fitts' Law** as described is our baseline. The model encompasses human psycho-motor behavior, originally developed on the basis of information theory. Fitts derived an Index of Difficulty (ID) for a pointing task given by equation 1.

*Equation 1*

$$MT = a + b \log_2 \left( 2 \frac{D}{W} \right)$$

- (2) **MacKenzie and Buxton's** model [45] is one of most adopted within the community [57], tailored to quantifying movement behavior for 1D and 2D tasks. This model compared several alternative formulations of Fitts' law to model 2D mouse-based pointing by varying target width and height. They found that an index of difficulty formulation that used the minimum values for width and height yielded high predictive power.

*Equation 2*

$$MT = a + b \log_2 \left( \frac{D}{W} + 1 \right)$$

- (3) **Welford's** [72] is also one of most widely adopted within the community [57]. Like variation (2), it tailored the model to quantifying human movement behavior for 1D and 2D tasks. Welford observed that the endpoint deviation in a 1D task followed a Gaussian distribution.

*Equation 3*

$$MT = a + b \log_2 \left( \frac{D}{W} + 0.5 \right)$$

- (4) **Murata and Iwase** [47] adapted McKenzie’s model [45] for 3D targets by accounting for a user’s angle of motion (e.g., direction) from an origin to a target for movement in three-dimensional space. They derived a model variation using  $\theta$ , the angle of motion from an origin to a target. This model evaluates the effects of target size, position, and depth on the time required to select 2D physical targets positioned vertically (e.g., on the coronal plane) with respect to the user. Traditional ID formulation resulted in poor predictive power for 3D movements. However, target location, reflected by the azimuth angle measured positive from the x-axis, exhibiting a sinusoidal relationship with movement time. Movement times were longer for targets positioned higher in the visual field than for targets positioned lower in the visual field. Based on this finding, they proposed an extended model.

Equation 4

$$MT = a + b \log_2 \left( \frac{D}{W} + 1 \right) + \sin(\theta)$$

- (5) We have also chosen to use the **Grossman and Balakrishnan** [20] model, which further extended the Accot and Zhai [1] model to include 3D target size and the direction of movement. Accot and Zhai improved on Mackenzie’s [45] model by using a weighted Euclidian norm to model the influences of target width and height independently and combined these effects into a single estimate of task difficulty to yield greater predictive power. However, they observed that the resulting model accurately predicted performance for 2D movements to 3D volumetric targets. Specifically, the Grossman model (Equation 6) for pointing in 3D environments takes into account the distance (or amplitude) of moment ( $A$ ), 3D dimensions ( $W, H, D$ ) and volume of the target. This model considers both movement and approach angle ( $\theta$ ) that should be accommodated by all components ( $W, H, D$ ). An additional weighted parameter is incorporated  $fW, H, G(\theta)$  that takes on different empirically determined values dependent on movement angle  $\theta$ .

Equation 5

$$MT = a + b \log_2 \left( \sqrt{fW(\theta) \left( \frac{A}{W} \right)^2 + fH(\theta) \left( \frac{A}{H} \right)^2 + fD(\theta) \left( \frac{A}{D} \right)^2} + 1 \right)$$

Note that the effective parameter adjustment is recommended by MacKenzie [44] by normalizing target width ( $We$ ) and Index of Difficult ( $IDe$ ) to reflect what the subject actually did. Welford [72] goes into more detail as to how to apply effective normalization for Fitts’ analysis. The main adaptation we made to the Grossman and Murata model was the use of the height difference between two targets as the Height parameter (i.e., delta height) in those models—whereas the Grossman uses the full length of one target for the Height. We use the center of the disc to measure the distance and the diameter of the cylinder for the width.

## 2.4 Mixing Pointing Models

We were curious to create a variation of the 3D Fitts Law model that is extended from Murata [47] (Equation 4) combined with Grossman [20] (Equation 5), where we introduce the height difference between

two targets (delta height as  $\Delta$ ) - (Equation 6). Our dataset produced  $a = 0.1, b = 0.07$ , and  $r^2 = 0.878$ . We did not include the baseline data points for flat targets where height is 0 as zero cannot be divided. We have also considered a Pythagoras based approach for modeling due to the hypotenuse distance (Equation 7) which did generate a much higher fit with  $r^2 = 0.837$ . It thus seems like an adaption of the Grossman model can be sufficient enough for describing interaction with tangible objects and that mixing it with others can also provide sufficient fit. In summary, delta height and elevation angle affect pointing performance with physical 3D objects. Additionally, factors such as direction of movement should also be included in future models.

Equation 6

$$MT = a + b \log_2 \left( \frac{\Delta H + A}{W} + 1 \right) + \sin(\theta)$$

Equation 7

$$MT = a + b \log_2 \left( \frac{\sqrt{\Delta H^2 + D^2}}{W} + 1 \right) + \sin(\theta)$$

## 3 EXPERIMENTATION PLATFORM

First, we describe the experimental platform used to study pointing with physical objects.

### 3.1 Overview

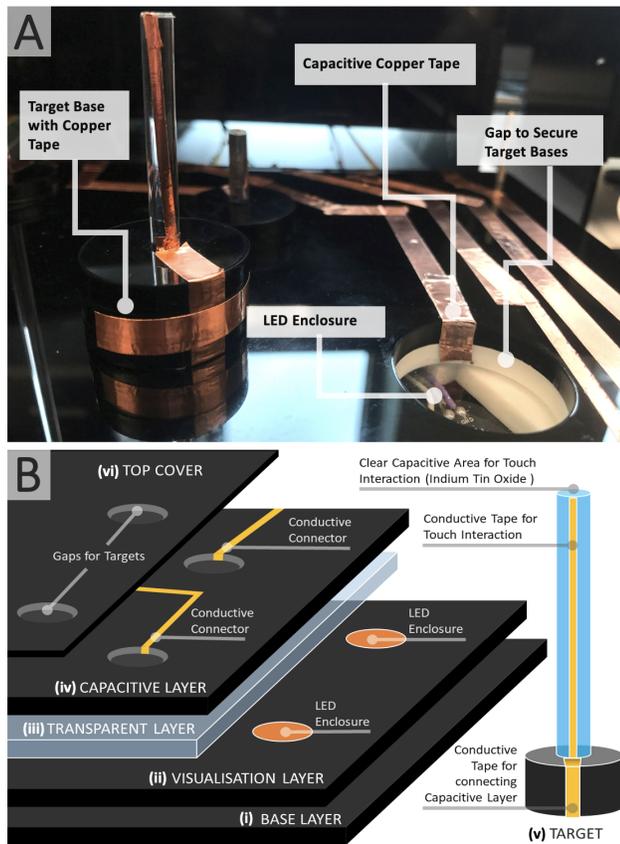
The experimental setup consists of a base onto which can be slotted interchangeable physical rods. (Figure 2). In order to detect touch on the top of the physical rods we used capacitive sensing. A change in capacitance is transmitted to the base (which hosts an Arduino board) via conductive pipelines, in our case copper tape (Figure 2A). We also added an LED to the bottom of each slot in order to provide basic user feedback diffused through the clear plastic rods.

### 3.2 Implementation

The *Base Layer* (i) supports the enclosure structure for the LEDs and layers above. We recommend using Perspex 3mm thick or above to ensure a strong foundation to hold substantial weight, especially for large targets. We use miniature flat RGB LEDs in gaps below the modular targets for simple visualizations. The *Visualization Layer* (ii) provides visual cues and feedback. The *Transparent Layer* (iii) provides support for the targets and ensures illumination for clear targets. The *Capacitive Layer* (iv) provides a circular gap above each LED to house a target base (see Figure 2B). For interactivity, conductive copper tape is secured on the surface of the layer.

The copper tape is connected to a 10k $\Omega$  resistor and two Arduino pins for digital serial read, recording capacitive sensing. The copper tape on the target base must contact copper on the *Capacitive Layer* (iv) gap as seen in Figure 2B. The gaps ensure that targets of varied widths and heights can be easily swapped to enable more arrangements and reduce construction time and replication.

The *Targets* (v) are positioned in the base of the setup arrangement and are made from clear, solid acrylic rods with an Indium Tin Oxide (ITO) film secured to the top to detect touch input (see Figure 2). A thin piece of copper tape running along the side of the target transmits capacitive input to an Arduino. Once a user presses the top of a target, the change in capacitance is recorded



**Figure 2: Modular target implementation and close-up of the platform set up with copper tape for capacitive sensing (A). Experimentation platform structure breakdown based on a set of laser-cut Perspex layers and target design (B).**

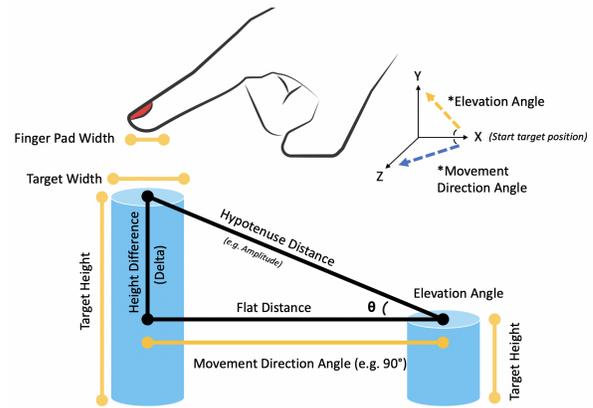
as touch input. The Arduino provides millisecond-level timing to record when a target is touched. The *Top Cover* (vi) ensures that electronics are not exposed, and that conductive tape is concealed to prevent any unnecessary touch detection outside target areas.

## 4 USER STUDY DESIGN

The goal of our study is to understand how physical factors affect pointing performance. For this, we used a multidirectional study set-up design, a variation of ISO9241-9 standard (2002). This is a common setup used for studying pointing and enabling realistic interaction behavior for users that is not restricted to one direction. However, adding physicality and 3D form to such a task increases the number of variables of interest. We first present a breakdown of these physical factors before explaining our experimental design and how we adapted this task to physical 3D targets.

### 4.1 Variables of Interest

Figure 3 illustrates the different variables of interest when studying a reciprocal pointing task with physical targets. As dimensionality increases, so does the range of variables that need to be taken into consideration, below we describe rational for variables chosen.



**Figure 3: Variables of interest to consider when studying pointing on physical targets.**

*Elevation Angle vs. Movement Direction Angle.* Elevation angle is on the YX plane (vertically) as the finger is raising up towards a higher target (Figure 3). It is calculated using trigonometry, with Delta Height, Flat Distance and Hypotenuse Distance (Figure 3). Movement direction angle is on the XZ plane (horizontally). When two targets are the same height (e.g., delta height = 0), the elevation angle on the vertical plane is always zero but movement angle on the horizontal plane is always greater than zero. Existing work with 3D target acquisition often focuses on vertical movements, i.e. where the angle corresponds to the angle relative to gravity. We focus on investigating both the horizontal and vertical movement, where gravity could impact performance. Note that in Murata’s model [47] elevation angle refers to the direction of movement around a central reference target which is different from our definition.

*Target Height vs. Delta height.* The target height is the actual height of the target and delta height is the difference in height between two targets. When two targets are of the same height (delta height = 0), pointing is similar to that of traditional 2D Fitts’ Law. What we believe is of interest, and not studied so far, is the variation of height, or delta height.

*Flat Distance vs. Hypotenuse Distance.* The distance between targets is a factor in Fitts’ experiments in 2D, where targets are on the same plane. For 3D targets, it may be appropriate to consider the vector of hypotenuse to reach a target at a different height as it is likely to have an impact on *MT* since the hypotenuse will be larger than the flat distance between targets of different heights.

*Finger as an Area Pointer.* Finger width should be taken into consideration as it is not a singularity like with a mouse cursor or a pen. The experimental hardware allows even a small contact point between the finger and the target to achieve activation [37].

### 4.2 Study Overview and Rationale

We can see that the range of possible factors to study becomes quickly exponential. Only a reasonable set of variables can be studied within an experimental design, we reduced the number of factors to a tractable set. Instead of varying independently target width, flat distance, and delta height, which could lead to a too large a dataset, we made the following choices:

- (1) We choose to *separate the circular task setup* into a left side containing the shorter rods, and a right side with the tallest rods. We choose this over alternating height. This choice was made to remove confounding factor of targets creating obstacles within the pointing movement that we know have an effect on performance [35].
- (2) We choose a setup in which each condition (i.e. each physical circular setup) contained *only one change of height*. The delta heights were 0mm (to test the baseline), 10mm, 40mm and 90mm. We chose an upper bound of 90mm as delta heights beyond this meant the setup would be too large for a table-top usage. Delta height was thus our first independent variable.
- (3) To further reduce the experimental design, we choose not to independently change the width and the distance but to vary the indexes of difficulties (second independent variable). We pick three values: one at each extremity of the ID function and one in the middle to cover a range of pointing tasks from easy to hard. We picked these extreme conditions for generating Index of Difficulty to clearly demonstrate the Fitts Law effect as recommended by MacKenzie [45]. We generated the highest ID (5.672) by selecting the smallest target width (5mm) to go with the longest flat distance (the traditional approach for calculating ID) between two targets (250mm). We then picked largest target width (30mm) and paired it with shortest distance between two targets (100mm) to generate the lowest ID (2.115). The middle ID (3.663) was set between both of these extremes ( $W=15\text{mm}$  and  $D=175\text{mm}$ ).

### 4.3 Experimental Design

We performed a circular Fitts' Law experiment with three different IDs (easy, medium, hard) and four delta heights (0mm, 10mm, 40mm, 90mm). This created 12 configurations (some are illustrated in Figure 1). We counterbalanced the ordering to remove/reduce ordering effects for each participant. Participants could take a break after every trial if needed. The study lasted approximately 1 hour and 30 minutes. One round on the circular set-up consists of 9 error free taps. Each user had to go around the set-up 25 times to complete one condition (e.g., 225 error free taps per condition). With 12 conditions, each participant performed 2,700 error free taps.

### 4.4 Apparatus

Cylindrical static bars with touch sensors on the top were fitted to our experimentation platform (Figure 4). Targets light up blue to show participants which target to select. A camera positioned above the set-up recorded the arm, hand, and finger position of the participant during the study.

### 4.5 Task

The subjects were told to begin at target "0" (12pm direction from them) and end on the top left target "9" (see Figure 4). This is one trial. Arrows indicate the path subjects follow using their index finger of the dominant hand, to alternating targets, clockwise around the circle. With such sequencing we could test both high to low, and low to high movement and thus investigate the effects of delta height on interaction.

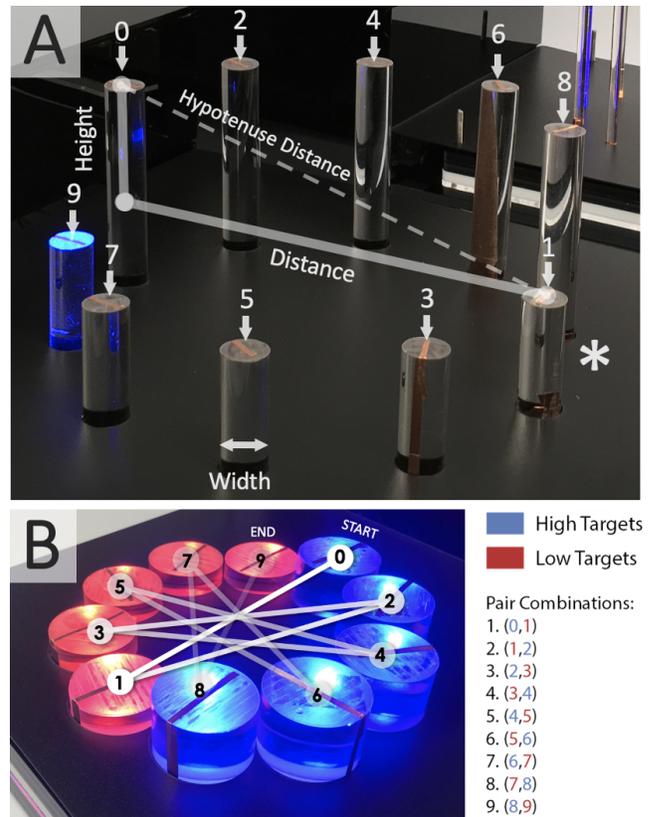


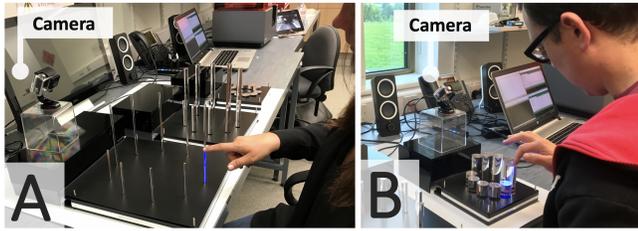
Figure 4: (A) Breakdown of experimental setup. (B) Physical 3D multi-directional tapping task breakdown, targets are all lit for clarity.

### 4.6 Procedure

Each participant performed the experiment in a single session. First, participants were introduced to the study and asked to fill out a demographic questionnaire. To prevent influencing how a participant interacted with targets, the purpose of the study was presented as a simple interaction task where speed and accuracy were the main objectives. Users were sat on a height adjustable chair. They had the option to adjust the chair's height based on the participant's height and arm length so that their hand was at approximately 90 degrees when placed on the table and within reach of the furthest target (see Figure 5A). Participants were told they could only interact with the circular targets using the index finger of their dominant hand whilst sitting. Their dominant hand was recorded in a demographic pre-study questionnaire.

At the beginning of each new condition the participants were presented with a practice run through that consisted of 90 error free taps around the setup. It had taken participants on average 30 seconds to complete 90 taps during training for each condition. Once the participant was satisfied with the training round, they were asked to complete a recorded condition until all targets turned red to indicate 25 trials (225 error free taps) had been completed.

If any errors or discrepancies occurred (e.g., missed taps, double taps, hand or arm bumps into a target) during a trial, the movement



**Figure 5: Participants seated and interacting with the study hardware. A GoPro positioned above the set-up recorded close-up interaction for each task.**

time recorded is mapped to the video recording for further investigation (see ‘dependent variables’ for how errors are recorded). Once all 12 combinations were completed participants were asked to fill out a qualitative experience questionnaire.

#### 4.7 Participants

We recruited participants through word of mouth and posters. In total, 19 participants (M = 11 and F = 8) ages ranging from 20 to 58 performed the study. We recorded ‘handedness’ of each participant and ensured they used their dominant hand during the study. Two participants were left-handed, one ambidextrous.

#### 4.8 Dependent Variables

We recorded two dependent variables: movement time and error rate. Interaction performance was measured as Movement Time (MT) between an even start-target (e.g., 0 or 2) and an odd end target (e.g., 3) in a trial. Downwards movement (0 to 1) was also recorded for additional path analysis (Figure 8). A trial begins when a participant successfully taps on target “0” and ends once target “9” is pressed (see Figure 4A). Each trial consists of 9 error free taps, without including target “0” as it is considered the starting position.

An error is recorded when a participant fails to hit the correct target. If an unintended target is tapped it is recorded as an error, but no error feedback is given to users visibly and they continue with the trial. Any taps considered an error were recorded but not included in the final dataset. The correct target must be tapped for them to proceed to the next one, until they reach target “9”, to complete a trial. When a participant hits a target that is not blue, our setup records this as an error. Although this is not a standard approach for recording Fitts’ Law errors, we justify our approach for error handling by highlighting the need to recording more quantitative data for physical interfaces as they differ significantly to their virtual counterparts. Additionally, there is more chance of a mistake in the physical case (e.g., hitting a rod with the back of your hand). Finally, participants were also asked to fill in a post study questionnaire and to select their preferred IDs and heights of target based on their user experience and perceived accuracy. The questionnaire consisted of multiple-choice answers and a short written section for participants to justify their choices.

## 5 RESULTS

Our analysis first looks at how our data for physical targets fits to existing pointing models, particularly the ones presented in the

**Table 1: Linear Fit – intercept, slope, and adjusted  $r^2$  using  $ID$  with traditional Distance. Each  $ID$  was calculated using each model’s retrospective equation.**

Models/ Variants	Distance $D$ & Width $W$ $MT = a + b.ID$		
	$a$	$b$	Adj. $r^2$
Fitts (equation 1)	0.15	0.05	0.721
MacKenzie (equation 2)	0.18	0.06	0.729
Welford (equation 3)	0.19	0.06	0.726
Murata (equation 4)	0.14	0.07	0.810
<b>Grossman (equation 5)</b>	<b>-0.08</b>	<b>0.08</b>	<b>0.930</b>

**Table 2: Linear Fit – intercept, slope, and adjusted  $r^2$  using  $ID$  with Distance as hypotenuse rather than distance. Each  $ID$  was calculated using each model’s retrospective equation.**

Models/ Variants	Distance ( <i>hypotenuse</i> ) & Width $W$ $MT = a + b.ID$		
	$a$	$b$	Adj. $r^2$
Fitts (equation 1)	0.13	0.06	0.759
MacKenzie (equation 2)	0.16	0.06	0.765
Welford (equation 3)	0.18	0.06	0.762
Murata (equation 4)	0.12	0.07	0.837
<b>Grossman* (equation 5)</b>	<b>-0.11</b>	<b>0.08</b>	<b>0.954</b>

related work *equations 1-5* (step 1). We then explore in further details the effect of our independent variables (step 2). We finish by exploring the qualitative feedback from our participants (step 3).

### 5.1 Step1: Best fitting pointing models

**5.1.1 Validating baseline with delta height 0mm.** The condition delta height 0mm was used as a baseline and to validate that our setup records standard Fitts’ Law in a two-dimensional tapping task. We used Fitts’, Welford’s, and MacKenzie’s models for  $ID$  (*equations 1-4*). The best fit model was MacKenzie’s formulation for  $ID$  (*equation 2*), where  $a = 0.17$ ,  $b = 0.06$ , and  $r^2 = 0.957$ . The  $r^2$  values for effective width were generally lower across all conditions where delta height was zero. These results show our setup successfully records and models Fitts behavior for standard flat targets.

**5.1.2 Error rate.** We chose to exclude the ( $We$ ) estimation calculation as the error rate needs to assume a Gaussian distribution of the endpoints. The error measured in this study does not take into account the endpoint distribution but rather single point contact anywhere on the top of the target, as a result we only report on the general error rate when a user hits the wrong target. We removed any outliers that were more than three standard deviations from the mean. 57 outliers were removed, 2.1% of 2,700 data points collected.

The average error rate for all conditions was 1.72% (MAX = 3.18% where width = 5mm, and MIN = 0.63% where width = 30mm). Targets with delta height 90mm had a higher error rate (1.2% above

average). As expected, targets with thinnest width (5mm) also had higher error rate (1.97% above average). Though when delta height was 10mm, the error rate was lower compared to when delta height was 40mm or 90mm. Based on observations from the video analysis, participants with the shortest times had the most errors. This is consistent with Fitts' speed and accuracy tradeoff [17].

**5.1.3 Movement time with delta height not zero.** We removed all times that were more than three standard deviations from the mean. We performed linear regression on movement time to understand which of the current Fitts' Law derivatives best models our dataset. Table 1 shows the intercept, slope, and adjusted  $r^2$  for  $ID$ , using the five Fitts' models described in the related work. When fitting the data, Murata's  $ID$  with an additional variable for elevation angle provides a suitable fit ( $r^2 = 0.810$ ). Their variation considers angle of elevation when modeling trajectory between targets. Though it is Grossman's model that provides the best fit with  $r^2 = 0.930$ .

Note that to obtain those results we had to make some adaptation to certain models, particularly Grossman's: the full target volume is used in their model and this does not accurately represent the local touch area used for single finger pointing. We also did not use a position-controlled 3D cursor and rectangular targets in a volumetric display.

We also performed regression for all five Fitts' models using the hypotenuse distance (Figure 4A) between a high and low target as a measure for distance. The regression showed an improved fit with the Fitts' model ( $r^2 = 0.759$ ), Welford ( $r^2 = 0.762$ ), and MacKenzie's model ( $r^2 = 0.765$ ) formulations for  $ID$ . Hypotenuse as distance increased the fit for Murata's formulation of  $ID$  where  $r^2 = 0.837$  and further increased the best fit for Grossman with  $r^2 = 0.954$ . See Table 2 for details.

**5.1.4 Summary (Step 1).** The Grossman model was the best match for our data whilst 2D models showed relatively low correlation (e.g., Welford). This suggests that pointing models for 2D virtual targets do not accurately depict tasks with 3D physical artefacts. It also shows that volumetric models can be transferred to physical environments with tangible targets. Additionally, hypotenuse as distance (Figure 4A) shows to be more appropriate than  $IDe$ .

## 5.2 Step 2: Analysis of Factors

To understand further how delta height affects movement time, we tested the impact of our independent variables (Fitts  $ID$  and delta height) on movement time. We performed a two-way within subject ANOVA where delta height was non-zero. The analysis revealed significant effects of  $ID$  (generated using the Shannon formulation [45]) and delta height separately as well as interaction between them on movement time. See Table 3 for details. We then performed pairwise comparisons using T-tests for each of the independent variables ( $ID$  and delta height) with Bonferroni adjustment. For delta height there is significant effect between pairs (10mm & 90mm) and (40mm & 90mm) where  $P = < 0.0001^*$  for both. For Fitts  $ID$  there was significant effect between all three pairs where  $P = < 0.0001^*$ .

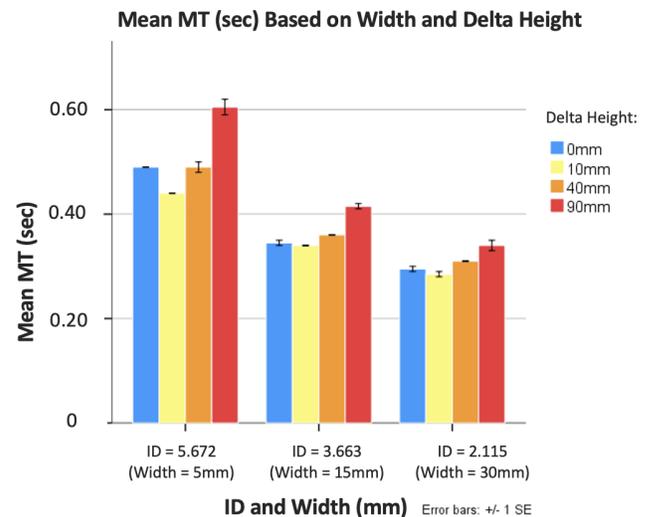
**5.2.1 Effects of delta height on movement time.** We wanted to understand how delta height of a target impacts movement time based on the target's  $ID$ . Figure 6 shows the relationship between target  $ID$  (using the Shannon formulation [45]) and delta height and how

**Table 3: Significant ANOVA main effects and interactions for mean movement time (sec).**

Factor	df effect	df error	F	P	Partial $\eta^2$
ID (Fitts)	1.00	18.00	172.83	< 0.0001*	0.79
Delta Height	1.00	18.00	53.03	< 0.0001*	0.51
ID x Delta Height	1.00	18.00	18.73	0.0004*	0.2

this effects the movement time. Particularly, we highlight that movement time is actually reduced when the target width (e.g., 5mm) is smaller than the human finger pad but the target is also slightly raised (10mm height). We observed a similar trend for all three  $ID$ s, as the target height increases the movement time also increases. The magnitude of effect of height decreases as  $ID$  increases.  $ID$  also has an independent effect on movement time, which increases as  $ID$  lowers - regardless of height. Finally, with smaller  $ID$ s, height has a much greater impact on movement time.

Overall, we see that as  $ID$  increases, movement time also increases, which is consistent with the original Fitts' Law. We observed a greater difference between movement time when delta height = 0mm and 10mm (slightly raised targets). This shows that slightly raised targets have a faster acquisition time when their width is 5mm. However, as  $ID$  increases that difference becomes less apparent. Note that these results are reported in the context of the  $ID$  being calculated as in the original Fitts' Law, i.e. not taking into account the hypotenuse. With the hypotenuse increasing with delta height it is thus very likely that this also increases the movement times. It thus suggests that the definition of  $ID$  may also need to be revised for physical 3D targets.



**Figure 6: Comparison of Movement Time (MT) between flat targets (blue bar) and raised targets.  $ID$ s generated using [45].**

5.2.2 *Effects of trajectory and direction on movement time.* When comparing direction of user movement from a high to a low target, and low to high target we see the expected increase in movement time as *ID* increases. Only when *ID* = 5.672 (width = 5mm, height = 40mm) an apparent decrease in time is shown for high to low targets in comparison to the opposite trajectory. We isolated each path (Figure 7) based on its trajectory, e.g. high to low or low to high, to gain insight as to how direction and angle of movement on the plane effects performance.

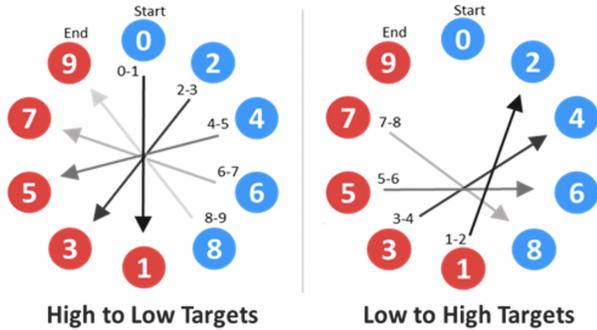


Figure 7: Direction of movement path for targets in a circular set up. Higher targets are always situated on the right side of the set up and colored blue in this diagram.

Figure 8 shows the mean movement time for all conditions (grouped by *ID*) where delta height is greater than zero for high to low target paths. We see that for direction there is an overall difference between paths 6-7 and 8-9 for each *ID* group. We predict that path direction from high to low has effect on performance together with delta height.

Figure 9 shows the mean movement times for low to high target acquisition. In Low-to-high direction, the movement distance is always the chord, which is only 95% of the designed distance. The *ID* of L-to-H is updated, respectively. We see that greater delta height yields slower movement time. This trend becomes even more apparent as *ID* increases. We aim to conduct further in-depth explorations of path and direction dependencies in future.

5.2.3 *Summary (Step 2).* In summary, delta height and movement direction affect pointing performance with physical 3D objects. Specifically, this is more prominent when *ID* and delta height increases for high to low target paths (see Figure 8). Our results suggest that such parameters should be embedded within pointing models (as well as the way *ID* is computed).

### 5.3 Step 3: Qualitative Feedback and Observations

To further understand the reason why physical factors affect pointing we look at the post study questionnaire. For preferred width, 16 participants selected the largest width (30mm width, *ID* = 2.115) and the rest choose 15mm width. The widest targets gave participants most confidence for accurate interaction due to their sturdy appearance and larger contact surface area. Based on participant

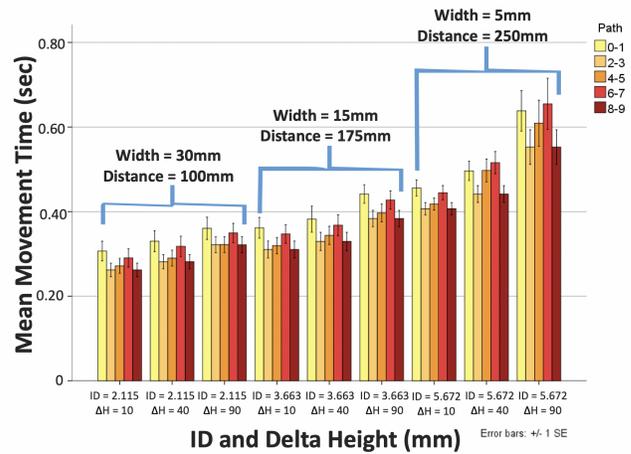


Figure 8: High to low target acquisition movement time, with a gradual increase in MT as delta height and *ID* increases. *IDs* generated using Shannon formulation [45].

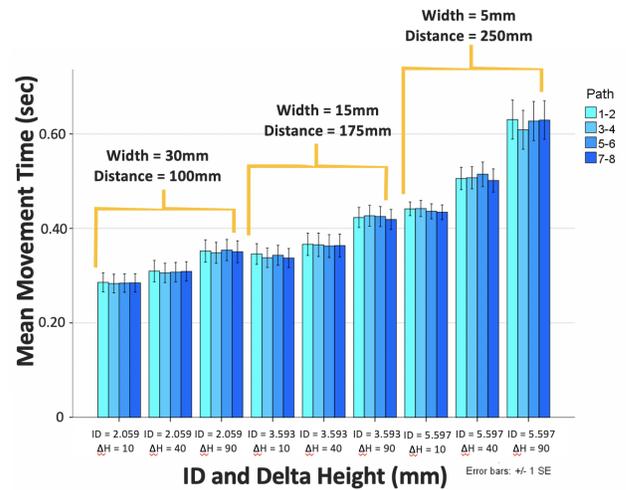


Figure 9: Low to high target acquisition movement time. We see a clear gradual increase overall in movement time as delta height and distance increases and width decreases. *IDs* generated using Shannon formulation [45].

feedback (and as expected) interaction was easier with shorter distances between wider targets. Video analysis shows participants consciously changing finger position on the target tops, from fingertip to finger pad, when hitting the thinnest targets (5mm width, *ID* = 5.72). Overall, participants’ observations are consistent with the Fitts’ analysis results.

13 participants selected the slightly raised targets (10mm delta height) as their preferred height. This corresponded with the enhanced user performance metrics presented earlier in “Effects of Height on Movement Time”. Most participants expressed their dislike of the highest targets (90mm delta height) due to occlusion and

physical arm strain. Five participants expressed preference for flat targets due to reduced occlusion as they hit unintentional targets less often than when delta height is 90mm.

Several participants found only slight differences between the flat targets and the plastic base when touching the setup surface. Whereas sharper haptic sensation provided with the slightly raised targets (10mm) when width was 5mm shows that it is more important for thinner targets to be raised due to finger occlusion. The minor elevation in height enabled sharper haptic sensation for users, this helped them to acknowledge they hit a target accurately without depending entirely on visual feedback.

One participant pointed out how height of a target effects their curiosity: *“It is interesting because though I am likely to approach a tall or very tall buttons, say in a Museum. Once I interact, I am more likely to prefer a short button for speed and confidence”*. We observed participants were initially apprehensive with hitting targets of a thinner width and greater height, as *“they looked fragile”* and participants were *“scared of snapping them if hit it too hard”*.

Participants approached the wider targets with much more confidence due to their more stable appearance. User confidence with wider target interaction yielded fastest movement time. However, the increase of speed with the wider targets also resulted in the greatest error rate for all conditions with largest width 30mm. Participants approached the wider targets with much more confidence due to their more stable appearance. User confidence with wider target interaction yielded fastest movement time. However, the increase of speed with the wider targets also resulted in the greatest error rate for all conditions with largest width 30mm.

**5.3.1 Summary (Step 3).** The reasons why form factor of targets affect pointing performance relies on complex cognitive and perceptual mechanisms that may be hard to model. For instance, compared to a virtual target, a physical one could produce pain to the users if approached too fast. Further, the perception that it could break also impacts approach rate. Our results suggest that those factors affect pointing performance.

## 6 DISCUSSION AND FUTURE WORK

Our study shows how delta height of static physical targets affects performance time based on adaptations of Fitts' Law interaction models. We compared five of the most commonly used Fitts' Law models to explore if existing GUI interaction paradigms can be adopted by physical user interfaces. We find that Grossman and Balakrishnan's [20] model (3D Fitts' Law) shows the best fit for our data as it considers the angle of elevation with hypotenuse distance as amplitude. Adjustment for accuracy for  $ID_e$ , using We based on error rates, shows a decrease in  $r^2$  for linear regression. We attempted to use hypotenuse distance as an adjusted effective Distance independent variable and saw an even better fit of  $r^2$  values for all current Fitts models compared. This is something we must investigate further to gain a better understanding of how to enhance adjustment for accuracy incorporating height.

### 6.1 Extending to Tangible 3D Fitts Law

Attempts have been made to take into account the direction of the movement with respect to the geometry of the target [20, 45] in 3D environments. Grossman and Balakrishnan's [20] models for 3D

targets are also based on this idea. In contrast, Murata and Iwase [47] study circular targets, so the role of angle is now different, performance differences are rather due to physiological constraints of directional hand movements. Murata and Iwase conducted their experiment on a vertical screen, but others [68, 73] have observed similar effects for direction-based pointing with a mouse.

**6.1.1 Toward Better Pointing Model for TUIs.** The extensive work with GUIs has shown the great benefit of having interaction models, but there is still a lack of empirical experimentation with physical user interfaces for constructing rigorous interaction models. Our findings have shown that form factors affect performance time but contrary to the original Fitts' Law, we do not think this is only due to motor factors but also cognitive affordances (e.g., something high and thin is perceived as more breakable, or might hurt your finger more than something flat and large). The direction of movement is also important as it effects which part of the target the user will hit (e.g., edge of target). As a result, the user may take more care when approaching targets from different angles.

## 6.2 Design Considerations

Beyond our findings encouraging more empirical investigation in the field of tangible interaction, our results can also be used to draw a list of design implications for developing physical interfaces:

**6.2.1 Error rate corresponds with interaction confidence.** We observed that conditions with lowest  $ID = 2.115$  show the highest overall error rate. Participants had more confidence going faster but at the same time made more mistakes. This is consistent with 2D Fitts' speed and accuracy tradeoff and can be mapped to tangibles. Thinner targets (5mm width,  $ID = 5.672$ ) produced lower error rates as participants approached them with more caution. Much like with traditional GUIs, designers should take into account the level of action a target has associated with it. A primary action (e.g., 'Save') needs to be easy to reach with a larger touch-area (e.g., 15-30mm target width). Secondary actions (e.g., 'Cancel' or 'Go Back') should have smaller touch area (e.g., 5-10mm target width) as reducing the contact area minimizes the risk for potential errors.

**6.2.2 Optimal height and width conditions.** In comparison to our baseline conditions (0mm height), a slight increase in elevation for a target with a small width (e.g., 5mm) can improve user performance. We conclude this is due to the haptic feedback gained with the additional slight elevation (e.g. 10mm delta height). The tradeoff must be studied in more detail to gain a better understanding at which point exactly that tradeoff is no longer effective.

**6.2.3 Considerations for tangible and shape-changing interfaces.** Current work on tangibles does not fully utilize interaction between width and height parameters, as well as vision and haptic dependencies. For example, Robinson et al. [51] design mobile tangible interactive features with 15mm width and 10mm delta height. Based on our findings, these dimensions would produce the same movement time as if delta height is 0mm. Considering their application is focused on mobile devices, where space is limited, we recommend a target width of 5mm and delta height of 10mm to enhance performance speed and save space on a smaller interface.

Based on our error records and video analysis, we recommend higher targets to be further back from shorter targets when users interact with larger scale public or table-top shape displays. Having higher targets further back reduces occlusion and enables users, regardless of handedness to interact more freely and move their hand around all targets. This dynamic can nevertheless be used to manipulate users' hand preference as it would bias towards using their non-dominant hand to interact with targets that may be occluded on one side.

**6.2.4 Designing for shape-changing displays.** For designing shape-changing displays, the ability to dynamically change physical form factors further enhances the opportunities to create adaptive user experiences and manipulate user performance directly [54]. Particularly, in public settings [16, 31], users are more likely to approach taller interactive targets. Once a user begins to interact with the display, those targets can then decrease in height to provide enhanced user performance for speed and accuracy.

### 6.3 Toward a Roadmap for Future Physical Interaction Studies

At a higher level of abstraction, we would like to discuss a challenge which we believe is crucial for the HCI community. Our paper only starts to expose the difficulty of studying pointing in the physical world with non-planar objects. We think there is a strong need for the HCI community to understand the problem in detail and to find solutions to overcome the intrinsic barriers that such studies imply.

**6.3.1 The Problem of Dimensional Complexity.** The problem with studying interaction and deriving models with non-planar physical devices is the opening of an exponential design space for experimental design choices. We believe that this exponential explosion of factors clashes with current practices (or perception of what are 'normal' practices) in HCI, and particularly through the use of statistical models such as null hypothesis testing. When designing a user study there is a trade-off between the number of factors, combined with the number of repetitions (or amount of data gathered) against the need to maintain the study counterbalanced and short enough to avoid confounding biases (fatigue, order). However, when studying physical interaction models, researchers need to choose not only the width, distance, and length of targets to study, but numerous other factors including height, material, rigidity, movement direction (potential collisions), and the object's shape itself—potentially infinite topologies. In comparison, most GUI experiments are relatively simple, e.g. in the case of pointing, we need only consider the width, distance, and length of a target and the input device.

We believe this clash between more traditional approaches and the need to explore a plethora of new factors to understand physical interaction models, creates an imbalance within the HCI community. More directly, our position is that such studies are less likely to be published or even conducted because they do not fit the traditional format of GUI-based experiments. They are thus more open to critique of the selected factors. This is problematic because, given the multitude of potential factors, a single study (or even small set of studies) cannot cover all possibilities. At the same, we need to encourage significant more exploration of this space. Our paper

then answers only a subset of questions given the factors we choose to study—there are certainly many other factors and combinations of factors to explore. We would strongly encourage the community to appreciate these differences: after all, we have 40+ years of studies on traditional GUIs (e.g. desktop, mouse) but significantly fewer on new and emerging form factors.

**6.3.2 Possible Solution 1: Systematic Exploration of Factors.** The first solution to this problem is to encourage more researchers to investigate physical factors by providing guidelines as to which factors are particularly important. Through our work we have highlighted a number of possible directions: further investigation is required to enhance our understanding of how direction together with trajectory affects user performance in physical 3D space. We also need to collect empirical data that incorporates hand and finger movement tracking to provide a better understanding of how movement direction affects the biomechanics of the user. For example, we found that wider targets resulted in greater error rate, but this could be the consequence of the smaller distance between the targets. Another direction is to go beyond static objects and develop our understanding of interaction between physical targets when elevation changes using modular actuators such as ShapeClips [24].

Beyond these first investigations, the community would also benefit from a route to exploring the experimental space in a more systematic way. Alexander et al. [3] previously proposed a roadmap for research in shape-changing interfaces, while Roudaut et al. [52] proposed a characterisation approach for novel form factors. Such works could be used and extended to form a framework that supports researchers in exploring this space and lowering the barrier to developing fundamental models of interaction in 3D space.

**6.3.3 Possible Solution 2: Toward a More Computational Approach.** Given the high dimensionality of the physical interaction space, another solution is to adopt computational approaches (e.g. Banovic et al. [6]) to assist modelling. For example, there is the potential to create simulation software that can predict the performance of human interaction in basic scenarios such as pointing, and then adapt these based on knowledge of different materials or physical setups. For example, studies have shown that pointing accuracy is tightly linked to the size of contact made between the finger and a surface [53]. This information could easily be computed and offered to designers or researchers when predicting the best interaction for users. This research direction echoes with Holman and Roudaut's work [26] that suggests computer aided interaction design. Of course, there is significant debate around what aspects of interaction can be quantified and what cannot, but we believe that simple interactions such as pointing could potentially be modelled and simulated. In the future, Machine Learning could also help to improve the predictions of such simulation software.

### 6.4 Limitations

**6.4.1 Effects of Fatigue.** The study required participants to perform long continuous movements repetitively and this can cause fatigue as well as impact the overall user experience. To reduce the impact of fatigue on our results (e.g., movement time) we counterbalanced the ordering of conditions for each participant. Given the long duration of the study (1 hour and 30 minutes average), participants

did have the option to take a break after every trial if needed. In most interaction scenarios with tangible surfaces we envision discrete rather than continuous movements to be performed by users (e.g., pointing to one object at a time). Nevertheless, we need to investigate the impact of both physical [46] and visual [25] fatigue for tangible interaction.

**6.4.2 Physical Limitations.** Bio-mechanical factors such as effects of posture and hand movement can impact muscles activation [4] and thus speed of movement. We ensured that all participants performed the study in the same pose to reduce inconsistencies in posture and angle of movement. Like previous work on pointing in 3D space highlights [7], we predict that targets on the dominant (typically right) side have slightly better performance than on the other side, based on movement bio-mechanics (e.g., dominant arm is stronger). Additionally, we suspect there is more effort required by a user when crossing the middle axis of the body with their arm when the target is closer to their chest and the arm is not extended. Collecting more empirical data that incorporates hand and finger movement tracking will provide a better understanding of how movement direction and speed affects bio-mechanics factors.

**6.4.3 Visual Issues.** Recent work identify how visual perception has a larger effect on selection than motor control [43]. For example, having multiple interactive objects along the same line of sight can confuse users and increase how long it takes to calculate depth. Our study had objects in a circular configuration to reduce this visual issues, however we do not take into account visual distraction from the targets lighting up. In terms of visual fatigue, it is advisable to avoid targets close to the user's eyes, as this reduces pointing performance and increases the likelihood for motions along the line of sight [25]. Additional considerations on visual perception impact should take into account calculating the target depth. Throughput could be used to evaluate this, however, we are unable to calculate accurate throughput as we exclude the effective Width estimation in this study. In future work we will explore a range of materials for targets and provide insights into how depth perception issues could be mitigated (e.g., differences between clear and opaque targets).

## 7 CONCLUSION

There is an increasing need to understand the effect of form factors on user performance for physical interfaces. Many Fitts' Law studies look into 3D interaction, though mainly in virtual environments, few investigate the physical space. We presented an empirical evaluation that investigated how physical features of targets impact user performance metrics. Our empirical evaluation shows that a pre-existing interaction model (e.g., Grossman) for volumetric displays can be generalizable to pointing on tangible objects. Our design implications also consider additional complexities such as materiality and affordance for physical interfaces. We believe these preliminary insights enhance the design space by mapping user performance trade-offs in physical UIs that can be mapped to pre-existing interaction models.

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