Data Physicalization with Haptic Variables: Exploring Resistance and Friction

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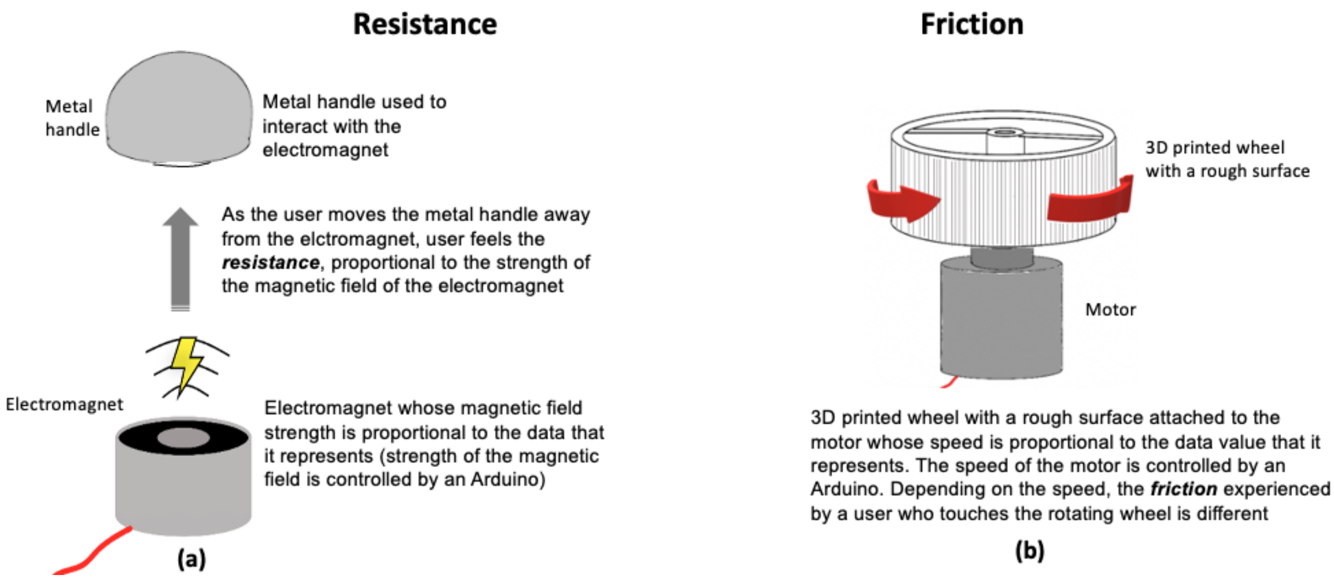

Figure 1: Resistance and Friction to encode data: (a) we used electromagnetic field strength as material for realizing resistance and, (b) motor speed combined with a rough surface to realize friction. Both the electromagnetic field strength and the speed of the motor were varied to realize varying levels of resistance and friction.

ABSTRACT

Data Physicalizations have the potential to create interactive and more engaging data experiences and to make data more accessible to a broader range of users than those reached by visualizations alone. Tapping into this potential necessitates an understanding of the strengths/weaknesses of the different encoding variables available to designers, and when these variables can be employed to convey data. This work provides a preliminary investigation of two kinesthetic variables (resistance and friction) and their performance during the answering of minima/maxima/cluster questions. We evaluated both encoding modalities with users for their efficiency and effectiveness in a lab-based study. While neither modality was found to be significantly more efficient or accurate, most users preferred reading data through resistance.

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CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in interaction design**; **Haptic devices**.

KEYWORDS

data physicalization, embodied experiences, encoding variables, haptic variables, friction, resistance

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1 INTRODUCTION

Data visualizations represent data using visual properties such as color, shape, or patterns. They are mostly screen-based and can be accessed and interacted with via desktop or mobile devices (e.g., [31, 32]). Data physicalizations, also called physical visualizations, on the other hand, are physical representations of data that encode data in geometric and material properties [24]. Unlike data visualizations that focus mainly on the sense of human vision, data physicalizations can present data to multiple human senses (touch, smell, hearing, taste, vision) using various physical representation modalities [30], making it possible to create embodied data experiences. Due to their physical nature, they can create novel, non-screen-based interactions that can actively engage the human body and the sensorimotor system, which involves tactile and kinesthetic interaction with physical objects to interact with digital data. Human cognitive processes such as perception, memory, learning, and attention have a strong connection with the active involvement of the sensorimotor system, bodily interaction with the environment, and tactile and kinesthetic aspects of body-object interaction [3, 12, 26, 36]. Therefore, data physicalizations have the potential to improve the perception and interpretation of data and overall engagement and human-data experience by exploiting tactile and kinesthetic aspects of physical media and using interactions that involve bodily engagement, touch, and kinesthetics. Encoding data in tactile and kinesthetic properties such as friction and resistance have been proposed in previous research [13, 30]. Although there is substantial work on exploring tactile properties (such as vibration amplitude, vibration speed, or temperature) for data physicalization [30], research on using kinesthetic properties is rare [22, 30]. There are three kinesthetic properties identified in existing research: resistance, friction, and kinesthetic location [30]. However, empirical research on using these kinesthetic properties and their effectiveness remains largely unexplored [22, 30]. When realized through interactive technologies (such as sensors and actuators), kinesthetic properties have a good potential to create kinesthetic interactions, interactions that involve bodily movement (thus the active involvement of the sensorimotor system) [9] providing cognitive and experiential benefits mentioned above. In this research, we therefore aim to explore the impact of two kinesthetic variables, resistance and friction. We created a data physicalization that encodes two types of data (ordinal and numerical) using resistance and friction, realized using electromagnetic field strength and motor speed respectively. The effectiveness and user experience of physically representing data using these two kinesthetic variables were evaluated using a user study with 18 participants. Our contributions are therefore: (a) a data physicalization artifact that uses resistance and friction as modalities to encode numerical data and that uses electromagnetic field strength and motor movement as material for representing data; (b) an empirical evaluation of the proposed modalities.

2 RELATED WORK

2.1 Data Physicalization for Post-WIMP, Beyond Desktop, Natural Interaction with Data

People used physical representations of data for many years (e.g. knots in threads to represent numeric data (as early as in 3,000 BC), Sumerian clay tokens [35], Ammaslik wooden maps[2, 7], Marshall Islands stick charts [8])) [1, 22, 24]. However, data physicalization emerged as a scientific discipline only very recently [24]. Various modalities have been explored for encoding data physically. These include, for example, light [19, 29], movement [5], temperature [38], vibration [15], force [20] and sound [15]. These enable multisensory data experiences. Theoretical frameworks are also emerging. For example, several design spaces (e.g. [1, 16, 18, 30, 34]), classifications of encoding variables for physically encoding data (e.g. [18, 30]) and interaction models (e.g., [23]) for designing data physicalizations emerged recently. Current research in data physicalizations shows that they improve memorability, help better perception, and increase engagement with data [24, 34].

Human perception and cognition are tightly coupled with action, involvement of the human sensorimotor system, and physical interaction with the real world (such as direct manipulation of tangibles during interaction) [6, 17, 27, 28, 37]. Novel interaction frameworks such as Reality-based Interaction (RBI) [21] provide conceptual foundations for designing beyond the desktop, post-WIMP (post-Windows, Icons, Menus, Pointer) and more natural interfaces and interactions that can involve action, human sensorimotor system and interaction with the physical world. RBI concepts center around using naive physics, body awareness and skills, environment awareness and skills and social awareness and skills in designing interactions [21]. With their physical and tangible nature, and with the ability to move beyond traditional desktop and mouse-based data visualizations, data physicalizations can facilitate realizing reality-based interaction with data. Thus, via RBI concepts, data physicalizations have the potential to improve the perception of data and provide more engaging and embodied human-data experiences.

2.2 Data Physicalization with Haptic Kinesthetic Variables

Data physicalization with haptic modalities has the potential to make data sensible for people with visual and auditory impairments, allow eyes-free interaction with data, make more feelable, embodied, and engaging data experiences, and allow the creation of novel interaction techniques (e.g., to explore the use of various human grasping gestures [4, 22] for interacting with data). Griffin [13] decomposed haptic sensations into three categories: those derived from touch (tactile), those derived from kinesthesia - bodily movement or tension (kinesthetic), and those derived from visual analogues (i.e., variables that can be perceived by both vision and touch) [13, 30]. Ranasinghe and Degbelo [30] identified variables that can be used to physically encode data for these three haptic sensation categories: tactile (vibration amplitude, vibration frequency, pressure, and temperature; kinesthetic(resistance, friction, kinesthetic location; visual analogues(tangible size, tangible elevation, tangible shape, tangible texture/grain, tangible orientation, and tangible location [30].

There exists some work on using tactile variables and visual analogues variables for data physicalization: e.g., van Loenhout et al. [38] compared the effectiveness and user experience of encoding data using temperature and vibration; Hogan et al. [15] used vibration to encode data and compared its effectiveness to visual and auditory representations. For a detailed list of work on tactile and visual analogues variables, we would like to direct the reader to [30]. On the one hand, compared to tactile and visual analogues haptic variables, only a couple of work (e.g., [20]) exists for the use of kinesthetic variables for data physicalization and this area remains largely unexplored (c.f. Table 7 of [30]). On the other hand, kinesthetic variables when realized through interactive technologies, show a good potential in creating kinesthetic interactions (interactions that can actively involve the human body in the interaction) [9] thus have a potential to provide cognitive and experiential benefits. Therefore, in this work, we aim to explore two of the three kinesthetic variables: resistance and friction.

3 SYSTEM DESCRIPTION

Data: To explore the effectiveness and user experience of conveying data using resistance and friction, we created a data physicalization that uses a dataset with statistics for the 10 neighborhoods of the municipality of Enschede in the Netherlands, as a use case. The dataset was taken from Statistics Netherlands [10] published by the Central Bureau for Statistics in the Netherlands (Centraal Bureau voor de Statistiek(CBS)) [10]. For the physicalization, we used the following data: number of crimes per year, income level and percentage of rental houses (all at a neighborhood level).

Realizing Resistance and Friction: *Resistance* is a kinesthetic haptic variable [13, 30]. When one attempts to move a metal away from an electromagnet, she can feel a resistance proportional to the strength of the magnetic field of the electromagnet. Electromagnetic field strength can be systematically controlled (by programming an Arduino) to vary the experienced level of resistance. We used this property to realize and encode data using resistance (c.f. Figure 1a).

Friction is defined as the haptic feeling felt when the hand moves across or through a surface [30] and is a kinesthetic haptic variable [13, 30]. We used a 3D-printed wheel with a rough surface (rough enough to feel the friction) that a user can touch by her finger (c.f. Figure 1b). To vary the experienced level of friction, we attached the wheel to a motor whose speed can be systematically varied using an Arduino.

Data Physicalization: We used a laser-cut map of Enschede as the base of our physicalization. The 10 neighborhoods of Enschede are engraved on the map (Figure 2a). A user can select the desired dataset (out of 3 datasets: income level, number of crimes, percentage of rental houses) using switches (on the top left of the panel in Figure 2a). The data representation mode (resistance, friction) can be selected using two switches (on the bottom left of the panel in Figure 2a). Attached to each neighborhood are an electromagnet (for experiencing resistance), a 3D printed wheel (for experiencing friction), and a switch (to switch on the neighborhood) (c.f. Figure 2b). When switched on, a user can interact either with the electromagnet using the metal handle (Figure 2d), by moving it away from the electromagnet or with the rotating wheel, by touching its rough surface with a finger (Figure 2c). The electromagnetic field strength or the speed of the motor are proportional to the data of the selected neighborhood. The color of the dataset switches and the neighborhood switches correspond to the familiarization phase and the testing phase (c.f. Evaluation in Section 4), the blue one was used for familiarization and the green ones were used for the actual user evaluation.

Both the motor and the electromagnet work on the same principles of electromagnetism. Therefore, we used a Pulse Width Modulation (PWM) signal which can be used to control both the speed of the motor and the magnetic field of the electromagnet. To practically achieve this, we used a motor driver (a 4-channel L293D motor driver). The motor and the magnet of a neighborhood was connected to its motor driver. All motor drivers were connected to an Arduino (Arduino Mega) allowing both the magnet and the motor to be turned on/off and controlled based on a PWM signal. A PWM signal can range from 0 to 255, where the voltage drops from a 100% at 255 to 0% at 0. For all datasets, the data was mapped to the range of PWM values where 0 is mapped to the lowest PWM value felt by the user and the highest value in the dataset to 255. Two different mappings were used to linearly distribute the data over the range of PWM values for both modalities. In initial tests of the motor, a value of 60 was discovered to be the lowest value at which the motor starts spinning. The mapping for the motor for a given data value is therefore: $(60 + ((Value/maxValue) * 195))$. For the electromagnet, a value of 100 was found to be necessary in order to produce a magnetic field strong enough to be observed by the user. The mapping for a given data value is therefore:$(100+((Value/maxValue)*155))$. Values were linearly distributed over the PWM signal ranges with the exception of the income data, which is categorical. A categorization was created based on the tasks for the experiment, which would require a minimum value, a maximum value, and two values in the same category. Because of the five neighborhoods represented by the installation, four categories were made. As the data is static for this experiment, values were hard coded into arrays for processing by the Arduino (3 datasets and separate mappings for both modalities » six different arrays were encoded). The Arduino takes the last dataset, modality, and neighborhood selected and chooses the right value from the right array. This value is then sent to the appropriate motor driver through the PWM pin, which the driver translates into a signal that controls the magnet or the motor.

4 PRELIMINARY EVALUATION

Study Design. We conducted a lab-based user study with 18 participants (nine male and nine female) to evaluate the effectiveness of conveying data using resistance and friction. During the user study participants performed data exploration tasks by interacting with the physicalization and answering questions related to the tasks. We used three types of tasks: minima, maxima, and cluster (Table 1), organized in two task sets. Each participant interacted with both

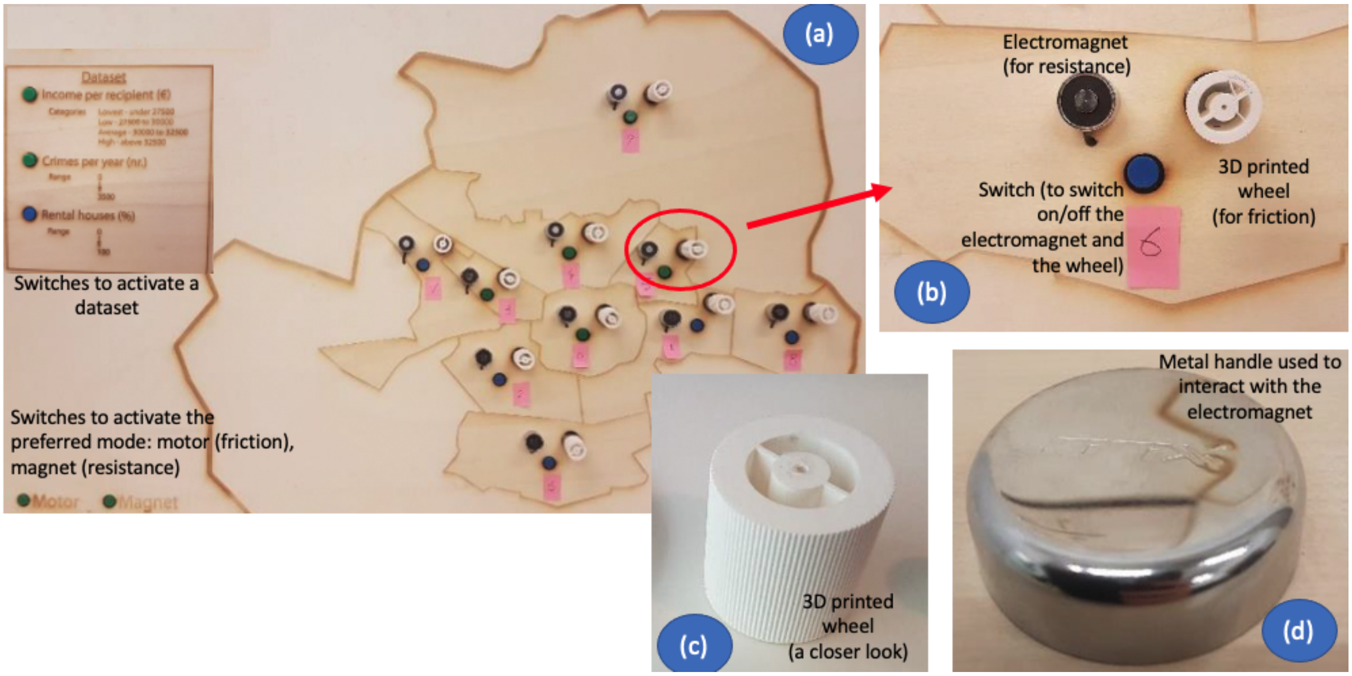


Figure 2: Users can explore data about 10 neighborhoods of the municipality of Enschede using the map based physical interface. To read data, one of the two modalities can be used: resistance or friction. The metal handle is used to experience resistance (moving the metal handle away from the magnet in the map interface). Friction can be experienced by touching the rotating wheel using a finger.

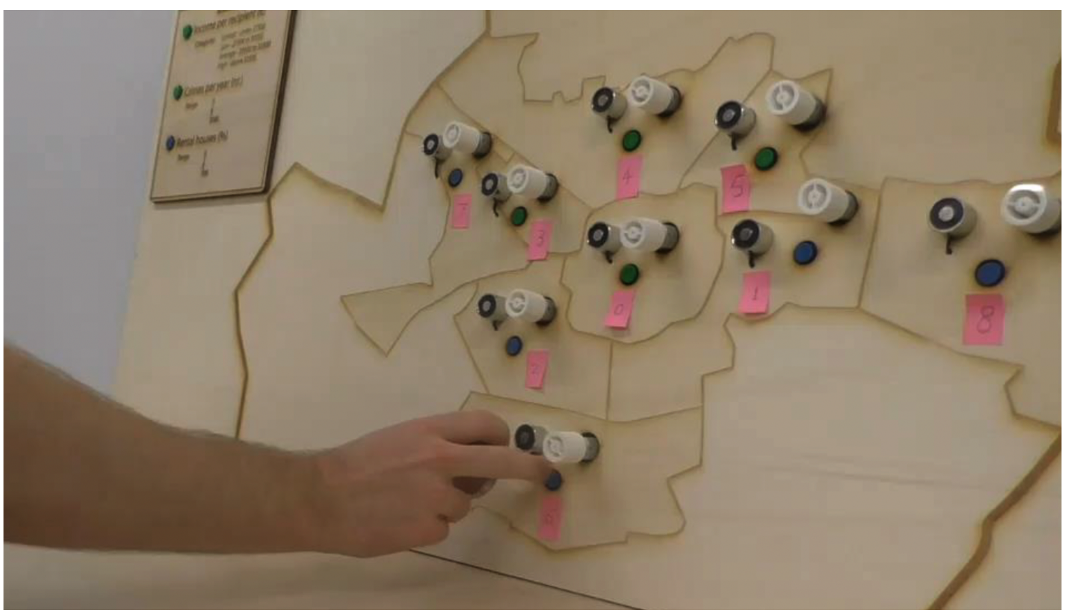


Figure 3: A user interacting with the physicalization: to experience friction, the user can touch the spinning wheel (see also Fig. 1(b)) from her finger; to experience resistance, a user can bring the metal handle (see also Fig. 1(a)) towards the electromagnet in the interface and try to take it away from the electromagnet. User feels the resistance when she tries to do this move.

modalities and both task sets. The order of task sets and the modalities were counterbalanced for different participants. Within each task set, the participants went through the questions in one specific order: minimum, then maximum, then cluster. All participants signed an informed consent form after a brief introduction to the objectives of the study. The possibilities of mild physical discomfort and mild fatigue were explicitly mentioned in the consent form. The users then got the chance to familiarize themselves with the two modalities and ask questions to the researcher five minutes before the experiment. After the familiarization, the participants answered questions about the datasets using each modality. At last, the researcher inquired about the participants' subjective experience: what they liked about both modalities, what they disliked, and which of the two they liked best. The dataset used for the familiarization (rental houses) is activated using the blue button (Figure 2a). The datasets used for the evaluation (crime/income) are activated via the green buttons instead (Figure 2a). The dependent variables of the study were: efficiency (time-on-task, extracted from the video recordings), effectiveness (accuracy of the answers), and subjective preference (which of the two modalities the participants reported to prefer and why). The independent variables were the modalities (magnet (resistance) vs motor (friction)), the type of question answered (minima, maxima, cluster) and the type of data (ordinal vs numerical). We used the bootES package [25] for the analysis (number of resamples, N = 5000). Confidence intervals of the mean differences between the two conditions that do not contain zero suggest statistical significance [33]. The institutional Ethics Committee approved the experiment.

Efficiency. Across all tasks, the users were slightly faster in answering the questions using the magnet (resistance) as opposed to the motor (friction). The trend is only reversed for answering cluster questions on numerical data, where the participants were slightly faster in the motor condition (Figure 4a). Nonetheless, there is no strong evidence of an advantage of one condition over the other, and both can be deemed comparable. The differences 'time (Magnet) - time (Motor)' in task completion times were: Minima/Numerical: -12 seconds (CI: [-39, 10]); Minima/Ordinal: -12 seconds (CI: [-26, 3]); Maxima/Numerical: -7 seconds (CI: [-19, 5]); Maxima/Ordinal: -3 seconds (CI: [-12, 10]); Cluster/Numerical: 0.9 seconds (CI: [-11, 13]); and Cluster/Ordinal: 0.1 seconds (CI: [-14, 17]).

Effectiveness. The two conditions seem also comparable regarding effectiveness. Still, there is evidence of motor (i.e. friction) being slightly more effective for answering minima/cluster questions on ordinal data (Figure 4b). The differences 'accuracy (Magnet) - accuracy (Motor)' between the two conditions were: Minima/Numerical: 11% (CI: [0%, 33%]); Minima/Ordinal: -33% (CI: [-78%, -11%]); Maxima/Numerical: -11% (CI: [-44%, 22%]); Maxima/Ordinal: -11% (CI: [-56%, 33%]); Cluster/Numerical: 11% (CI: [-33%, 33%]); and Cluster/Ordinal: -44% (CI: [-89%, -22%]).

Subjective Preference. 16/18 participants (i.e. 89%) indicated a preference for the magnet (resistance) as an interaction modality for the tasks. Nearly all mentioned as a rationale for this choice that the data differences were more noticeable with that modality. As P5 phrased it: "I preferred the magnet as I feel you can feel the difference better as the force on your hand is continuous". Additional advantages of the use of the magnet included intuitiveness (" I have a slight preference for the magnet because it felt intuitive and easier to compare than pushing my finger against a spinning lid", P17); comfort ("less discomforting to my finger", P16); and increased confidence ("With the magnet, I was more sure about my answer", P6). The users also suggested a few improvements regarding the use of magnets as a modality. These include familiarization time (P9), the adjustment of the orientation (P7), and the removal of background noise, which was perceived as a distraction (P9, P13). In the participants' own words: "I doubt the accuracy a bit, and you need a bit of explanation before you really get it, but when I understood it is really cool and it kept my attention. The thing I noticed was that the noise, especially from the magnets could tell me something as well, so that it draws more attention than the magnets itself. This could be fixed with more accurate and higher frequency drivers?" (P9). Or "Sound of motor was distracting and paid attention to the sound instead of the force" (P13). And finally: "Magnet would be [even] better if it did not have to be interacted with [in an] exactly perpendicular [fashion]" (P7).

One mentioned advantage of the motor (friction) was the low physical demand ("Touching the motors or using the magnet was fun and not really physically demanding", P14). Besides, two participants perceived it as easier than the magnet: "Easier because of the sound it makes" (P2); and "The motor gave a clearer view of whether a variable was high or low. Also liked that you could use your finger to 'feel' the data" (P12). The main drawback of the motor is the fact that 'stopping when touched' seems counter-intuitive: "The motor stops when touched so it is hard to estimate the speed. Maybe a slower spinning motor would be more clear" (P10); "The motor stops when touched so it is hard to estimate the speed" (P4).

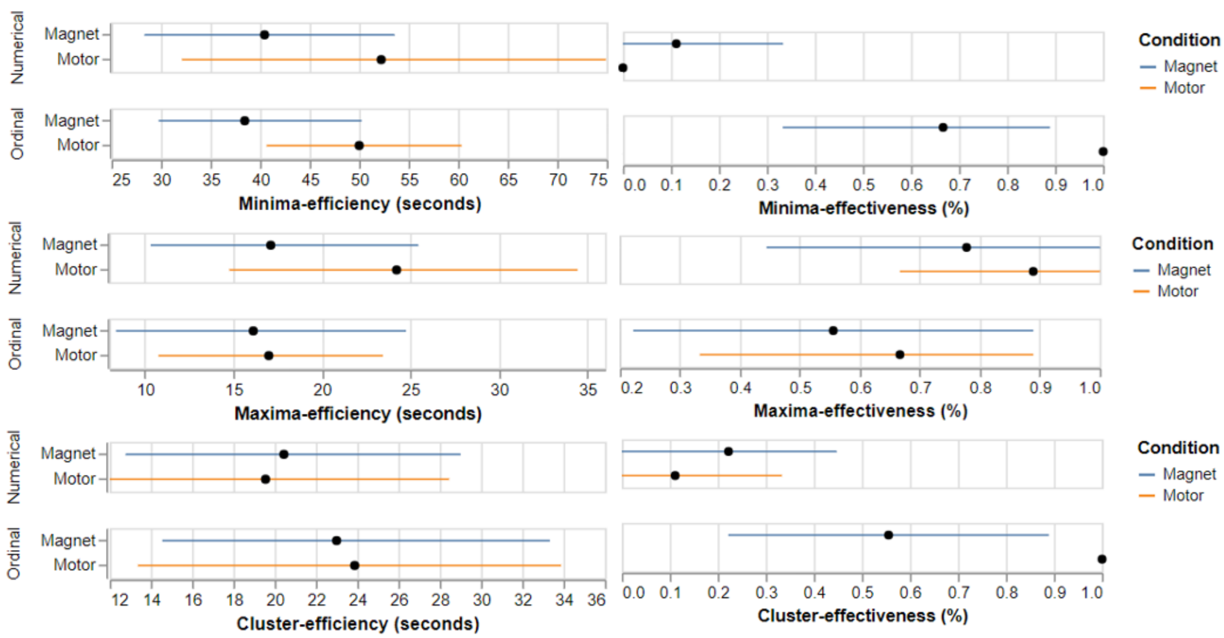
5 DISCUSSION AND CONCLUSION

Takeaways: Based on the results (Sec. 4), we can summarize the following key findings about the two modalities: (1) Across all tasks, the Magnet could reach up to 70% in accuracy during data reading, while the Motor could reach up to 100%. To put things in perspective, previous work has indicated that temperature as encoding modality could reach up to 50% accuracy while vibration reached up to 100% on similar tasks [38]; (2) both modalities are likely equally fast for the tasks at hand (minima/maxima/cluster reading on ordinal/numerical data); (3) Motor has a slight advantage with respect to effectiveness. Nonetheless, given that the majority of participants seemed less confident with the motor modality, the advantage observed may be due to lucky guesses in combination with the relative simplicity of the questions to be answered. Hence, a follow-up study is needed to confirm the existence of this advantage; 4) Magnet was preferred as an interaction modality by the majority of the subjects in the experiment. These few lessons learned can be used, for example, during subsequent studies using resistance and friction to communicate data.

Implications: This work demonstrated the potential of using friction and resistance as modalities for kinesthetic encoding of data. We foresee several practical benefits that could shine and inspire future implementations of human-data experiences using data physicalizations. Kinesthetics can create more physical, dynamic

Table 1: Data Exploration Tasks

Task set 1 (numerical data)	
Task Type	***Description***
Minimum	Which neighborhood has the lowest amount of crimes?
Maximum	Which neighborhood has the highest amount of crimes?
Cluster	Which neighborhood has a similar amount of crimes to neighborhood 03?
Task set 2 (ordinal data)	
Task Type	***Description***
Minimum	Which neighborhood(s) are in the lowest income category?
Maximum	Which neighborhood(s) are in the highest income category?
Cluster	Which neighborhood(s) are in the same income category as neighborhood 00?



(a) Efficiency. **(b) Effectiveness.**

Figure 4: Evaluation results: a) Users could answer some questions in as fast as 17 seconds with the Magnet and the Motor; b) The Magnet could reach up to 70% in accuracy during data reading, while the Motor could reach up to 100%.

and natural interactions with data that involve direct manipulation and human body skills. This therefore, allows creating more playful, immersive, embodied and engaging interactions with data, especially for special user groups such as children or visually-impaired (currently there are only limited potential ways to create interaction with data more engaging and feelable, for example for visually impaired). They can be used in classrooms to create more embodied learning experiences, for teaching geographically distributed data (currently, both the HCI [11] and Cartography [14] communities strive to make existing maps (and geographic data) more accessible and engaging). We therefore think that these two modalities will spark creativity that can guide designers in creating more engaging and immersive experiences with data. We also think that this system and our initial findings can provide an avenue for the CHI community to discuss different modalities for data encoding toward creating more embodied and engaging data experiences, as well as accessibility and social inclusion of data physicalizations.

Future work: With the metal needing to be applied directly perpendicular to the magnet, some users struggled to get used to the interaction with magnets during the familiarization phase. The core functioning of the electromagnet makes it challenging to create a field that could be interacted with from different angles. Potentially, multiple magnets could be combined to emulate this effect. Another interesting factor to look into is whether a repulsive force could be more effective than the attractive force used in the project. Two magnets with unequal poles will have to be used to do this. This could possibly solve the issue of needing to apply a metal object perpendicularly and could lead to more enjoyable methods of interaction.

Exploring means for optimizing the interaction strategy for the motor (friction) is also an interesting direction for future research. With the main limiting factor being the strength of the motor, a potential way to improve the user experience is calibration. We have to find a balance between the strength of the motor and the discomfort experienced, which would ideally be evaluated during the specification stages of developing the concept. A higher torque motor operating at the same speed or slightly faster could potentially be more accurate and efficient.

Finally, to increase the confidence in the observed (non-)effects, subsequent studies should diversify the user base and include additional evaluation criteria in assessing both modalities (e.g., perceived task load, finger and wrist fatigue). Most importantly, while single values for friction/resistance were used in this study, a more systematic evaluation of the impact of different resistance/friction values on the overall user experience (discomfort, fatigue) would be useful to achieve a greater understanding of the modalities suitability for the conveying of data. Furthermore, relevant research communities can explore various ways of varying the electromagnetic field and its strength so that they can be easily used to encode data and to design interactions that are closer to human grasping styles.

Another valuable area to explore further is the new interaction types involving various object handle shapes and grasping styles [4]. Different object shapes can enable interactions that utilize natural human grasping styles. Such interactions could provide a richer user experience, much closer to natural human interactions, thus better reality-based and embodied experiences.

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