Point n Click: A Glove-Based Cursor Control Device

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Abstract

Traditional pointer devices like mice typically require flat surfaces to function effectively, which may not always be available in certain scenarios, such as remote pointer manipulation or object selection from a distance. This study explores the development and evaluation of a glove-based pointer device, enhancing it with missing mouse functionalities and additional movement features. The evaluation compares the glove against a conventional mouse in a simulated computer usage environment, focusing on pointer movement and target selection. Results show an average selection time of approximately 2.9 seconds for targets roughly 800 pixels apart when using the glove. While slower than the mouse, the findings suggest that the glove-based device presents a viable alternative for pointer control without reliance on 2D surfaces.

CCS Concepts

• **Hardware → Sensors and actuators**.

Keywords

pointer device, mouse, human interface device, accelerometer, gyroscope, magnetometer, capacitive sensors, glove, arduino, transfer function, cursor

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1 Introduction

Many devices, such as the widely used mouse, trackpad, pen and tablet pair, and VR controllers, are used for device interaction and pointer control. While these are popular and effective, they can pose challenges and limitations depending on the context. For example, mice generally require a decently sized flat surface, trackpads can be small or limited in size, while VR controllers are more optimized for immersive VR environments rather than the 2D space and screens, and also cost a decent amount of money.

There could also be several user examples, such as presentations, some creative work, or hands-free computer navigation, where the said devices can be limited. Inefficiencies may arise in the context of presentations, wherein multiple devices could be necessary to deliver the presentation. Mobility limitations within users could also lead to accessibility concerns in general.

To address these challenges, this study aims to extend an alternative interface, a glove-based pointing device, designed to provide an intuitive interface and a way to control the pointer through the use of various hand motions and simple gesture recognition. Unlike traditional input devices, the proposed glove-based pointer will use hand motions and simple pointing recognition, enabling interaction without reliance on physical surfaces.

Given this goal, the study will aim to maintain most ease of plug-and-play of the existing input devices while adding new features on top. Specifically, the following will be kept in mind while redesigning the previous version of the glove interface from [9] and combining some features from [20]:

- The pointer glove should still be lightweight and portable.
- It should operate without requiring extensive calibration or external hardware apart from the glove and any receivers.
- The glove should be able to handle mouse-like inputs, namely pointer manipulation and clicking, without requiring physical contact with a 2D surface.
- Latency should be generally low to allow smooth input-to-feedback translation.
- The solution should also work in general computer navigation.

To evaluate this, several research questions can be constructed:

- **RQ1** Does the proposed glove-based pointer provide the necessary functionality for general computing and accessibility purposes?
- **RQ2** How does the device's usability compare to traditional input methods and the previous version in terms of accuracy, reliability, and ease of use?
- **RQ3** How does the device perform compared to the original?
- **RQ4** Is the system intuitive for users?

2 Original Interface

The mouse is already a golden standard used for moving the pointer across the 2D screen. Moving to wireless mice also allows for a non-in-person interaction with the computer, wherein users can move the pointer while standing from a distance. That said, these traditional mice require a surface, usually flat, underneath the mouse to function properly. This can be troublesome when standing at a distance, especially in situations such as presenting from a distance - that requires both a clicker and a pointer, or simply using the computer from a distance.

A possible alternative to pointer movement is a gesture-based system that uses accelerometers, and gyroscopes, as shown by [9]. The solution focused on translating the gestures to pointer movement, specifically for scenarios of in-person presentation control.

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While innovative, the prototype turned out to be slower than the device it was being compared to, the CheerPod [7]. While this could be due to hardware limitations on the sensor used, the glove prototype also lacked some features available for the Cheerpod and consequently, the mouse, such as clicking capabilities, and wireless signal transmission.

3 Proposed Improvements and Redesigned Interface

The study aims to extend the previous glove-based pointer system by addressing its lack of certain mouse functionalities and improving cursor control. The redesigned system adds direct pointer manipulation, mouse-like clicking capabilities, and improved sensors. These changes also address the limitations of traditional mice, which require a flat surface to function efficiently. Gesture recognition will allow users to move the cursor to predefined screen areas by pointing, providing near-instantaneous repositioning similar to eye tracking. Additionally, adding mouse-like interactions ensures a more familiar user experience, making the glove a viable alternative to traditional pointing devices.

3.1 Initial Setup

The main Arduino Pro Micro [3] attached to the glove will still be the primary controller and pointer manipulator in the project. The motion sensing will also use the current MPU-6050 [10] sensor as a baseline to capture hand orientation and estimate hand gestures. This will be compared to the MPU-9250 [15], which has an added magnetometer, which could improve the movement or gesture-to-pointer translation accuracy while combating drift. Calibration will likely be used to measure the distance of the glove from the screen, which will contribute to the calculation of the user's point gesture to a spot on the screen. If, due to external circumstances, the sensor cannot be acquired, a stand-in HMC5883L [2] will be used alongside the MPU-6050 (or 6500) instead.

Infrared transmitters and receivers [14], [13] will be used for finger gesture recognition. It should be noted that this will be limited to only the normal pointing gesture (pointing finger extended). These are rated to have a range of about 10 meters at maximum. Capacitive touch sensors, specifically the TTP223B [12], will also be added to simulate mouse clicks. For example, touching the thumb and index finger could be mapped to the left mouse button, while touching the thumb and right finger could map to the right mouse button. The pin out of this is shown in Figure 1

An additional setup will be required to communicate the IR signals from the transmitter to the receivers. Given this, there are two options - 1) use a separate Pro Micro board or something similar to simulate the Mouse library, or 2) communicate the signals instead via Bluetooth. The second option was opted for to keep the Mouse movements limited only to one device, thus potentially improving stability. Given this, the ESP32 lineup, specifically the ESP32-WROOM [21], was chosen and interfaced with the IR receivers, as shown in Figure 2. Meanwhile, an HC-05 Bluetooth module [8] was added to the other board for wireless connection and communication.

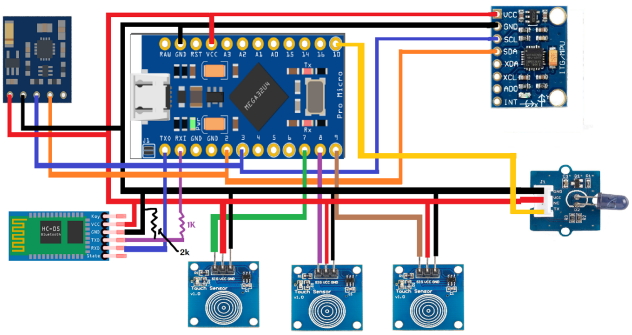

Figure 1: Sample Schematic of the Arduino Pro Micro controller (top-middle) connected to the HMC5883L compass (top-left), MPU-6050 (top-right), Bluetooth module (bottom left), IR Emitter (middle-right), and the Capacitive Touch Sensors (Bottom-row).

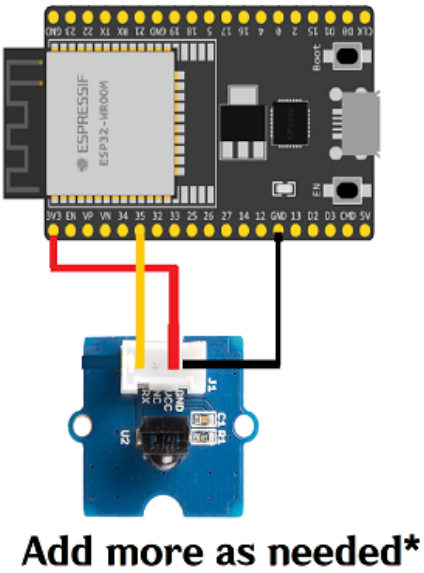

Figure 2: Sample Pinout Schematic of an ESP32-WROOM (top) connected with an IR Receiver. Multiple Receivers will be added as necessary.

3.2 Design Iterations

Preliminary testing of each iteration was conducted and was used as the basis for improvements made on the firmware and hardware choices or designs in the project. One main issue was the touch capacitive sensors. The initial prototype had intended for three capacitive touch sensors, mapping to left, middle, and right clicks, respectively. These were initially set up on a breadboard and could be tested individually, hence why the setup seemed fine. That said, when they were attached to the glove, having the three side-by-side felt unnatural. This was because the sensors themselves were too

large, and they could block each other's boards when the user's fingers were curled.

Apart from this, the drift from the gyroscope and accelerometer was also investigated. Ideally, this would be fixed by adding a magnetometer and manually adding fusion functions for the three devices. That said, upon testing, popular Attitude and Heading Reference System (AHRS) libraries that do this, such as Mahony [5] and Madgwick [4], require a lot of storage space on the Arduino Pro Micro. An alternative could be to manually implement a lightweight version, but this led to difficulties in program implementation and integration. Thus, a small alternative of simply re-setting the MPU based on the magnetometer's readings after a set period of time was opted for.

3.3 Final Setup

As discussed above, the glove-based pointer system underwent multiple refinements during development. For instance, after some testing, it was found that 9-axis sensors, including the MPU-9250 and other similar boards, were generally being phased out. Along the same line, getting a fake 9250 was also common, wherein the chip would only house an MPU-6500 and would lack the magnetometer. In fact, this occurred during the material-gathering portion of the project, in which a lookalike was purchased and obtained instead of the original intended chip. Thus, it was decided that the final design would reuse the previous MPU-6050 plus a stand-in HMC5883L to act as the missing magnetometer, as discussed in the previous subsection.

Along the same lines, as mentioned earlier, only two capacitive sensors were used. The initial version also had them unshielded, which led to unintentional registered taps. To address this, modifications in the form of a grounding shield was added on one side of each sensor. This caused them to be less sensitive and only receptive in one area, thus improving click accuracy but also limiting its sensitivity to one side's specific area.

The IR transmitter was the most stable piece and was left as is.

The Bluetooth module that was added in the final design also allows for easier upgrading to a full wireless solution. Wireless, in this case, refers to the removal of the cable attaching the Pro Micro board on the glove to the computer. This could lead to better usability but will not be explored in this project. Pictures of the final setup of the glove and receivers are shown in Figures 3 and 4.

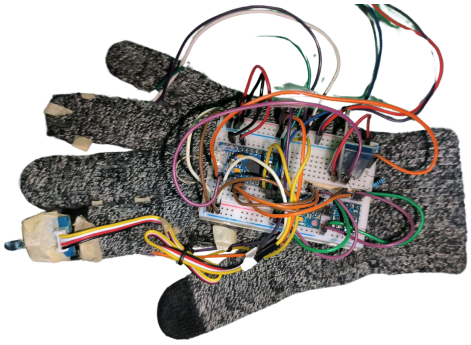

Figure 3: Final Physical Setup of the Updated Glove.

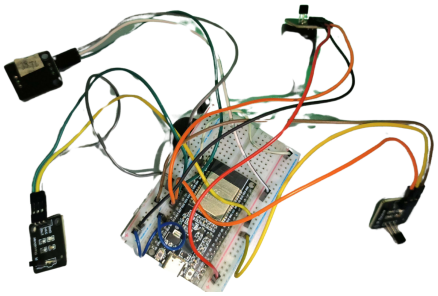

Figure 4: Physical Setup of the Receivers Connected to an ESP32-WROOM.

3.4 Summary of Firmware and Hardware in the Final Setup

The final system consists of the following firmware and hardware components:

3.4.1 *Firmware and Libraries Used.*

- **Mouse** [6]: Allows certain boards to control cursor movement of the connected computer. Positioning is based on the relative position of the cursor rather than the absolute position.
- **I2C Device Library** [18]: A collection of classes for streamlined communication for I2C devices. This library was specifically used to interface the MPU6050 with the microcontroller. Technically, the library also supports the HMC5883L.
- **Adafruit HMC5883 Unified** [1]: A sub-library that interfaces and abstracts data from the HMC5883L. This was chosen over the I2C Device Library version because sensor readings are converted into standardized units, thus leading to more simplified integration.

3.4.2 *Hardware Used.*

- **Arduino Pro Micro** [3]: Serves as the main microcontroller for processing sensor inputs and controlling the mouse pointer.
- **ESP32-WROOM** [21]: Bluetooth and WiFI capable microcontroller. Handles IR receiver signals and transmits data to the Pro Micro via Bluetooth.
- **TTP223B** [12]: Touch capacitive sensors that detect touch-based gestures to simulate mouse clicks.
- **HMC5883L** [2]: A magnetometer used to help correct drift in hand orientation tracking.
- **MPU6050** [10]: A 6-axis motion sensor used for tracking hand movement and angle.
- **IR Transmitter** [14]: Mounted on the glove to send signals for pointing.
- **IR Receivers** [13]: Placed around the screen to detect IR signals and determine pointing direction.

3.5 Scope and Limitations of the Device

Given this setup, the glove will be limited to only left and right-click inputs. Scrolling and actions like dragging will not be considered

due to hardware design limitations and choices. Hence, the testing facility will also be created to match only these features - manipulating the mouse pointer and selecting or clicking on a target. Additionally, while wireless data transmission will be implemented for the IR setup, a full wireless device will also be out of scope for the project. This is because moving to a wireless solution would require additional design considerations and could affect usability, such as requiring on-board power and charging.

4 Methodology

4.1 Experimental Design

A general-purpose testing facility was created to evaluate the proposed glove design. This would replicate general computer usage, wherein a user would move their mouse across the screen to navigate and click through buttons at random distances and from a set of shapes, similar to Fitts' Law [11]. Each test consists of five trials or shapes to click through. A sample screenshot is shown in Figure 5.

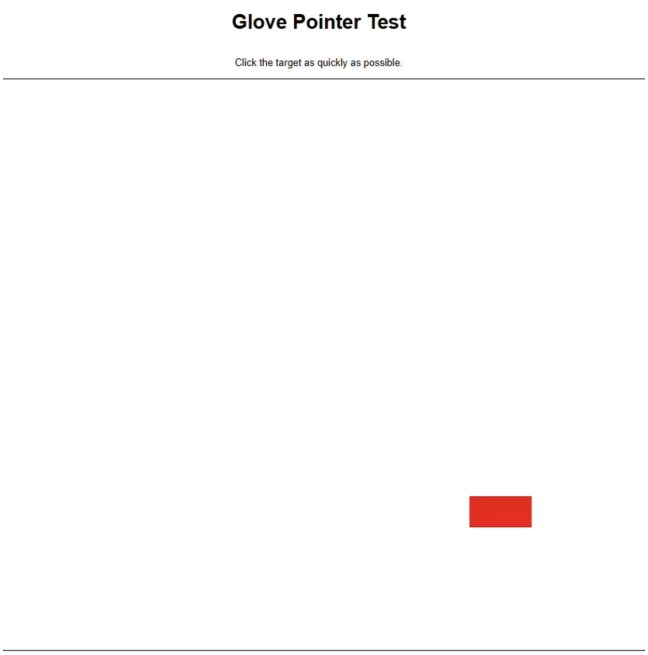

Figure 5: Sample Screenshot of the Testing Facility with a Rectangle Target generated.

A 13-inch MacBook Pro (2017) with a screen resolution of 1440 by **900** was used for testing. The mouse sensitivity is set to 4/10, while the trackpad sensitivity was set to 6/10. Both of these were constant throughout the tests. Normal room lights were also kept on during the tests, and the users sat at a comfortable distance, mimicking a normal desk sitting position.

10 participants were involved in the study. Each participant would do the task about five times each. The tests were carried out using the (1) baseline mouse, again set to a constant sensitivity, and (2) the final version of the glove, as mentioned above and shown in Figure 3, and (3) the same as 2, but asking the participants to try to use the IR. While no formal testing was done for the previous iterations, the final design incorporates the earlier mentioned refinements to enhance usability and reduce errors.

4.2 Performance Metrics

The variables measured include total time (TT), which represents the time required to accomplish each button click, and the corresponding distance (D) between each button, and the button size (W). This aligns with Fitts' Law [16], which predicts the movement time (MT) required to move to a target based on D and W. Specifically, this is expressed as:

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

Additionally, the Index of Difficulty (ID) with respect to the distance and width can be calculated as:

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

And the respective throughput per device is calculated using the overall total time:

$$TP = \frac{ID}{TT}$$

This theoretical framework is used to compare the efficiency of the glove-based pointer system to the traditional mouse by calculating the expected movement time based on target distance and size and comparing it to the measured movement time [16].

Other than Fitts' Law metrics, the errors, such as missed or extra clicks, are also recorded. Additionally, hover time is tracked to measure how long the cursor remains inside the target area before clicking, while correction time accounts for overshooting—when the cursor enters the target but exits before successfully clicking. The delay between entering the target to clicking the target is also logged, both in terms of first entry and most recent entry. To analyze movement patterns, the full cursor path is logged, allowing for the computation of path efficiency, i.e., how directly the cursor moves toward the target. With this, extra features such as the velocity, total overshooting time, the length of the path taken and its respective ratio compared to the straight-line distance, and the extra movement in percentage can also be calculated.

Additionally, a comparative analysis was performed on the usability and efficiency of input methods. This analysis, including a T-test [22] which assessed statistical significance, determined whether the glove-based pointer system offered comparable performance to a traditional mouse in terms of movement time, path efficiency, error rate, hover time, and correction time if applicable. While the mouse and glove-based pointer system differ in fundamental interaction mechanics, this comparison aimed to assess whether the glove system can serve as a feasible alternative for pointer-based tasks, particularly in scenarios where traditional mouse usage may be impractical.

4.3 Model Creation

Using the data gathered, regression models were also created, with variables such as task completion time and error counts as the target. This was done using the other variables, like distance, the device type, or the shape of the target button.

To explain each further, the model for task completion time was created using Ordinary Least Squares (OLS) regression [19]. This attempts to calculate and find the best fitting line given the data gathered. Separate models were initially created to test the features, and any that showed a high Variance Inflation Factor (VIF) were removed. A regression combining the two datasets was also created.

Additionally, Poisson regression [17] models were created for the error modeling. Poisson regression is commonly used for count data, making it suitable for predicting the number of errors based on various task-related factors. Since error counts are discrete and often skewed toward lower values, this model estimates how the measured variables influence the likelihood of errors occurring.

To account for overdispersion—where the variance of the error counts exceeds the mean—a Negative Binomial regression model was also tested. However, after evaluation, the Poisson model was retained as it provided better overall performance in predicting error counts for both the glove and traditional mouse datasets.

5 Results and Discussion

A total of 51 sessions, resulting in 255 trials, were gathered for the mouse. For the glove, 61 sessions were recorded, totaling 305 trials. The second test of the glove had 51 sessions with 255 trials. However, two glove sessions had to be removed due to minor bugs caused by the random-target generator of the testing facility. Additionally, trials with optimal path ratios higher than 15, along with error counts greater than 10, were also removed. The final counts of each was 250 for the mouse, 292 for the first glove, and 246 for the second glove test.

5.1 Fitts' Law Modelling

Table 1 shows the regression fitting Fitts' Law across the various tests. A graph showing the models of MT versus ID for the two devices is also shown in Figure 6, 7, and 8. Note that Glove 2 in this and succeeding sections will specifically refer to the second glove test done earlier, while mentions of "both devices" will refer to the mouse and glove tests as a whole.

Table 1: Fitts' Law Regression Results and Throughput

Metric	Mouse	Glove	Glove 2
Regression Results			
Intercept	0.4456	-0.6235	-1.5962
Intercept p-value	< 0.0001	0.251	0.039
ID Coefficient	0.0662	0.4467	0.5643
ID Coeff. p-value	< 0.0001	< 0.0001	< 0.0001
R^2	0.095	0.131	0.121
Throughput (bits/s)			
Mean Throughput	8.47	3.07	3.56

All three models show a significant positive relationship between Index of Difficulty (ID) and movement time (MT), aligning with Fitts' Law predictions. This confirms that as tasks become more difficult, completion time increases for both input devices. This also makes sense as the conversion and translation from either glove input or mouse input is inherently the same. Both directly manipulate the mouse pointer, which implies both would be affected by "higher difficulty" tasks.

However, a difference appears when comparing the two input devices' coefficients. Specifically, the glove has a much higher coefficient for ID (0.447 and 0.5643) compared to the mouse (0.066), indicating that task difficulty affects the glove much more than the mouse. Additionally, the lower R^2 values, 0.095 for the mouse, 0.131, and 0.121 for the glove models, suggest that other factors also influence completion time beyond just task difficulty. This result makes sense, as the task itself involves not only moving the pointer to the target but also clicking on the target itself, which could add delays, as to be discussed later.

Apart from this, the average throughput of the two devices was 8.47 bits/second, 3.07 bits/second, and 3.56 bits/second for the mouse, glove, and Glove 2, respectively. This is a large difference, with the mouse having over double the throughput of the glove in both cases. However, this large difference could be due to two reasons. The first is the inherent difference in familiarity with the two devices. Many of the participants were avid long-term mouse users, but the glove had a learning curve that required getting used to. This is shown by the fact that Glove 2 had a higher average throughput than glove 1, indicating that some basic familiarity, plus potentially the pointer-teleportation feature, improved the glove as a whole. The second possible reason is because of how the inputs translate to pointer movements. The movements of a mouse and other "2 dimensional" input devices can be translated easier since it is direct 2D to 2D. This means that stopping the pointer, or making a sharp movement to make the pointer move in a different direction is much easier. On the other hand, the glove relies on the gyroscope's tilt, which can be harder to translate from 3D to 2D, as well as being harder to control, especially when the users are not particularly familiar with the device.

Another aspect was that the IR setup was not used much, even for Glove 2 sessions. This could still be due to unfamiliarity or that the receivers were too far or inconvenient to point to. The movement caused by the feature also appeared a little jarring and inconsistent at times, which could have impacted the trials in the test.

5.2 T-test for Metrics

5.2.1 Mouse versus Glove. Table 2 shows the comparison of various movement and error metrics between the mouse and glove tests. Boxplots showing the distributions are also included in the appendix. Overall, all three categories have several significant performance differences between the two devices.

For movement, the mouse had faster total times and, correspondingly, higher velocity despite the similar average distances per trial. This directly indicates that accomplishing tasks with the mouse is faster than with the glove, which matches the throughput calculations seen earlier. That said, both devices had an average path ratio

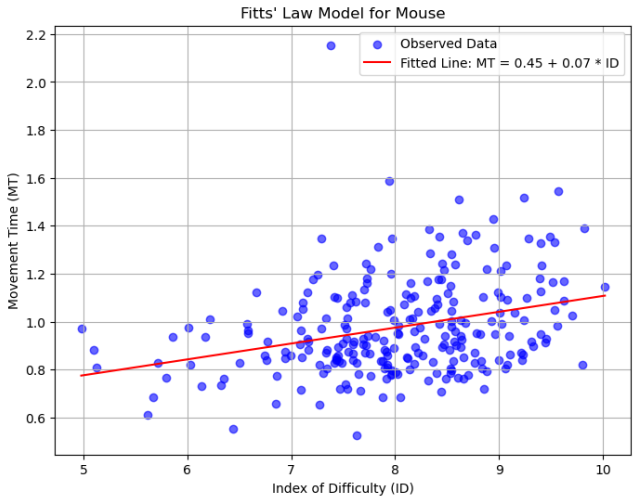

Figure 6: Graph of Fitts' Law Model for the Mouse

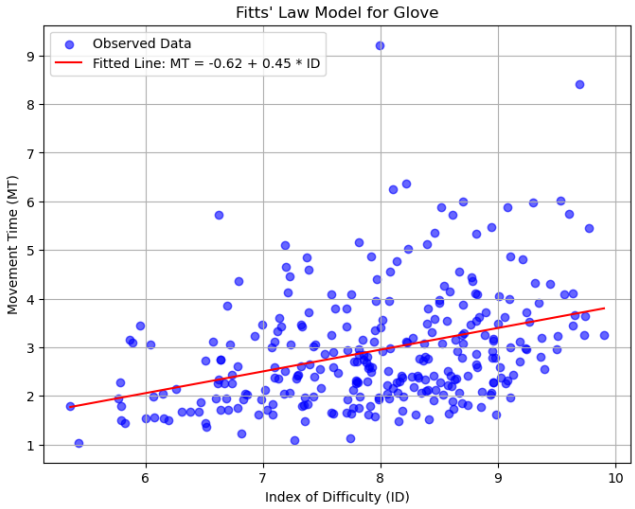

Figure 7: Graph of Fitts' Law Model for the Glove

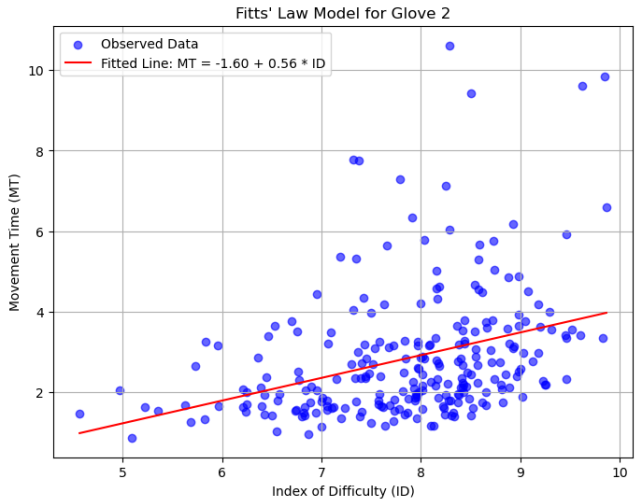

Figure 8: Graph of Fitts' Law Model for the Glove2

Table 2: Comparison of Performance Metrics between Mouse and Glove

Movement				
Metric	**Mouse**	**Glove**	**t-stat.**	**p-value**
Total Time	0.9765	2.9295	-27.3785	0.0000
Distance	813.76	812.84	0.0293	0.9766
Velocity	543.56	178.29	21.10	0.0000
Optimal Path Ratio	3.7455	3.7701	-0.1330	0.8943
Error Metrics				
Metric	**Mouse**	**Glove**	**t-stat.**	**p-value**
Total Misclicks	0.0360	0.1747	-4.7006	0.0000
Time-Based Error Handling				
Metric	**Mouse**	**Glove**	**t-stat.**	**p-value**
Hover Time	0.3484	0.5096	-5.4307	0.0000
Total Overshoot Time	0.0377	0.2924	-5.6669	0.0000
First Entry Click Delay	0.3424	0.7349	-7.3324	0.0000
Most Recent Click Delay	0.2953	0.4101	-5.3591	0.0000

of about 3.7, indicating both devices took a path that was more than three times longer than what was optimal, though this is likely just due to user inefficiency.

As for the error metrics, the glove did have significantly more total misclicks compared to the mouse, averaging about 0.175 compared to 0.036 misclicks per trial, thus resulting to a p-value of 0.0. On the other hand, both devices had a fair share of overshoots at 0.152 and 0.188 for the mouse and glove, respectively. This means that there was no significant difference, as the p-value only resulted in 0.301.

Finally, for the time-based metrics, all four measured values had significant differences between the mouse and the glove. Hover time, overshoot time, and delays between entering and clicking on a target were all significantly lower for the mouse compared to the glove. This generally aligns with the finding earlier, wherein the overall completion time and throughput of the mouse was higher than the glove.

Overall, while movement efficiency remained largely unchanged, the glove introduced significantly more errors and required longer adjustment times before users could complete a trial. These findings suggest that while the glove-based input method may be functional, its current form results in greater difficulty in precise control and selection, especially with higher ID tasks, as mentioned in 5.1.

5.2.2 Glove versus Glove 2. Meanwhile, Table 3 shows the summary of the comparison of said metrics between Glove 1 and Glove 2 sessions and trials. Similarly, boxplot graphs are also provided in the appendix.

The first five metrics, namely Total Time, Distance, Velocity, Optimal Path Ratio, and Total Misclicks are all generally better to a small extent, but not significantly, as shown by the T-test. That

Table 3: Comparison of Performance Metrics between Glove and Glove 2

Movement				
Metric	**Glove**	**Glove 2**	**t-stat.**	**p-value**
Total Time	2.9295	2.8422	0.7088	0.4788
Distance	812.8467	762.2212	1.7130	0.0873
Velocity	178.2907	185.0767	-0.8362	0.4034
Optimal Path Ratio	3.7701	4.0183	-1.3834	0.1672
Error Metrics				
Metric	**Glove**	**Glove 2**	**t-stat.**	**p-value**
Total Misclicks	0.1747	0.1220	1.5003	0.1341
Time-Based Error Handling				
Metric	**Glove**	**Glove 2**	**t-stat.**	**p-value**
Hover Time	0.5096	0.3621	4.6779	0.0000
Total Overshoot Time	0.2924	0.1630	2.4485	0.0147
First Entry Click Delay	0.7349	0.4784	4.0547	0.0001
Most Recent Click Delay	0.4101	0.2872	5.2519	0.0000

said, the final four metrics that deal with Hover Time, Overshoot Time, and the two Click Delays, are all significant. This indicates that Glove 2 trials had a small amount of time spent hovering, overshooting the target, or delays between entering and clicking the target. Similar to earlier, this could indicate that the users were more experienced with the glove already, and could better correct any overshoots or were already pre-emptively preparing themselves to click on the target once they reached it.

That said, the performance of Glove 2 versus the mouse is likely still not close, as indicated by the throughput shown earlier. Factors like the Total Time, specifically due to movement Velocity, between the mouse and Glove 2 are too great of a difference in comparison with the slight improvements in Delay-time.

5.3 Modelling the Completion Time

Regression models were created to predict the total completion time based on the various features earlier. Initially, the models used all of the features, including those engineered, such as the Optimal Path Ratio. These were eventually removed due to high variance inflation factor (VIF), thus resulting in strong multicollinearity. Tables 4, 5, and 6 show the breakdown of the regressions and how the various factors contribute to the task modelling.

The p-values of ID, Extra Movement %, Hover Time, and Error Count show that they are all significant predictors in the models, except for Error Count in Glove 2. In particular, ID remains the strongest predictor across all models, with a significant positive coefficient. This aligns with Fitts' Law, as shown earlier, where task difficulty directly affects movement time. Notably, ID has a much larger effect in the glove models compared to the mouse, reiterating that task complexity has a stronger influence on glove-based interactions.

Hover Time has the largest effect in the glove models, with a coefficient of 2.146 in Glove 2 and 1.371 in Glove 1, compared to just 0.472 for the mouse. This suggests that delays due to hovering are more pronounced in glove-based interactions, likely caused by difficulties in confirming a selection, leading to hesitation before clicking, or possibly missing the clicking sensor on the glove.

Similarly, Extra Movement Percentage is much more influential in the glove models, with coefficients of 0.124 (Glove 1) and 0.341 (Glove 2), compared to just 0.022 for the mouse. This means that glove users make more unnecessary or longer movements, possibly due to overshooting caused by control difficulties (as discussed in

Table 4: Refined OLS Regression Results for Completion Time (Mouse)

Variable	Coef.	Std. Err.	t-stat.	p-value
Constant	-0.023	0.125	-0.182	0.856
Distance	3.36e-05	2.54e-05	1.323	0.187
Index of Difficulty (ID)	0.096	0.014	6.993	0.000
Extra Movement %	0.022	0.006	3.948	0.000
Hover Time	0.472	0.038	12.522	0.000
Error Count	0.234	0.050	4.697	0.000
Target Shape	-0.014	0.006	-2.092	0.037
R-squared	0.503			
Adjusted R-squared	0.491			
Condition Number	1.33e+04			

Table 5: Refined OLS Regression Results for Completion Time (Glove)

Variable	Coef.	Std. Err.	t-stat.	p-value
Constant	-2.895	0.722	-4.011	0.000
Distance	3.96e-05	0.000	0.284	0.777
Index of Difficulty (ID)	0.601	0.088	6.812	0.000
Extra Movement %	0.124	0.038	3.256	0.001
Hover Time	1.371	0.116	11.792	0.000
Error Count	0.668	0.110	6.086	0.000
Target Shape	-0.075	0.045	-1.659	0.098
R-squared	0.527			
Adjusted R-squared	0.517			
Condition Number	1.22e+04			

Table 6: Refined OLS Regression Results for Completion Time (Glove 2)

Variable	Coef.	Std. Err.	t-stat.	p-value
Constant	-6.5495	0.813	-8.057	0.000
Distance	0.0003	0.000	1.484	0.139
Index of Difficulty (ID)	0.9393	0.093	10.108	0.000
Extra Movement %	0.3410	0.042	8.173	0.000
Hover Time	2.1458	0.273	7.854	0.000
Error Count	0.2259	0.227	0.996	0.320
Target Shape	-0.0455	0.052	-0.880	0.380
R-squared	0.509			
Adjusted R-squared	0.496			
Condition Number	9.42e+03			

5.2). For Glove 2 specifically, this could be due to the teleportation feature. The pointer would be teleported to a set spot, then extra movements could be tracked when moving the pointer back towards the target.

Along the same lines, Error Counts have a stronger effect in Glove 1 than in the mouse, but in Glove 2, Error Count is no longer a significant predictor. This suggests that missed clicks are harder to correct with the glove, but the extent of this effect depends on the model variant, possibly indicating the experience, as mentioned earlier.

Surprisingly, Distance and Target Shape remain weak predictors across all models. This could be because both values are already incorporated into the ID calculation, which may explain the relatively high multicollinearity, as shown condition numbers exceeding 9,000–10,000.

It should also be noted that all models had R^2 values around 0.5 - 0.503 for the mouse, 0.527 for Glove 1, and 0.509 for Glove 2. This means that only about half of the variance in task completion time is explained, which is decent but leaves room for other external factors, such as human behavior and input inconsistencies that are unmodeled.

Apart from this, the three datasets can be combined to analyze whether the features behave differently across the two respective devices. Table 7 shows these values, confirming the earlier findings. Specifically, that the mouse is faster than the glove, that ID affects the glove more, and that hover times and the extra movements are bigger issues found for the glove compared to the mouse. Surprisingly, the R^2 improves to about 0.693. This could be due to the larger and more varied data, which, along with device types, can make certain relationships more easily identifiable. The smaller multicollinearity between the variables could also be the factor, which can be seen as the value is only 243 for this graph, compared to the over 10,000 mentioned above.

Table 7: OLS Regression Results for Completion Time (Combined Model)

Variable	Coef.	Std. Err.	t-stat.	p-value
Constant	0.4528	0.608	0.744	0.457
Index of Difficulty (ID)	0.0431	0.068	0.632	0.528
Extra Move. %	0.0055	0.029	0.185	0.853
Hover Time	0.4495	0.211	2.126	0.034
Error Count	0.2479	0.279	0.887	0.375
ID × Device	0.5482	0.052	10.623	0.000
Extra Move. % × Device	0.1223	0.034	3.628	0.000
Hover Time × Device	0.9342	0.239	3.902	0.000
Error Count × Device	0.4102	0.299	1.374	0.170
ID × Device^2	0.8950	0.100	8.930	0.000
Extra Move. % × Device^2	0.3337	0.043	7.723	0.000
Hover Time × Device^2	1.6972	0.289	5.871	0.000
Error Count × Device^2	-0.0540	0.324	-0.167	0.867
Device Type	-3.4051	0.443	-7.695	0.000
R-squared		0.693		
Adjusted R-squared		0.687		
Condition Number		243		

Graphs showing the overall prediction versus observed total times for the three models are also shown in Figure 9, 10, 11, and 12.

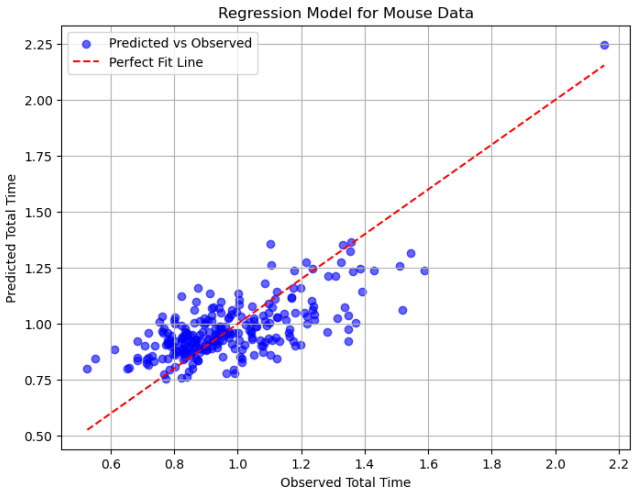

Figure 9: Regression Model for Mouse

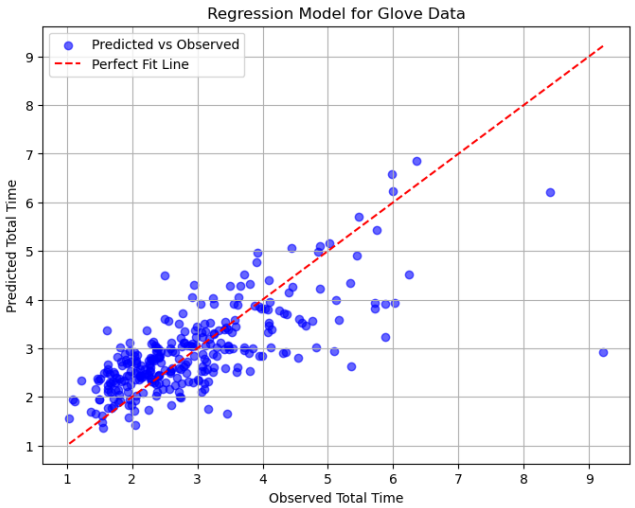

Figure 10: Regression Model for Glove

5.4 Modelling Missed Clicks

The missed clicks done with both devices can also be investigated and modeled. The main features are shown in Table 8, 9, and 10 respectively.

The model generated for the mouse performs poorly, as the calculated pseudo-R^2 is very low, at 0.132. Additionally, none of the variables are statistically significant as the p-values are also very high. There is also instabilities for the overshoot time and clicking delays, as the standard errors calculated were at 12 and 16.

Figure 11: Regression Model for Glove 2

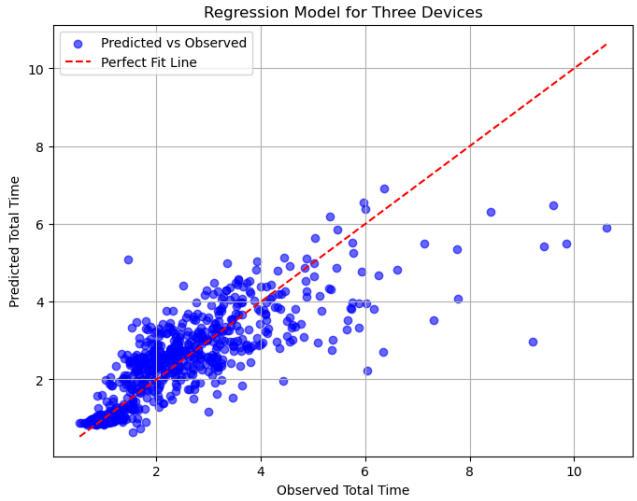

Figure 12: Regression Model for Combined Data

As for the first glove model, this models the misclicks better, with a pseudo-R^2 of about 0.320. The hover time and the most recent click delay are the most significant. It should be noted that these two values are somewhat related, and equal in many cases. However, the second glove model only had a pseudo-R^2 of 0.199, and none of the features are particularly significant.

This result is also likely due to the low sample size of errors encountered in the observations. In further investigation, only 9 trials out of the 250 had at least one error. In comparison, 51 out of 292 glove trials had at least one misclick, while glove 2 trials had 30 misclicks out of 246 trials. This difference, where the mouse trails had fewer errors and the glove trials had more errors, likely contributed to the difference in the model fits.

Apart from this, the longer hover times and clicking delays for the glove could indicate that the users are ensuring that they are within the target before clicking. That said, the inherent fewer amount of misclicks when using the mouse already shows how users are more comfortable using the mouse and that the glove is outperformed by the golden standard. Similarly, the lower misclick count for Glove 2 compared to Glove 1 indicates the same idea.

Table 8: Poisson Regression Results for Error Count - Mouse

Variable	Coef	Std Err	P-value
Intercept	-6.8680	5.505	0.212
distance	-0.0005	0.001	0.645
ID	0.4902	0.571	0.391
extra_movement_percentage	-0.2212	0.357	0.536
hover_time	-5.5222	6.396	0.388
target_shape	-0.0711	0.248	0.774
total_overshoot_time	-0.2235	16.005	0.989
first_entry_click_delay	7.2083	16.515	0.663
most_recent_click_delay	-0.9631	12.778	0.940
Log-Likelihood		-33.779	
Pseudo R-squared		0.1321	
Observations		250	

Table 9: Poisson Regression Results for Error Count - Glove

Variable	Coef	Std Err	P-value
Intercept	-1.8657	2.237	0.404
distance	0.0003	0.000	0.410
ID	0.0632	0.273	0.817
extra_movement_percentage	0.0931	0.109	0.395
hover_time	4.4308	1.700	0.009
target_shape	-0.1026	0.142	0.471
total_overshoot_time	1.6557	2.457	0.500
first_entry_click_delay	-1.3153	2.498	0.598
most_recent_click_delay	-9.4164	2.001	0.000
Log-Likelihood		-99.526	
Pseudo R-squared		0.3199	
Observations		292	

Table 10: Poisson Regression Results for Error Count - Glove 2

Variable	Coef	Std Err	P-value
Intercept	-5.3299	2.479	0.032
distance	-0.0007	0.001	0.260
ID	0.3300	0.276	0.232
extra_movement_percentage	-0.0209	0.107	0.845
hover_time	2.5383	1.806	0.160
target_shape	0.0549	0.134	0.682
total_overshoot_time	-0.9760	3.356	0.771
first_entry_click_delay	1.1068	3.424	0.747
most_recent_click_delay	-2.3236	2.118	0.273
Log-Likelihood		-75.753	
Pseudo R-squared		0.1985	
Observations		246	

Finally, it should be noted that the variables Total Overshoot Time, First Entry Click Delay, and Most Recent Click Delay were added to the feature list after doing some trial and error. These engineered features are technically already related to some of the previous features. That said, adding them appears to have significantly increased the modelling performance for the glove data at the cost of slightly decreasing the performance of the model for the mouse. Hence, it was decided to leave them in for consistency across the results.

The graphs showing the predicted versus the observed error counts is shown in Figure 13, 14, and **??** for the mouse and glove models, respectively. Note that Poisson regression predicts the expected counts given the input values, hence why many of the predictions are non-integer values.

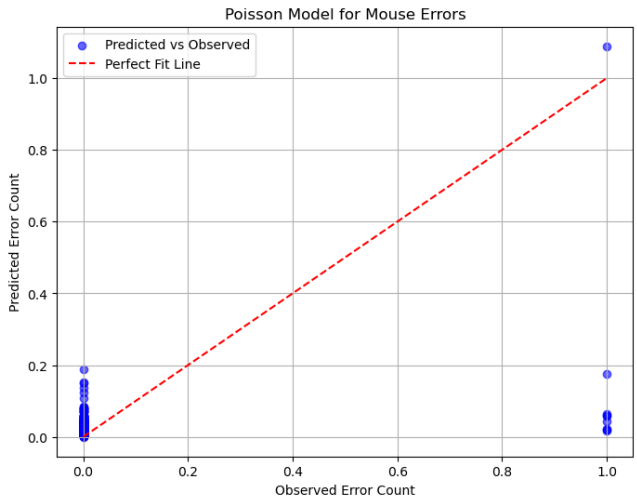

Figure 13: Regression of Total Errors for Mouse

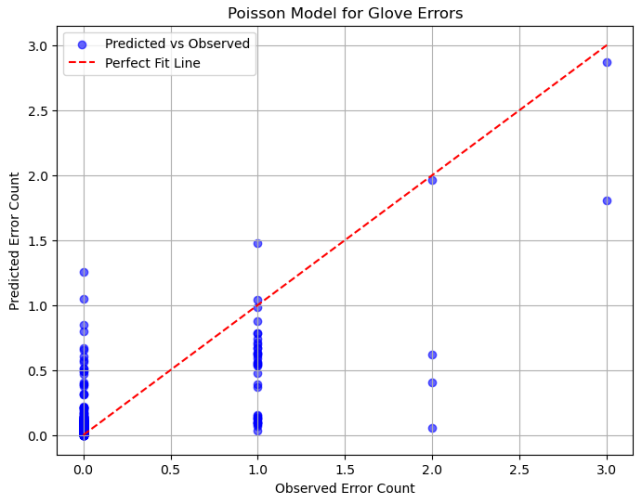

Figure 14: Regression of Total Errors for Glove

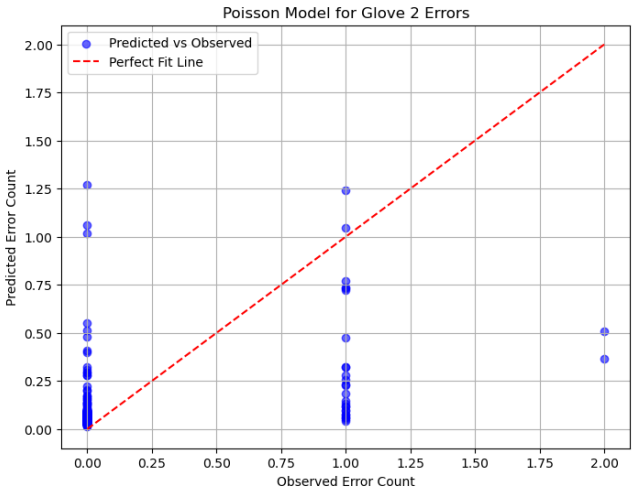

Figure 15: Regression of Total Errors for Glove 2

5.5 Performance Insights

The glove is functional for general computer navigation that involves pointer manipulation and simple target selection. However, in terms of accuracy and ease of use, the study has shown that it falls short compared to the traditional mouse in all measured aspects. This suggests that while the glove is already usable, further refinements could enhance its overall performance and user experience.

Additionally, while not explicitly measured, it is likely that users would require some time to adjust to the glove's movement and input method. Given that participants only had a few minutes of exposure to the device, their initial performance may not fully reflect its potential with extended use and familiarity. In particular, while the pointer movement latency may be low, the hover times were still higher for the glove compared to the mouse. This indicates that more time is required for the user to accomplish the clicking part of the task, translating to possibly higher cognitive processing time for the glove. That said, the velocity of the glove itself also shown that the overall movements are slower for the glove.

Users also largely preferred to use the normal hand movements and gestures to move the pointer rather than using the IR setup. As stated earlier, this could be due to the lack of familiarity, the inconvenience of suddenly pointing the fingers, or possibly some hardware issues and inconsistencies that appeared during the tests. Improvements to the transitioning between normal movement and pointing movement could also help lessen this inconvenience.

Apart from that, some drift still occurs. This is largely due to several hardware limitations. As mentioned earlier, the setup of an MPU6050 plus HMC5883L was used instead of a single chip with all three sensors - gyroscope, accelerometer, and magnetometer. Using two separate modules results in a requirement to have an external fusion function, which, unfortunately, due to hardware limitations in flash storage, was not possible. While this does not have much direct impact on short-form tests, long form usage of the glove would definitely require anti-drift mechanisms for better user experience.

Overall, even with the numerous challenges, the glove presents a unique alternative to traditional pointing devices. It offers a hands-free, 2D-surface-independent method of interaction that could be beneficial in scenarios where conventional input devices are less practical. Improved versions could become a niche substitute for the usual input devices used today.

6 Conclusion and Recommendations

6.1 Recommendations

Several improvements could be made to make the glove device more usable as an alternative to the conventional pointer-movement and selecting devices. On the hardware side, moving to full wireless as the Bluetooth module and other Bluetooth board is already available. This could involve swapping the setups of the boards to have the ESP32 connected to the glove, then having the Pro Micro connected with the computer.

Swapping the two boards could also improve or eliminate the effects of drift on the MPU. To explain, the ESP32 has more flash storage, which was a limitation mentioned earlier. Hence, with the ESP32 on the glove instead, the AHRS libraries could then be implemented properly, thus potentially leading to calibration and fusion between the MPU6050 and the HMC5883L. Along the same vein, just using a proper module with all three sensors - the accelerometer, gyroscope, and magnetometer, integrated would likely be the best fix.

Additionally, reducing the size of the touch sensor or area could be investigated. This would make it more natural and easier to move the fingertips, without having a board attached. Potentially, metallic sheets wrapped around the fingertips could be used instead.

Apart from this, adding more IR receivers and improving the IR locations, both physically and where they translate to on screen, or using some form of gesture or pointing angle recognition could be an area to explore. That said, the angle recognition could be difficult to implement, as the main glove relies on the MPU6050's gyroscope as the main controller of the pointer movement.

In terms of testing, increasing the number of trials and potentially diversifying the testing facility can improve the performance of the models on the respective tasks. Other than that, conducting a qualitative assessment could result in a more comprehensive study of how the glove compares with other input methods, such as various pain points annoyances for improvement, or areas where the users could find themselves preferring the glove.

6.2 Conclusion

The new iteration of the glove has shown an avenue for non-in-person computer usage that requires pointer manipulation and target selection, which is evident in the task completion of RQ1. That said, in terms of RQ2 and RQ3, the glove performed worse in all aspects compared to the mouse, namely requiring more time to complete the tasks and also having considerably more missed clicks and overshoots. Familiarity and improving the movement mechanisms do appear to improve the usability though, as shown by the small differences between the two glove tests. Additionally, it performed better than the previous iteration in terms of mimicking a mouse, as clicking could now be done. The device was also less intuitive for users, as they appeared to have some difficulties in familiarizing themselves with the new input device for RQ4, compared to their familiarity with a mouse.

The glove's performance does not yet match that of a traditional mouse and has many areas for improvement, particularly in reducing error rates, improving user intuitiveness, and optimizing total task completion time. That said, this study demonstrates its potential as a feasible alternative in specific contexts. It can cater to niche scenarios where traditional mice may be impractical, such as hands-free or non-in-person environments.

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I would like to thank the DLSU Center for Automation Research (CAR) laboratory for their assistance in providing insights, tools, and solutions to several hardware-based difficulties and issues encountered during the designing phase of the project.

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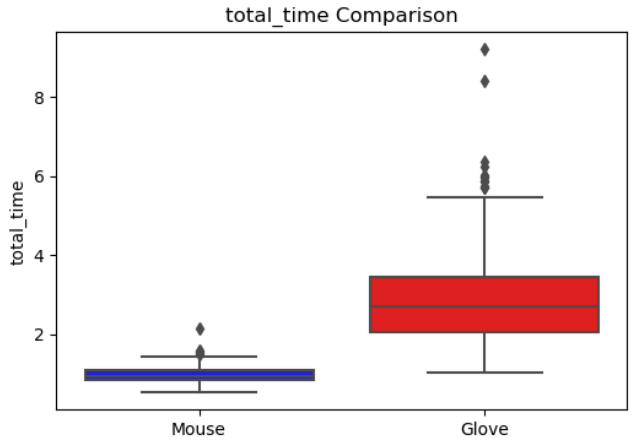

Figure 16: Boxplot of Total Times of Mouse and Glove

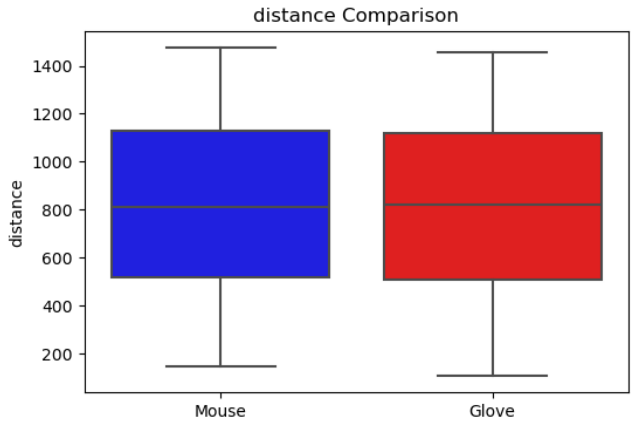

Figure 17: Boxplot of Target Distances of Mouse and Glove

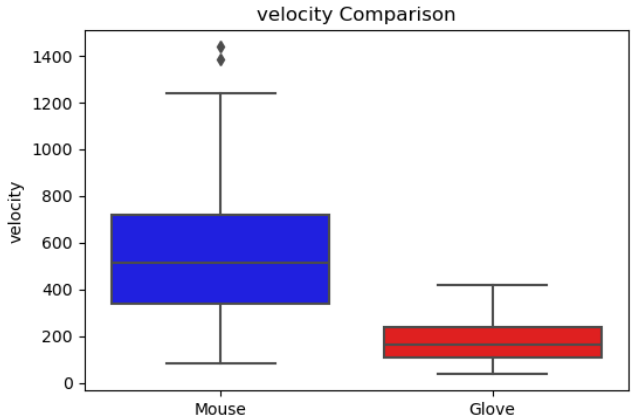

Figure 18: Boxplot of Velocities of Mouse and Glove

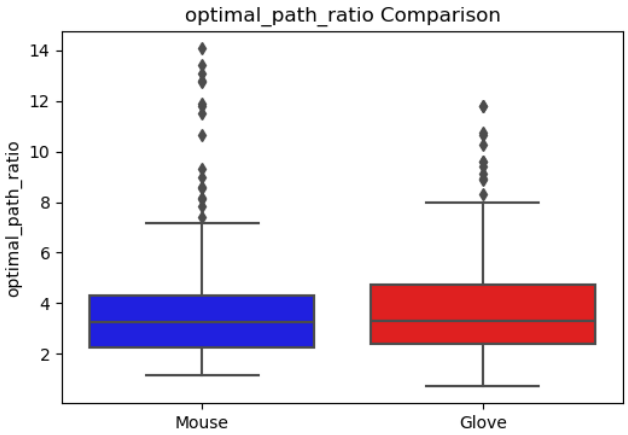

Figure 19: Boxplot of Optimal Path Ratios of Mouse and Glove

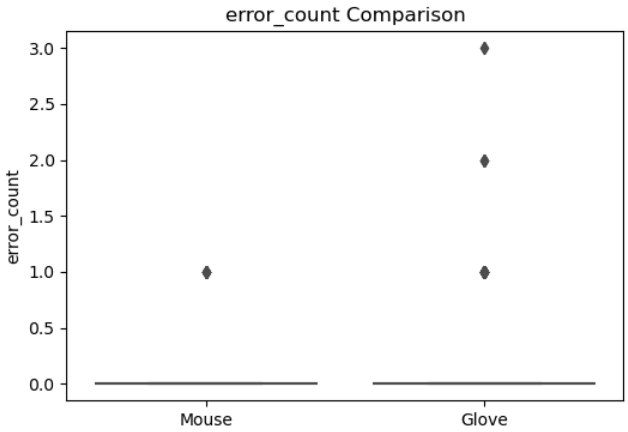

Figure 20: Boxplot of Error Counts of Mouse and Glove

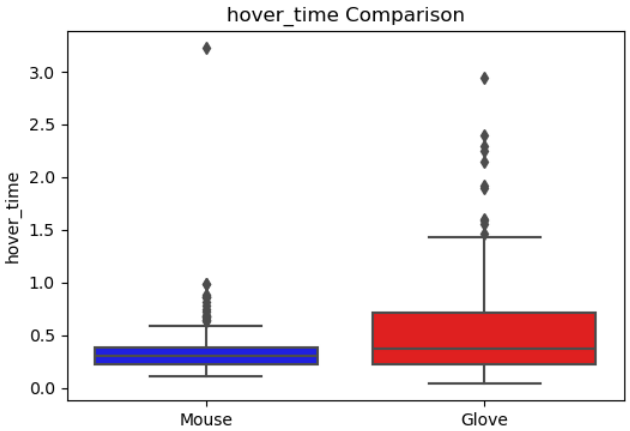

Figure 21: Boxplot of Hover Times of Mouse and Glove

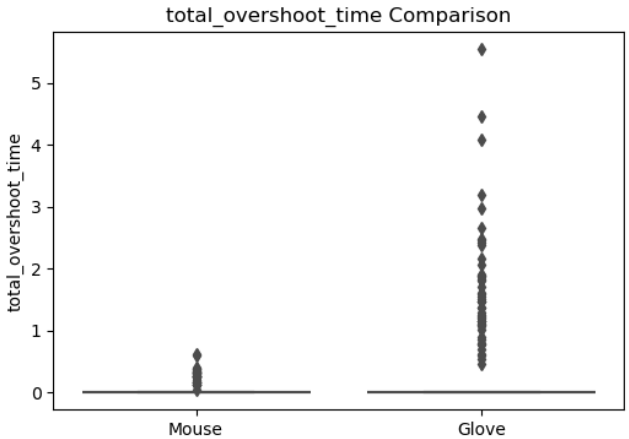

Figure 22: Boxplot of Overshoot Times of Mouse and Glove

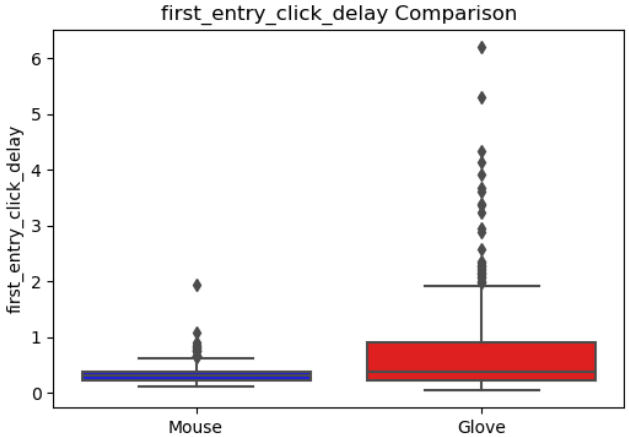

Figure 23: Boxplot of First Entry Delays of Mouse and Glove

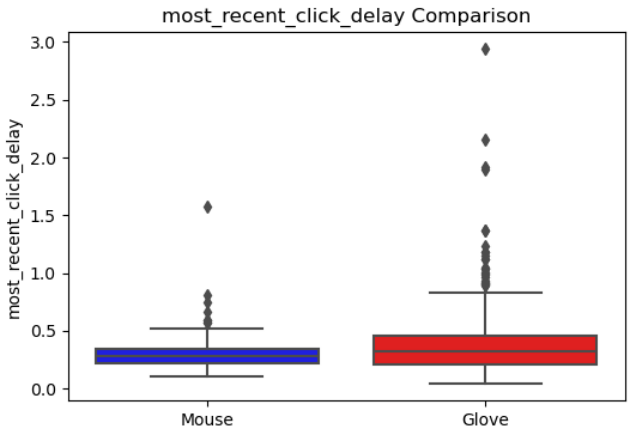

Figure 24: Boxplot of Most Recent Entry Delays of Mouse and Glove

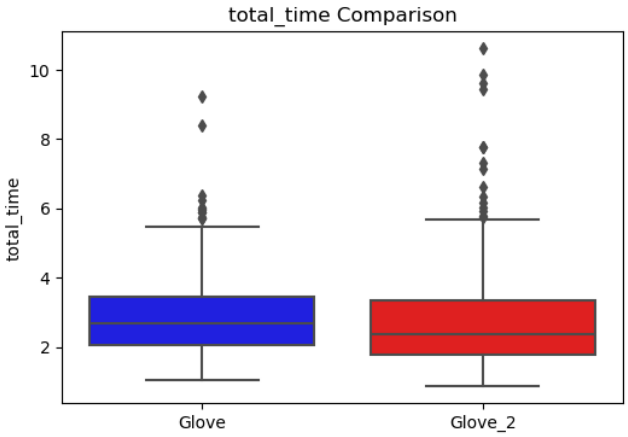

Figure 25: Boxplot of Total Times of Glove 1 and Glove 2

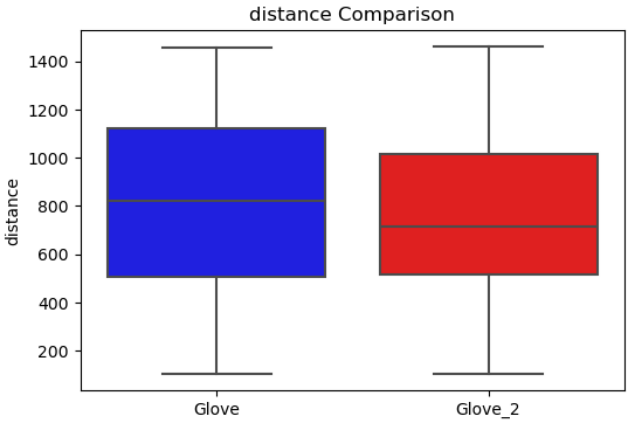

Figure 26: Boxplot of Target Distances of Glove 1 and Glove 2

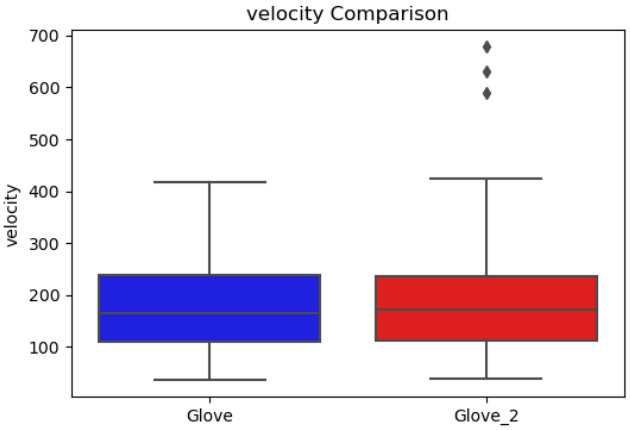

Figure 27: Boxplot of Velocities of Glove 1 and Glove 2

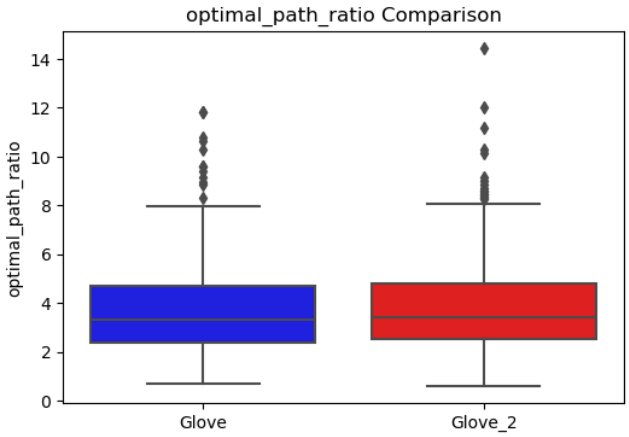

Figure 28: Boxplot of Optimal Path Ratios of Glove 1 and Glove 2

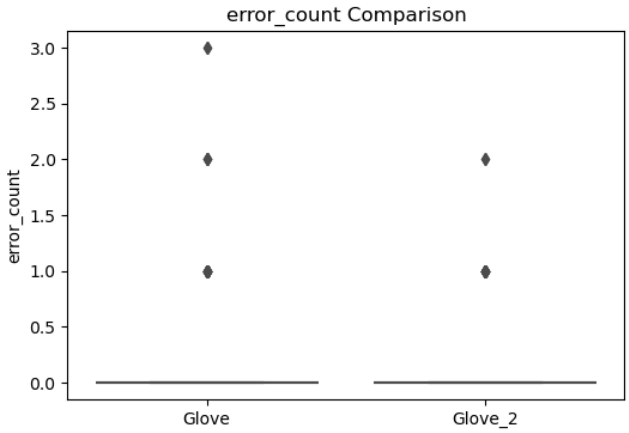

Figure 29: Boxplot of Error Counts of Glove 1 and Glove 2

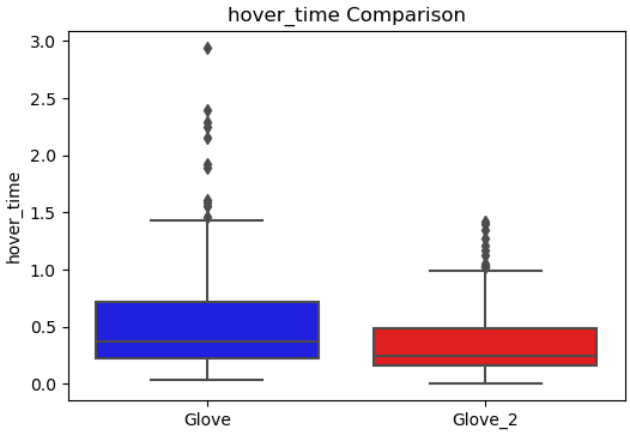

Figure 30: Boxplot of Hover Times of Glove 1 and Glove 2

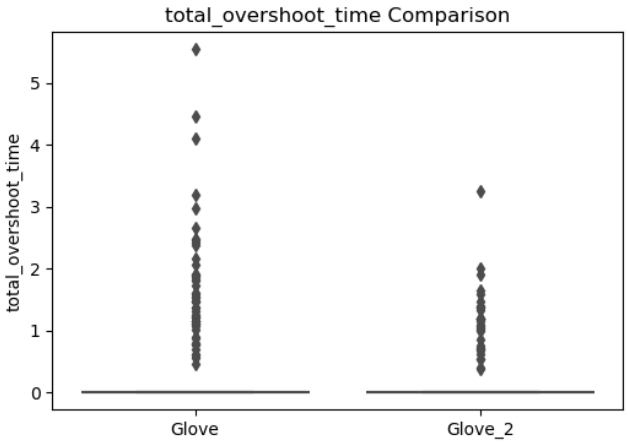

Figure 31: Boxplot of Overshoot Times of Glove 1 and Glove 2

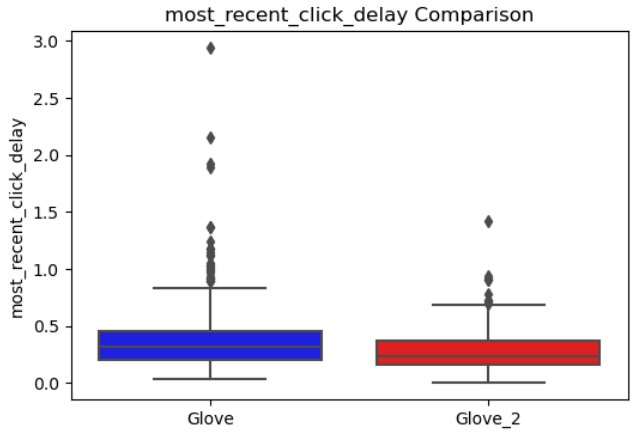

Figure 33: Boxplot of Most Recent Entry Delays of Glove 1 and Glove 2

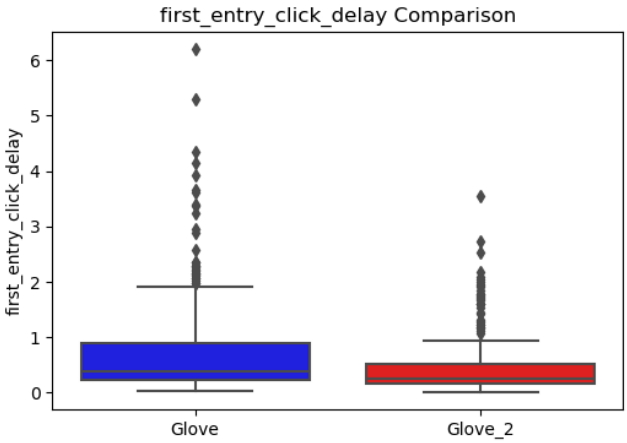

Figure 32: Boxplot of First Entry Delays of Glove 1 and Glove 2