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A Sensor-Based Wireless Head-Mounted Mouse for People with Upper Limb Disability

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Declaration of Authorship

This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by **Mr. Mohammad Ridwan Kabir**, under the supervision of **Dr. Md. Kamrul Hasan**, Professor, Department of Computer Science and Engineering (CSE), Islamic University of Technology (IUT), Dhaka, Bangladesh. It is also declared that neither of this thesis nor any of its part has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others have been acknowledged in the text and a list of references is given.

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Abstract

Disabilities of the upper limb, which may be caused either due to *accidents*, *neurological disorders*, or even *birth defects*, impose limitations and restrictions on the interaction with a computer for the concerned individuals, while using a generic optical mouse. In this thesis, we propose the design and development of the working prototype of a sensor-based wireless head-mounted Assistive Mouse Controller (AMC), facilitating interaction with a computer for people with upper limb disability. Leveraging a combination of low-cost, Inertial Measurement Units (IMUs) and Infrared (IR) sensors, the proposed AMC tracks the user's head rotation and cheek muscle twitches for mouse cursor movement on the screen and actuation of different mouse clicks, respectively. The performance of the AMC has been juxtaposed with that of a generic optical mouse in different *pointing tasks*, utilizing Fitts's law, as well as in *typing tasks*, using a virtual keyboard. Furthermore, this work also provides an in-depth analysis of the *usability*, *user satisfaction*, and *acceptability* of the proposed AMC, featuring the System Usability Scale (SUS), the Quebec User Evaluation of Satisfaction with Assistive Technology 2.0 (QUEST 2.0) framework, and the Technology Acceptance Model (TAM), respectively. Highlights of the results of these analyses along with the research challenges and potential avenues for future research have been reported as well.

Keywords - Upper Limb Disability; Wearable Sensors; Assistive Mouse Controller; Prototype Development; Fitts's Law; Usability Analysis; System Usability Scale; User Satisfaction Analysis; QUEST 2.0; User Acceptability Analysis; Technology Acceptance Model.

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Chapter 1

Introduction

Physical disability is the complete or partial loss of motor functionality of the human body arising out of either any *disease*, *birth defect*, *accidents*, or *amputation*. According to a collaborative report by the World Health Organization (WHO) and the World Bank (WB) in 2011 [1], it was stated that about 15.3% (978 million) of the world population (6.4 billion as of 2004) suffered from "moderate or severe disability", while 2.9% (185 million) of them had "severe disability". In the same report [1], human motor activities have been categorized into 3 correlated areas, such as –

(a) ***Impairments***, which are related to the abnormalities or the alterations of the structural units of human body. For example – *paralysis*, *amputation*, *birth defects*, etc.

(b) ***Activity limitations***, which focus on the difficulties faced during execution of a particular task.

(c) ***Participation restrictions***, the discriminations faced by disabled individuals at different points of their daily lives such as employment, transportation, etc.

Compared to the broad spectrum of physical disability, upper limb disability refers to the complete or partial loss of motor functionalities of the arm, shoulder, and/or hand, which may be caused due to – stroke [2–5], spinal injury [6, 7], cerebral palsy [8–11], Amyotrophic Lateral Sclerosis (ALS) [12, 13], contractures due to fractures and burns, deformation of limbs at birth [14, 15] or because of amputation [16–18], etc. Correlating with the categories of human motor activities as mentioned in the preceding paragraph, these impairments affect the lives of the disabled people in terms of both *activity limitations* and *participation restrictions* [19]. Moreover, research [20–22] findings suggest that such people are more likely to be depressed due to their limitations in terms of mobility, social engagement, and economic status, thereby, making their Health-Related Quality of Life (HRQoL), a crucial concern. Therefore, exploring alternative modalities to overcome the limitations of activity and to ensure unrestricted participation, while improving the socio-economic status and HRQoL of the disabled people is still of interest to the research community [19].

Due to the technological advancements in the twenty-first century, pervasive and ubiquitous computing [23] have increased our dependency on computers for any task as simple as – "*checking today's date*", to a complex task, such as – "*writing a computer program*". With the help of a generic computer mouse, a user can move the cursor on the computer screen, actuate mouse clicks, and perform various other complex interactions, such as – browsing the web, file navigation, playing games, etc. However, other interacting devices, such as – touchpad, joystick, trackball, etc. have also been developed for doing the same in different contexts. Although a keyboard is used for typing and carrying out other relevant tasks on a computer, alternatively, a mouse or any similar device may be used for the same purpose through a software-defined on-screen keyboard, otherwise known as a virtual keyboard. From this discussion, it may be stated that a computer mouse serves as a generic pointing device, ensuring seamless interaction with a computer for healthy individuals.

Although normal people, due to their physical capability, can use the generic handheld pointing devices without any difficulties, the scenario is quite different for the people with upper limb disability, as the corresponding causal factors of such disability hamper motor functionalities in different manners. For example, for patients with ALS, disability is characterized by motor dysfunctions (e.g., spasticity, muscle weakness or paresis), however, the brain and the eye functionalities are preserved as residual or unaltered abilities [12, 24–27]. On the contrary, motor capabilities of upper limb amputees [18] are limited by their amputated body part(s), respectively. Research have shown that unlike a normal person, the residual sensory abilities of a disabled individual intensifies over time, compensating for their lost ability [28–32]. For instance, people suffering from blindness exhibit strong memory [28, 29] and a superior sense of hearing [30–32] compared to their healthy counterparts. Similarly, people with upper limb disability, through utilization of their residual motor capabilities, accomplish different tasks in their daily lives [33–36]. Since a generic computer mouse is hand-held, such people require special devices, otherwise known as Assistive Technologies (AT) or Assistive Devices (AD) [37] that leverage their residual motor capabilities to facilitate alternative input modalities for interacting with a computer. Hence, any AT that functions as an alternative to a generic computer mouse or a similar pointing device, facilitating Human-Computer Interaction for a disabled individual, may be termed as an Assistive Mouse Controller (AMC).

1.1 Motivation and Scopes

To date, researchers have explored various technologies for developing AMCs, which may be categorized into 4 categories, such as – 1) Vision-based, 2) Electromyography (EMG)-based, 3) Electrooculogram (EOG)-based, and 4) Wearables Sensor-based. The motivations behind these explorations were –

(a) To make interaction with a computer accessible to individuals with upper limb disability.

(b) To analyze the feasibility of different gestures and sensor technologies as an alternative input modality.

(c) To analyze the influence of different usability and human factors on the acceptance of a particular technology.

(d) To analyze the impact of such technologies on the HRQoL of the disabled community.

Intuitively, people with a certain disability may find a particular AMC technology convenient for them, while it might not be the same for people with a different type of disability. As mentioned earlier, eye movement is one of the residual motor abilities of patients with ALS [12, 24–27]. Therefore, AMC technologies that exploit eye movement tracking, using either Vision-based [39–42], Electromyography (EMG)-based [43–46], or Electrooculogram (EOG)-based [24, 27, 47, 48] approach, may be more appropriate for them compared to those that exploit Head Motion Sensing technologies [45, 49–51]. This leads to the consideration of multiple external factors such as *perceived usefulness*, *perceived ease-of-use*, *comfort*, *affordance*, *accessibility*, *satisfaction*, etc. while designing acceptable and user-friendly AMCs for people with upper limb disability [19, 38, 52–59], due to which the development of such AMCs is still an active research area. To analyze the usability, user satisfaction, and acceptability of different ATs in general, several frameworks, such as – the System Usability Scale (SUS) [60–65], the Quebec User Evaluation of Satisfaction with Assistive Technology 2.0 (QUEST 2.0) [25, 66–68], and the Technology Acceptance Model (TAM) [39, 53–55, 69–74], respectively, have been developed.

Therefore, it may be surmised from this discussion that while developing an AMC, 3 fundamental factors need to be considered, such as – 1) the availability of residual motor functionalities, 2) the feasibility of existing sensor technologies capable of leveraging these functionalities as alternative input modalities for interacting with a computer, and 3) the factors (*perceived usefulness*, *perceived ease-of-use*, *comfort*, *affordability*, *accessibility*, etc.) affecting the *usability*, *user satisfaction*, and *acceptability* of the AMC technology under development. The underlying motivations of this work can be summarized as follows –

(a) The development of AMCs as alternative input modalities to human-computer interaction for people with upper limb disability is still an active research area.

(b) To the best of our knowledge, a wearable AMC technology, leveraging a combination of low-cost IMUs and IR sensors for registering head movements and cheek muscle twitches, respectively, has not yet been conceptualized.

(c) For a wearable AMC, extensive investigation into its performance in different tasks, usability, user satisfaction, and its acceptance to users, have not been conducted in prior studies, paving the way for a novel investigation.

1.2 Objective

Based on the overview, our objective is to design, develop and evaluate, a sensor-based head-mounted wireless AMC, facilitating an alternative input modality to human-computer interaction, for people with upper limb disability. In this work, we have used a combination of – 1) low-cost Commercial Off-The-Shelf (COTS) Inertial Measurement Unit (IMU), featuring *MPU9250*, as motion sensor for capturing head-movement for cursor control and 2) Infrared (IR) sensors for detecting cheek muscle twitches for actuating mouse clicks, while overcoming some, if not all the shortcomings of the existing state-of-the-art AMCs. In short, the following aspects have been addressed -

(a) Design and development of a working prototype of a sensor-based wearable AMC, leveraging head movements and cheek muscle twitches, while considering different principles associated with the design of wearable assistive technologies [19,38]. Apart from the basic mouse controls, such as – cursor movement and mouse clicks, we have defined a special gesture that will allow a user to enable or disable the AMC, so that he/she can interact freely with his/her surroundings.

(b) Comparative analysis of the performance of people with upper limb disability and their healthy counterparts, leveraging the proposed AMC and a generic optical mouse as interaction devices, respectively, in different tasks, such as – pointing and typing. In the case of pointing tasks, the comparative analysis has been performed applying Fitts's law, where a novel derivation for accurately quantifying the perceived difficulty of such tasks under the influence of subjective behavior and context of interaction has been proposed and evaluated. For the typing tasks, the comparative analysis has been performed with the help of relevant performance metrics, derived from the users' data.

(c) Investigation into the usability, user satisfaction, and user acceptance of the proposed AMC, leveraging different state-of-the-art questionnaires and frameworks.

1.3 Thesis Outline

In **Chapter 1**, we have discussed our study in a precise and concise manner. **Chapter 2** deals with the necessary literature review for our study and their development so far. In **Chapter 3**, we have elaborated on our approach to the design and development of the proposed AMC from both hardware and software perspectives. **Chapter 4** elaborates on the different experiments conducted as part of this study, their results, and observations. Finally, **Chapter 5** provides a summary of this study in terms of research challenges, future research scope, and concluding remarks. The final segment of this study contains the references to all the related works in this area of research.

Chapter 2

Literature Review

Due to the recent technological advancements, the design and development of Assistive Mouse Controllers (AMC) for physically challenged individuals have gained a new dimension, making it a prominent research area. Interaction data from the users may be recorded either using *computer vision*, *electromyography*, *electrooculogram*, or *wearable sensors*. These data are further processed, and mapped to appropriate system calls to provide an alternative input modality for the physically challenged people to interact with a computer. In this section, we elaborate on the existing state-of-the-art AMCs, their limitations, and justify our scope and motivation for developing a sensor-based wireless head-mounted AMC.

2.1 Existing Assistive Mouse Controllers (AMCs)

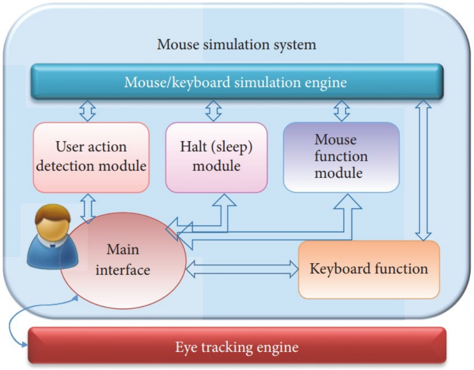
2.1.1 Vision-based AMCs

Existing vision-based AMCs in the literature map a user's eye gaze to a particular screen coordinate through gaze fixations, extracted from real-time video feed either using eye trackers, webcams, or other types of imaging sensors such as an optical mouse for moving the cursor. For mouse click operations, dwell-time-based or eye blink-based mechanisms are among the popular ones. However, before such AMCs can be used, user's eye gaze needs to be calibrated using different calibration techniques.

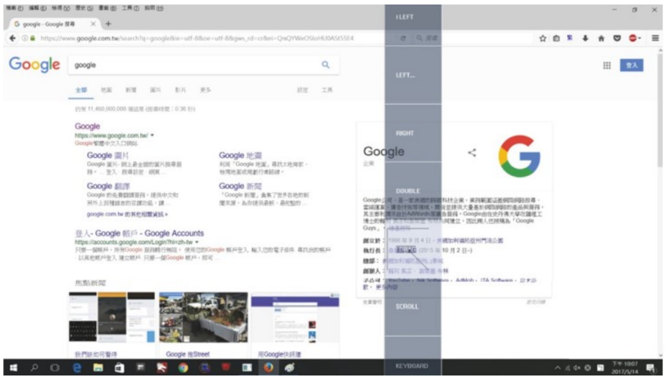
Using a low-cost eye tracker, such as the *Eye Tribe Tracker*, Zhang et al. [39] have developed a software application for mouse control through eye gaze. Their proposed system architecture, as shown in **Fig. 2.1a**, is divided into two engines, such as the *Eye Tracking Engine* and the *Mouse/keyboard Simulation Engine*. The *Eye Tracking Engine* is responsible for mapping the eye gaze tracking data with mouse cursor movement function. The *Mouse/keyboard Simulation Engine* on the other hand, contains the main virtual interface of the application, as shown in **Fig. 2.1b**, from which various mouse and keyboard functionalities, such as left-click, right-click, drag, scroll, etc. can be activated through a short dwelling time measured using eye fixation. The authors have performed two experiments, a *searching* task, and a *web browsing* task and have evaluated their system using the Technology Acceptance Model (TAM) [53, 54, 69] and

System Usability Scale (SUS) [61].

Leveraging nose tracking for cursor movement, and either, facial gestures such as eye wink, eye blink, etc., or dwell-time-based mechanism, researchers [42,75–77] have previously developed interfaces that provide people with upper limb disability accessibility to a computer, as shown in **Fig. 2.2**.

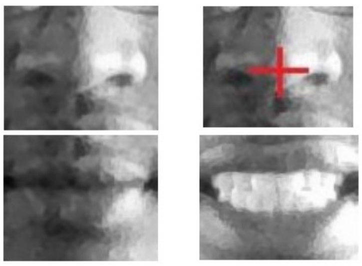


(a) System Architecture.



(b) Mouse control toolbar.

Figure 2.1: Eye gaze tracking and dwell time-based Assistive Mouse Controller (AMC) as proposed by Zhang et al. [39] (image adopted).



(a)

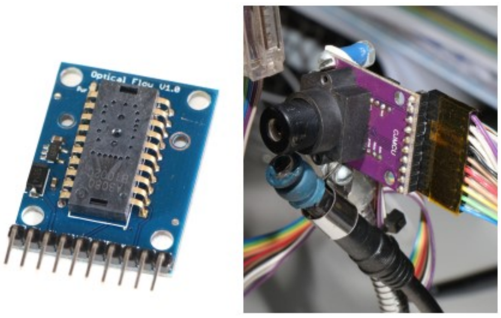
(b)

(c)

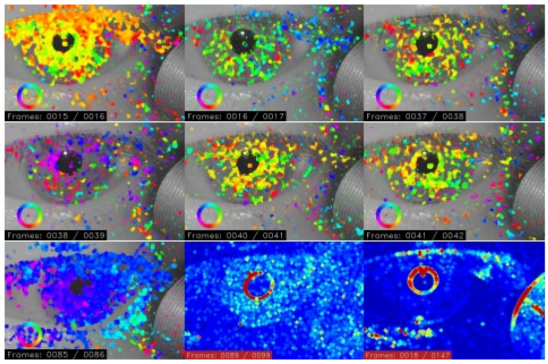
(d)

Figure 2.2: Nose tracking and different facial gestures or dwell time-based Assistive Mouse Controllers (AMC) as proposed by - (a) Khan et al. [42] (b) Varona et al. [75] (c) Gorodnichy et al. [76] and (d) Kabra et al. [77] (images adoptedfrom respective sources).

Researchers [40, 41] have also explored optical mouse sensors, (*ADNS-3080*), as shown in **Fig. 2.3a**, as alternatives to eye trackers and webcams for tracking the user's gaze, in the development of low-cost and computationally inexpensive AMCs. However, in both studies, an additional light source had to be incorporated for eye movement tracking with these sensors. Researchers in [40] have used such imaging sensors for tracking the movement of the episclera (white part of the eye), as shown in **Fig. 2.3b**, whereas, in [41], the same has been used for pupil tracking, as shown in **Fig. 2.3c**, facilitating mouse cursor movement. Researchers in [41] have implemented an eye blink-based mechanism for mouse click operations, whereas in [40], only the feasibility of cursor control through episcleral surface tracking have been explored.



(a)



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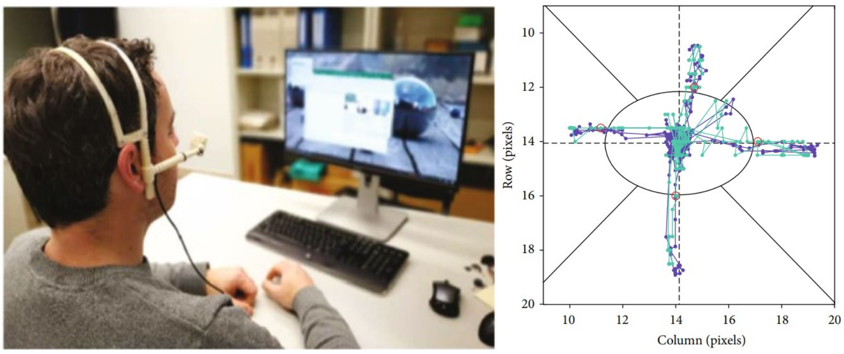


(c)

Figure 2.3: (a) Optical Mouse Sensor *ADNS-3080*. (b) Episcleral movement tracking for mouse control by Borsato et al. [40] and (c) Eye pupil tracking for mouse control by Tresanchez et al. [41] (images adopted from [40, 41]).

To address the "*Midas Touch*" problem [78] of dwell-time-based click actuation where, unwanted mouse clicks are actuated due to eye gaze fixation, a unique click actuation technique through muscle shrugging, using either eyebrow shrugging, or opening and closing action of the jaw, as shown in Fig. 2.4a, was proposed in [79]. Their proposed actuation technique was built upon the detection algorithms provided by the software packages, "*Camera Mouse*" [80,81] and "*ClickerAid*" [82], as shown in **Fig. 2.4b** and **Fig. 2.4c**, respectively.

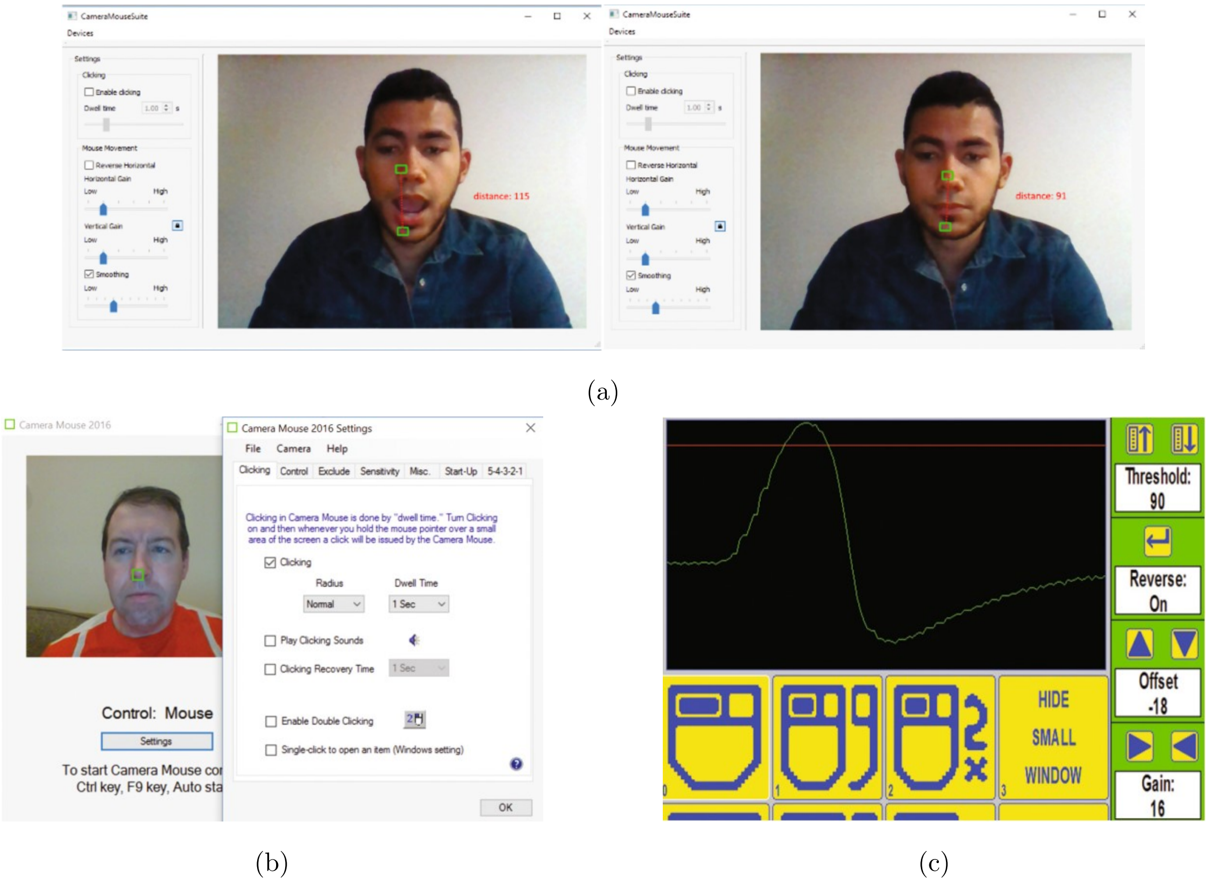


Figure 2.4: (a) Opening and closing action of the jaw for mouse click actuation by Zuniga et al. [79] (b) Interface of the "*Camera Mouse*" software package and (c) Interface of the "*ClickerAid*" software package (images adopted from [79]).

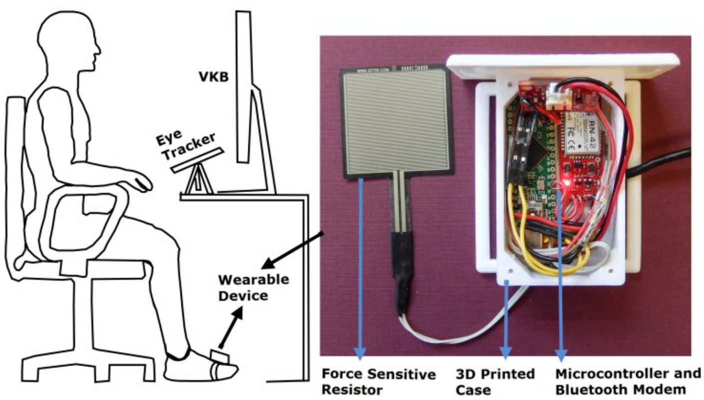


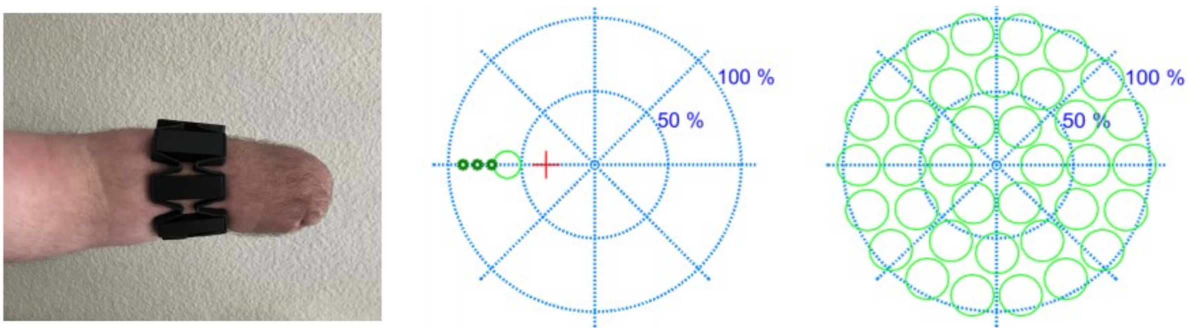
Figure 2.5: Assistive Mouse Controller (AMC) featuring eye tracking and pressure sensor-based footwear by Rajanna et al. [83,84] (image adopted).

Furthermore, Rajanna et al. [83, 84] have also developed a system for people with arm or hand impairment that uses eye gaze for pointing at a screen-element while selection is actuated by exerting pressure on a pressure sensor-based footwear, as shown in **Fig. 2.5**.

2.1.2 Electromyography (EMG)–based AMCs

Electromyography (EMG) signals refer to the measurement of very low electric potentials generated due to muscle contractions [85]. These signals can be measured with electrodes placed on the skin in a non-invasive manner, where the signal amplitudes are proportional to the exerted muscle force.

For people with upper limb disabilities, especially amputees, EMG signals are retrieved from the contraction of their residual muscles [86], which can then be used to determine the type of intended motions, such as - *wrist flexion/extension, ulnar/radial deviation* [43]. Leveraging this feature of EMG technology, researchers have explored the feasibility and performance of myoelectric cursor control for amputees [43] with the help of a myoelectric armband, as shown in **Fig. 2.6a**. The EMG band has eight bipolar EMG electrodes, with a sampling rate of 200Hz at 8-bit resolution. With this configuration, they were able to extract simple amplitude related features, however, for more complex feature extraction, more electrodes and complex setup are required. The retrieved muscle contraction signals were transferred wirelessly via Bluetooth. Before the device could be used for mouse cursor control, the users had to go through a training phase for device calibration and preparation for the subsequent test phase.



(a) (b) (c)

Figure 2.6: (a) Myoelectric armband worn by an amputee for retrieving EMG signals due residual muscle contractions. (b) User-feedback interface during training phase. and (c) Mouse cursor control interface during testing phase (images adopted from [43]).

As shown in **Fig. 2.6b**, from the myoelectric signals, obtained during the training phase, three types of feedbacks were visualized, such as - 1) Estimated position of the cursor, indicated by a *red cross*, 2) Current position of the target, indicated by a *large green circle*, and 3) Potential future target positions, indicated by *small green circles*. During the training phase, different parameters are determined and continuously adjusted for proper detection of intended motion. After 5 iterations of the training phase, the users were given a different screen containing several target locations in green circles, as shown in **Fig. 2.6c**. Their objective was to move the *red cross* to various target locations, while maintaining position for about 1 *second*. Their research outcomes suggest feasibility of the EMG based AMC technology, at the cost of more complex and expensive setup.

For making computers accessible to people with high-level spinal cord injury, researchers in [44] have proposed two cursor control methods, "*auto-rotate*" and "*manual rotate*" using a single-site surface EMG sensor. In connection to this, they had used two disposable *Ag/AgCl* center snap electrodes, which were placed on the temporalis muscle of the users, 2.5cm apart, and a *gold disc* electrode with conductive paste was placed on the ear lobe as reference point. In the "*auto-rotate*" method, the cursor was set to rotate automatically at a predetermined velocity. It moved forward only when the temporalis muscle was contracted. On the contrary, a subject had control over both forward and rotational motion of the cursor through muscle contraction. A threshold value was set to distinguish between signals that indicated intention of the user to manipulate forward or rotational motions of the cursor. They evaluated their proposed methodology through a pointing task-based experiment, utilizing Fitts's law. The outcome of their study suggests the viability of an AMC using such an EMG sensor. The user interface of their control methods is outlined in **Fig. 2.7**.

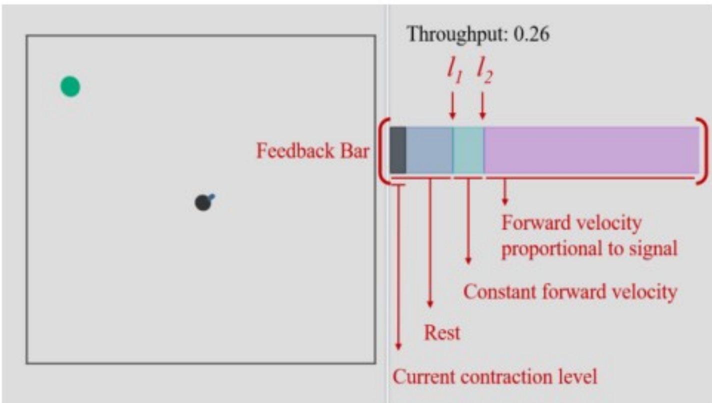


Figure 2.7: User interface for manipulating rotational and forward motions of mouse cursor, leveraging single-site EMG signal acquisition (image adopted from [44]).

2.1.3 Electrooculogram (EOG)-based AMCs

Electrooculogram (EOG) is used to measure the corneal-retinal Transepithelial Potential Difference (TEPD), which is produced due to horizontal and vertical movements of the eye [26,47,48]. For measuring TEPD of a particular eye, a pair of skin electrodes are attached on both sides of the eye and a third electrode, acting as a ground or reference, is normally placed on the forehead or earlobe [48], as shown in **Fig. 2.8**. TEPD is likely to fluctuate in different lighting conditions, making light adaptation and training an integral part of EOG-based AMCs. To reiterate, although ALS is a neurodegenerative disorder, it does not affect the brain functions or the eye movement, and therefore, EOG-Based systems are best suited for people suffering from ALS [25, 26].

Figure 2.8: Placement of electrodes for Electrooculogram (EOG) signal acquisition (image adopted from [93]).

To facilitate typing through recognition of eye movement patterns, real-time EOG-based systems have been developed [24, 27, 89–92] for people with ALS, some of which have been outlined in **Fig. 2.9**.

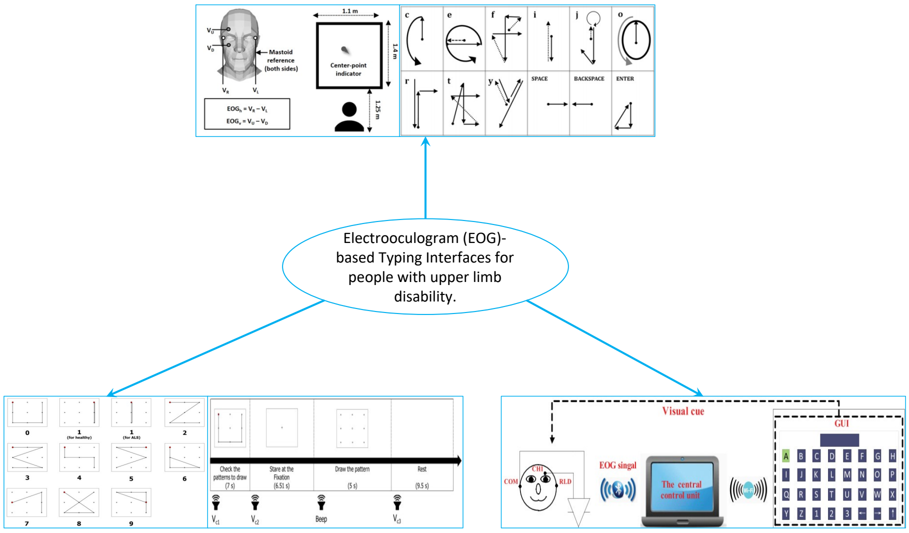
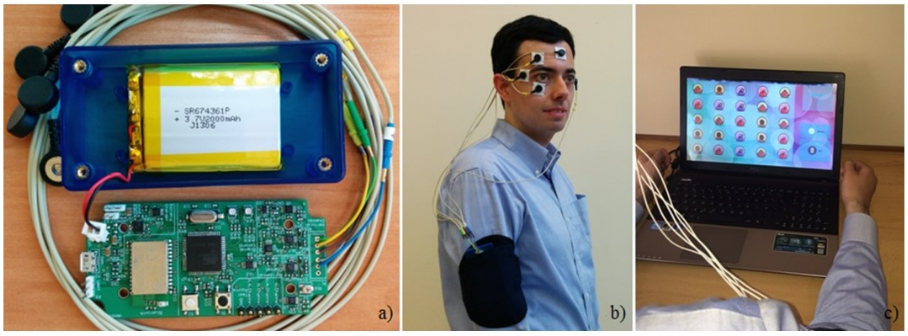
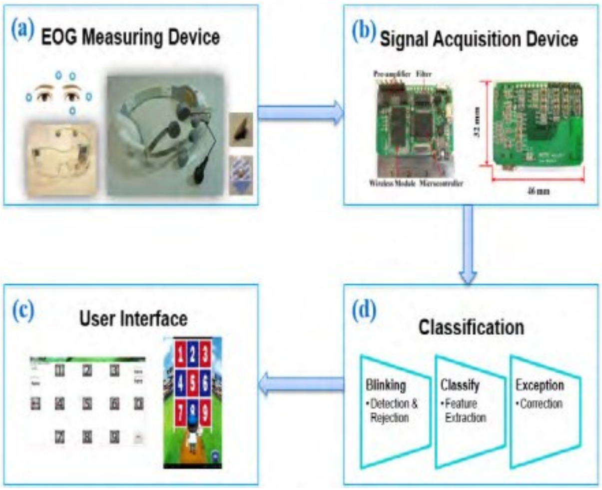


Figure 2.9: Electrooculogram-based typing interfaces (images adopted from [24, 27, 97]).

Furthermore, researchers have also developed game interfaces for people with motor disabilities, which are exclusively played through eye movements [93, 94], as outlined in **Fig. 2.10**. EOG-based AMCs that leverage eye movements to extract relative gaze position on the screen have also been proposed [95–99], facilitating interaction with a computer for people suffering from neurodegenerative disorders.



(a)



(b)

Figure 2.10: Electrooculogram (EOG)-based assistive gaming interfaces - (a) "*tile matching*" game (image adopted from [93] and (b) "*baseball*" game (image adopted from [94]).

2.2 Sensor-based Wearable AMC Technologies

Apart from Vision, EOG and EMG – based AMCs, sensor-based wearable AMC technologies have also been developed for assisting people with upper limb disabilities, leveraging their residual motor functionalities as alternative input modalities. Among these alternatives, head movement is a natural, effective, and the most common modality for moving a cursor [45,49–51]. Other alternatives include but are not limited to tongue muscles movement [100], and Brain Computer Interfaces (BCI) [101].

Velasco et al. [51] have developed an AMC for people with cerebral palsy, where the subjects can move the cursor through their head movements, as shown in **Fig. 2.11a**. The cursor movement is mapped with absolute movement of the head. They proposed a pointing facilitation algorithm "*MouseField*", which provides UI elements to have some sort of gravitational effect on the cursor. Whenever the cursor comes within a certain radius, D_{min} of the UI element, it gets captured by that element's gravity field, as shown in **Fig. 2.11b**. To escape from the gravity field, the cursor needs to be moved outside a radius of D_{max}, or in other words, the cursor will be free from the gravitational effect at a distance D_{eff} from the center of the element, as shown in **Fig. 2.11c**. They had designed a video game, featuring pointing tasks, which had to be played with and without the "*MouseField*" algorithm in action.

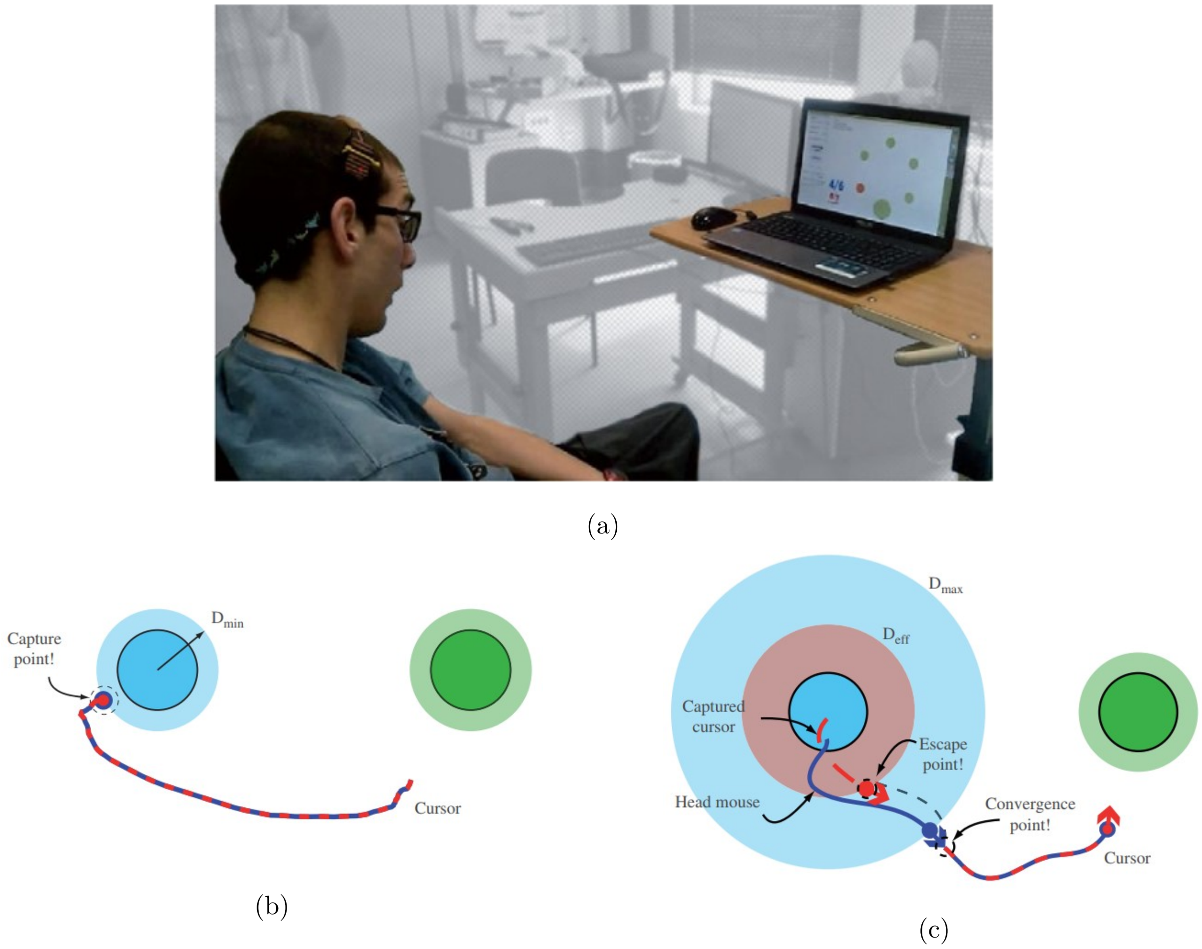


Figure 2.11: (a) Head mounted motion sensor-based AMC by Velasco et al. [51]. (b) Illustration of mouse cursor capture by a UI element, featuring "*MouseField*" algorithm. and (b) Illustration of mouse cursor release from a UI element, featuring "*MouseField*" algorithm (images adopted from [51]).

Most of the studies [45, 49, 51], involving head movement detection for cursor control, have used head-mounted Inertial Measurement Sensors (IMUs) for tracking 3D head movement. However, Gorji et al. [50] have used Infrared (IR) sensors mounted inside a collar, which is wearable on the user's neck, below the chin level, as shown in **Fig. 2.12**, for measuring user's range of head tilt motion. The raw data from the IR sensors were passed through a moving average filter on the preceding 15 data from the sensors, for eliminating ambient noises. For cursor movement, they have designed two separate modes, such as the *joystick* mode and the *direct mapping* mode. In the *joystick* mode, the cursor is set to move *horizontally* and *vertically* at a specific speed, while the sensor data are used to determine the direction of movement. For each of the IR sensors, they have determined a lower and upper thresholds during a calibration phase, which spans only 0.1 *seconds*, while the user maintains his/her head in resting position. On the other hand, in the *direct mapping* mode, the data from the IR sensors are mapped directly to the cursor position on the screen. Similar to the *joystick* mode, a calibration phase, lasting about 4 *seconds*, is accommodated in the *direct mapping* mode as well. During this phase, the user is required to perform a set of training movements, such as moving the head maximally in *up*, *down*, *left*, and *right* directions for measuring sensor thresholds in respective directions. For both of these modes, they conducted two experiments that involved - 1) moving the cursor, following a predefined path on the screen, and 2) guiding the cursor within a predefined location on the screen, as shown in **Fig. 2.13**. They evaluated user performance using Fitts's law, while considering the metrics, such as - *Index of Difficulty* (ID), *Path Efficiency* (PE), and *Throughput* (TP).

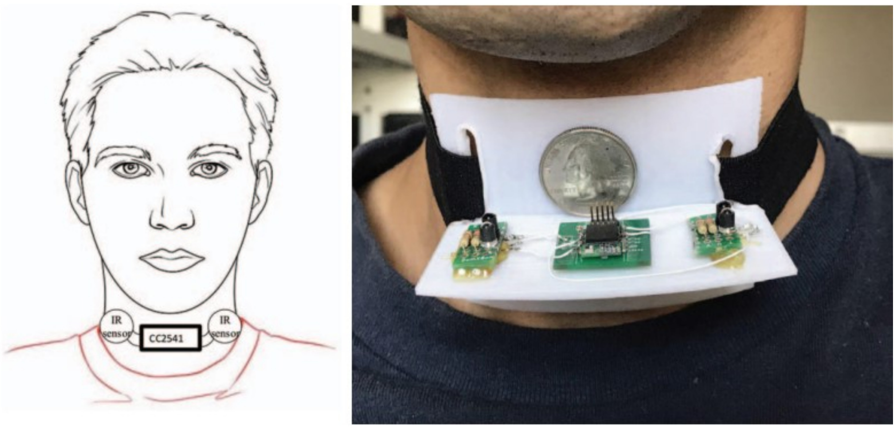
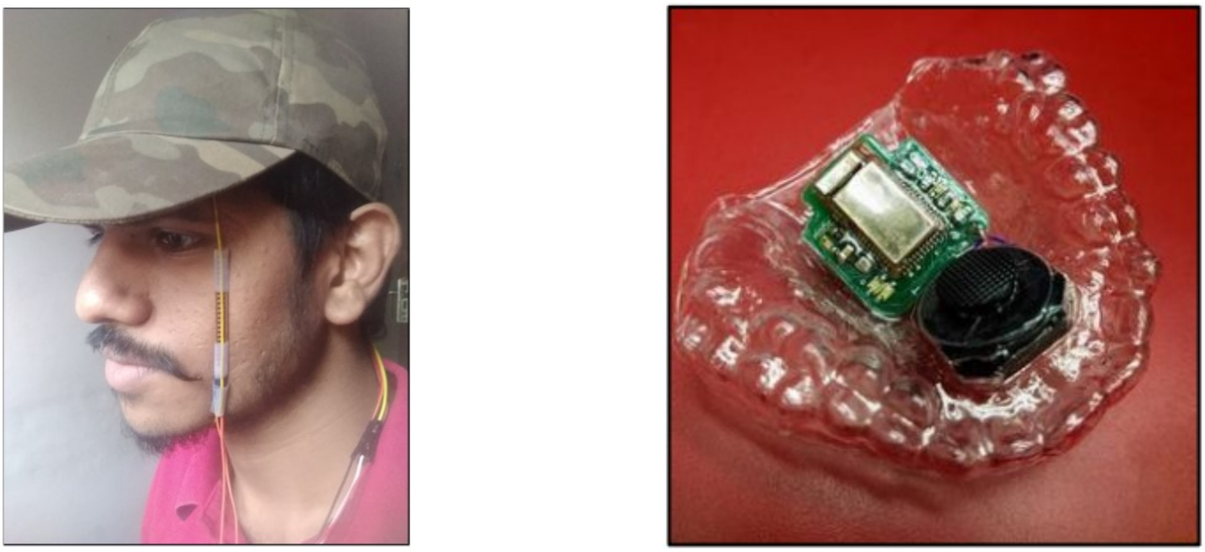


Figure 2.12: Infrared (IR) sensor-based wearable AMC by Gorji et al. [50] (image adopted from [50]).

(a) (b) (c) (d)

Figure 2.13: Moving the cursor, following a predefined path on the screen in - (a) *joystick* mode and (b) *direct mapping* mode. Guiding the cursor within a predefined location on the screen in - (c) *joystick* mode and (d) *direct mapping* mode (images adopted from [51]).

For mouse click actuation using wearables, dwell-time-based approach [51], EMG-based approach [45], BCI-based approach [49,101] have also been explored in the literature. In addition to these approaches, researchers have also leveraged various residual motor capabilities for actuating mouse clicks. For example, authors in [102] have used flex sensors for detecting cheek muscle twitches, whereas tongue muscle was used for clicking a joystick, embedded in a user-specific mouth retainer, was explored in [100], as shown in **Fig. 2.14a** and **Fig. 2.14b**, respectively.



(a) (b)

Figure 2.14: Mouse click actuation featuring - (a) cheek muscle twitches, registered with flex sensors, and (b) tongue musccles, registered with joystick button, embedded in a user-specific mouth retainer (images adopted from [100, 102]).

Yamamoto et al. [103] conducted a single case study, involving a user with mixed type of cerebral palsy, to verify the use of a wearable and stretchable strain sensor for click actuation. The authors mainly studied the feasibility of their proposed click actuation method compared to the user's previous input method, where pressing *left* and *right* buttons of a trackball emulated *left* and *right* mouse clicks, respectively. However, for cursor movement, the user was allowed to move the track ball with his neck as he used to do it prior to the case study, as shown in **Fig. 2.15a**. The proposed stretchable strain sensor, simulated a *mouse button release* event, when relaxed, and a *mouse button press* event, when stretched, as shown in **Fig. 2.15b** and **Fig. 2.15c**, respectively.

(a) (b) (c)

Figure 2.15: (a) Mouse cursor movement using a trackball. (b) Illustration of *mouse button release* mechanism using a stretchable strain sensor. and (b) Illustration of *mouse button press* mechanism using a stretchable strain sensor (images adopted from [103]).

2.3 Limitations of Existing AMC Technologies

2.3.1 Limitations of Vision-based AMCs

Processing the high resolution, real-time video feeds from eye trackers and webcams is computationally expensive, and therefore, challenging for devices with low computational power to ensure smooth user interaction. A critical requirement for vision-based AMCs to work properly is to ensure proper lighting condition for calibration and accurate detection of facial [42, 75–77] or eye gaze [39–41] features. For eye gaze-based AMCs, gaze tracking may be challenging due to image resolution, different lighting conditions, user's dependency on eyeglasses due to poor eyesight and skin color of the user. Although eye gaze-based cursor movement has its benefits [58], there are some inherent issues with this approach from the perspective of user experience, such as –

(a) As stated in [58], the human eye is not the most accurate pointing device. In addition to that, when a user controls a mouse cursor with eye gaze, he/she cannot move the cursor to a particular Region of Interest (ROI) and fixate on any other screen element at a different ROI, simultaneously, as opposed to the AMCs developed using head movements or other interaction techniques.

(b) As the eyes are used both for cursor movement (*through eye movement*) and mouse click operations (through *eye blink, wink*, or *dwell time-based mechanism*), users may find it challenging to perform both actions simultaneously.

(c) A particular problem of the dwell-time-based click mechanism using eye gaze fixation is the "*Midas Touch*" problem [78], arising from unwanted selection of interface elements due to low pointing accuracy of eye gaze-based AMCs [58].

(d) Another disadvantage of vision-based AMCs is that existing eye trackers and webcams can not detect and track a user's eye gaze beyond a particular distance from the PC or workstation. As a result, for interacting with the computer, the user has to maintain a particular distance from the PC or workstation, which under certain circumstances may be inconvenient and non-ergonomic.

2.3.2 Limitations of Electromyography (EMG)-based AMCs

EMG and BCI signals are susceptible to external noises and are highly dependent on the exact and accurate placement of electrodes [87] for accurate gesture recognition, every time a user intends to use it as an AMC. One of the inherent problems of EMG technology is that the retrieved signals are typically weaker and varies from person to person [88], thereby, requiring a user-specific device calibration and gesture recognition for further applications such as AMCs. Although deep learning techniques [46] have been proposed for mitigating the need for user-specific device calibration and gesture recognition, the computational expense for fulfilling the simple objective of an AMC seems unreasonable.

2.3.3 Limitations of Electrooculogram (EOG)-based AMCs

Although EOG is a promising low-cost AMC technology that is still being researched, it has its own set of research challenges, such as –

(a) EOG-based systems are limited by their low spatial resolutions, as it is difficult to estimate the absolute gaze position due to noise from nearby sources of bio-potentials [27, 93, 95].

(b) Pre-processing complexity of EOG signals [93] is comparatively high.

(c) The characteristics of the EOG signals vary due to the variation in the number, the type (*dry* or *wet*), the material, and the placement of electrodes [24, 90, 91, 93–95].

(d) Furthermore, from an ergonomic perspective, it is intuitive that continuous eye movements for controlling a mouse may pose certain health issues, thereby, affecting user's performance and comfort.

Based on these discussions, it may be stated that EOG-based AMCs and/or ATs facilitating human-computer interaction, may be a last resort for people, whose residual motor capability is their eye movements, for example, patients suffering from ALS.

2.3.4 Limitations of Wearable Sensors-based AMCs

Existing state-of-the-art wearable devices have few limitations. For example, the device in [100] is totally user specific as it is placed in a retainer inside the user's mouth. Fatigue of tongue muscle and hygiene issues may arise due to repeated and prolonged usage. Due to the unrealistic setup of the IR sensors in [50], the sensor readings are susceptible to fluctuations, due to changes in lighting conditions. Thus, the performance of the device might not be consistent in all environments, unless a software or hardware-based compensation mechanism is adopted. The calibration phase in their proposed device requires a user to perform certain training movements, which may compromise the ease-of-use of the device. Furthermore, in scenarios that require rapid movements of the mouse cursor, their device may not be a viable option. Again, the device proposed by Yamamoto et al. [103] can not be used by individuals with amputated or disabled upper limbs

Chapter 3

Proposed Approach

Based on the literature review, few vital points need to be considered during the design and development of a head mounted prototype of wireless head-mounted Assistive Mouse Controller (AMC), such as –

(a) The associated design principles.

(b) The factors that may influence user acceptance of a new technology.

(c) The possibilities of any detrimental effects on the user's health due to prolonged use.

(d) The difficulties that a user may face while using and adapting to the new technology.

(e) The performance reliability of the device.

In connection to this, we have developed a working prototype of a sensor-based wireless head-mounted AMC, combining low-cost Commercial Off-The-Shelf (COTS) Inertial Measurement Unit (IMU), and Infrared (IR) sensors to enhance human-computer interaction for individuals with upper limb disability. It exploits head movements, measured in degrees of rotation using the IMU, followed by a conversion to $2D$ screen coordinates, facilitating cursor movement on the screen. The movement of the cursor is bound with the absolute movement of the head. Data from the IR sensors are used to detect cheek muscle twitches for mouse click actuation. As mentioned in the earlier, IR sensor readings are subject to fluctuations due to changes in the ambient lighting conditions, for which we have designed an algorithm for overcoming this limitation. Furthermore, we have incorporated gesture control that will enhance the user's experience while interacting with the device. A device driver, with customizable features, had also been designed that handles the mapping of the wirelessly received sensor data from user interaction with the AMC to appropriate system calls for mouse cursor movement and click actuation. Most importantly, due to variances in the form-factor of the human head, adjustable head-straps have been facilitated. The IR sensors are placed on a visor mechanism with vertically adjustable housing, which can be slid up and down, allowing 2 degrees of adjustments to fit differently shaped cheek muscles for proper sensor reading. The working prototype of the

AMC is depicted in **Fig. 3.1**. In this section, we elaborate on the associated design principles, followed by prototype development, and system design and implementation of the proposed wearable AMC.

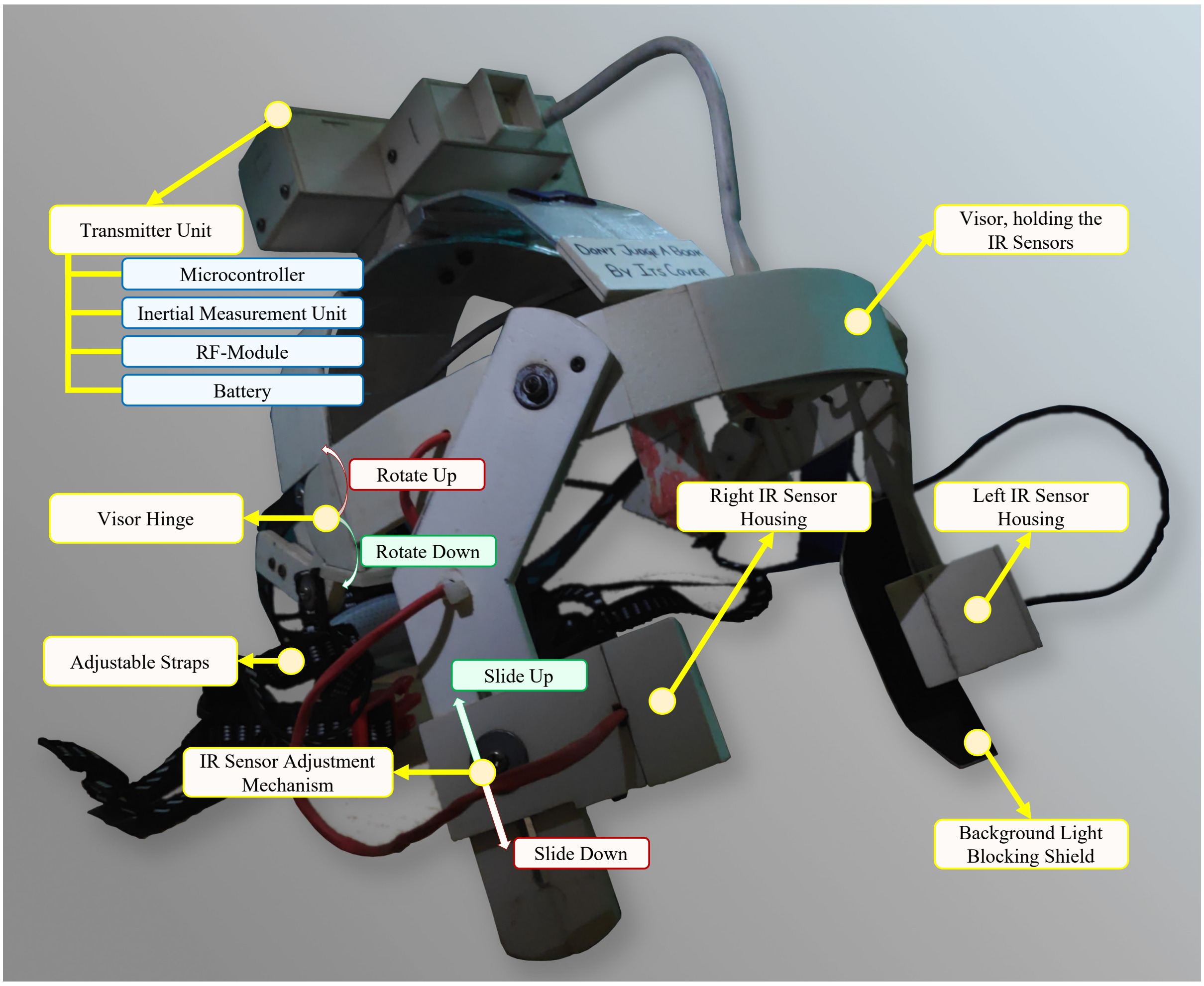


Figure 3.1: Working prototype of the proposed Assistive Mouse Controller (AMC).

3.1 Associated Design Principles

Considering the limited motor capabilities of people with upper limb disability, their residual motor functionalities are usually leveraged as alternative input modalities for human-computer interaction. These residual capabilities vary from person to person, and therefore, various design principles play a crucial role in the design and development of a wearable AMC, making it a challenging process. Previous studies [38], have identified 20 principles associated with the generic design of such wearables, such as – *aesthetics, affordance, comfort, contextual-awareness, customization, ease-of-use, ergonomics, fashion, intuitiveness, obtrusiveness, overload, privacy, reliability, resistance, responsiveness, satisfaction, simplicity, subtlety, user-friendliness* and *wearability*, which facilitate effective consideration of human factors in the early stages of prototype development and may be grouped into three broad categories, such as – 1) Device Accessibility Principles (DAP), 2) Device Interaction Principles (DIP) and 3) Device Usability Principles (DUP). An overview of these design principles is depicted in **Fig. 3.2**. This section briefly elaborates on, how and why, these design principles have been either incorporated or discarded in the context of this study.

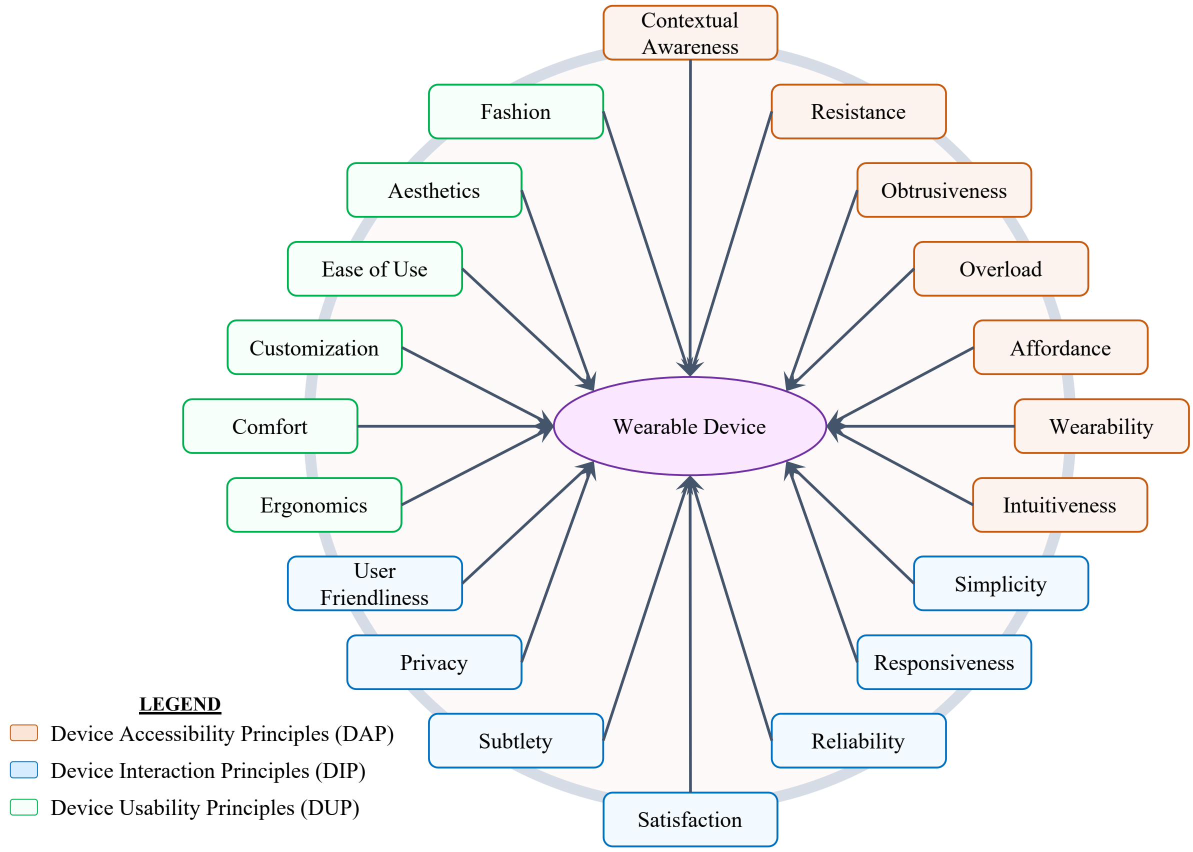


Figure 3.2: The design principles involved in the development of the proposed Assistive Mouse Controller (AMC).

3.1.1 Device Accessibility Principles (DAP)

Accessibility relates to the facilitating conditions that allow a physically challenged person to interact with technology just like their healthy counterparts [104]. As seen from **Fig. 3.2**, Device Accessibility Principles (DAP) include *contextual awareness, resistance, obtrusiveness, overload, affordance, wearability,* and *intuitiveness*, which actively facilitate equivalent user experience despite physical barriers [104]. A brief description of each of these principles, in connection to this study, is provided in this section.

3.1.1.1 Contextual Awareness and Resistance

According to Motti et al. [38], *contextual awareness* and *resistance* deal with a clear understanding of scenarios, where the wearable device will be used, affecting the design process of the device. For the proposed head-mounted AMC, the target users are people with upper limb disability, who will not be able to wear the device themselves, and therefore, are most likely to be dependent on a caregiver. Thus, the device needs to be designed in such a way that it is easily wearable with assistance from a caregiver. Furthermore, the device is most likely to be used indoors at room temperature. Therefore, it was not necessary to choose heat-resistant materials for developing the prototype of the device. However, light weight, yet durable material was preferred.

3.1.1.2 Obtrusiveness and Overload

For wearable devices, whose functionality depends on sensor-data, mostly gather data from various anatomical parts of the human body [38]. When it comes to the case of people with upper limb disability, depending on the type of sensors used, residual motor capabilities play a significant role. The *overload* principle deals with designing wearable devices in such a way that while interacting with the device, primary tasks of a user are not hampered [38].

Therefore, it must be kept in mind that while using wearable devices, a user's natural movements should not be hampered in any manner. In other words, the user should be able to interact with his/her surroundings even while using the device. In the context of the proposed AMC, the mouse cursor movement is designed in such a way that in whatever direction a user moves his/her head, the cursor will follow. Again, as mouse clicks are actuated with cheek muscle twitches, talking while using this device may result in false actuation of mouse clicks. Considering these scenarios, a user will not be able to interact with his/her surroundings while using this device. This has led to the consideration of two gesture controls, one for *enabling* and the other for *disabling* the mouse functionality. Furthermore, since head rotation is involved, the AMC needs to be designed in such a way that it does not disrupt this motion.

3.1.1.3 Affordance and Wearability

Affordance, according to Motti et al. [38], prioritizes the shape and anatomical constraints of the human body. Given the residual motor capabilities of the people with upper limb disability, affordance, in this context, resembles whether they can move their head or twitch cheek muscles.

Wearability and *affordance* are closely related with each other, as *wearability* is associated with the form-factor of wearable devices with respect to that of the human body [38]. While for the majority of the people with upper limb disability, the ability to perform these movements is retained, few cases may arise, where these are not retained. In the process of conceptualizing the proposed AMC, head movement and cheek muscle twitches, with references to previous studies [45, 49–51, 102], were considered as the most natural forms of interaction, which can be leveraged to develop a non-invasive technology. Thus, in the context of the proposed AMC, only people with upper limb disability who can move their head freely and perform cheek muscle twitches, can afford to wear, and use it.

3.1.1.4 Intuitiveness

Intuitiveness, in terms of accessibility, means the capability to immediately perceive the interaction mechanism of any wearable device. In other words, it resembles *affordance* in terms of human cognition [38]. In the context of this study, any individual with upper limb disability, possessing basic knowledge of computing and interacting with different elements of a user interface, are considered to have the intuitiveness required to use the proposed AMC.

3.1.2 Device Interaction Principles (DIP)

Once the Device Accessibility Principles (DAP) have been resolved, the next most important principles to consider are the Device Interaction Principles (DIP), such as – *simplicity, responsiveness, reliability, satisfaction, subtlety, privacy*, and *user-friendliness.* These principles, once incorporated in the design and development lifecycle of wearable devices, play significant roles in ensuring efficient, effective, and reliable user-interaction. A brief description of each of these principles, with respect to this study, is provided in this section.

3.1.2.1 Simplicity

Simplicity of interaction is bound with affordance and principles that affect human cognition, such as intuitiveness, ease-of-use, etc. [38]. In connection to this, we aimed to design the interaction mechanism of the proposed AMC in such a way that, even a novice user, finds it simple to use. Hence, the *left*, *right*, *up*, and *down* movements of the cursor were mapped with respective head motions, and the left/right mouse clicks were mapped with respective twitching of the cheek muscles.

3.1.2.2 Responsiveness

Responsiveness of any wearable device for human-computer interaction is a measure of how fast, or how slow, the consequence of an action is materialized. Low responsiveness compromises user acceptance of a particular interaction device, while a highly responsive system allows the corresponding users to accomplish any task efficiently and productively [38]. In connection to this, real-time cursor movement and mouse click actuation using the proposed AMC is significantly important for people with upper limb disability. The raw sensor data are subject to various noises, and therefore, if these noises are not filtered properly, it will result in a jittery movement of the mouse cursor, compromising precision and responsiveness in the process. To facilitate this, different smoothing algorithms were adapted to ensure seamless interaction.

3.1.2.3 Reliability

According to Motti et al. [38], *reliability* concerns the precision (*data accuracy*), effectiveness (*expected responses*), confidence of interaction, and safety associated with any wearable device. Given the proposed AMC, the algorithms that were adapted, ensured reasonable precision, and effective, intuitive, and safe interaction mechanisms, thereby ensuring reliable means of human-computer interaction.

3.1.2.4 Satisfaction

Satisfaction with wearable devices involves various aspects, such as – effectiveness, performance, etc. [38]. During the development phase of the proposed AMC, it was hypothesized that the device would be able to meet user satisfaction, given its simple, reliable, and intuitive interaction mechanism. To get a complete picture of user satisfaction with the AMC, we have used the Quebec User Evaluation of Satisfaction with Assistive Technology 2.0 (QUEST 2.0) [66], which will be elaborated in **section 4.4**, "***User Satisfaction Analysis of the Assistive Mouse Controller (AMC)***". To summarize, the users were satisfied with the overall performance of the proposed AMC.

3.1.2.5 Subtlety

Subtlety refers to the discreetness of user-interaction such that it does not become a source of disturbance for others. Furthermore, it also involves ensuring interaction mechanism of wearable devices, such that it prevents drawing unnecessary attention from people, compromising privacy

[19, 38]. Initially, when conceptualizing the interaction mechanism of the proposed AMC, a provision for auditory feedback was considered, every time a user actuated left/right mouse click. However, considering the subtlety of interaction, we realized that such feedback would be annoying for the users and people near them, which might compromise users' satisfaction with the device. Furthermore, it would draw unnecessary attention of people nearby, which is undesirable.

3.1.2.6 Privacy

Privacy is related to subtlety of interaction, where information intended for the user does not become a source of disturbance for his/her surrounding [38]. It also concerns collection of users' personal or interaction data without their consent [19]. However, to interact with a computer with the proposed AMC, the users did not require opening any account. Furthermore, the device is an alternative means of controlling a mouse, and therefore it does not gather any sort of personal or interaction data that the users might consider, a breach of their privacy.

3.1.2.7 User-Friendliness

User-friendliness may be correlated with principles, such as – intuitiveness, simplicity, subtlety, and privacy, which affect user satisfaction with a wearable device. Given that these principles were considered while developing the AMC, it may be stated that the device is user-friendly, which will be further analyzed in **section 4.4**, **"*User Satisfaction Analysis of the Assistive Mouse Controller (AMC)*"**.

3.1.3 Device Usability Principles (DUP)

Usability of a prototype may be considered as the last stage of developing a wearable device. The Device Usability Principles (DUP) primarily encapsulate the idea of how easily a user can adapt to a particular wearable device [104], which influences its user acceptability. The contributing principles in this regard are – *ergonomics, comfort, customization, ease-of-use, aesthetics*, and *fashion*. A brief description of each of these principles, in the context of this study, is provided in this section.

3.1.3.1 Ergonomics, Customization, and Comfort

The principles, *ergonomics*, *customization*, and *comfort*, are inter-related. With respect to the human anatomy, *ergonomics*, in the context of this study, is the process of designing wearable devices in such a way that they are a good fit for the targeted user base [38, 105]. *Comfort* with any wearable device is highly influenced by its ergonomic design, which may include factors such as – shape, weight, flexibility, tightness, etc. of the device. *Customization* is another important factor, which is correlated with these factors, which can be described from both software and hardware perspectives of a wearable device. For example, the adjustable head straps and IR sensor housing of the proposed AMC are customizable features from a hardware perspective, while the device driver features, such as – mouse sensitivity, invert mouse-click, etc., are customizable features from a software perspective.

3.1.3.2 Ease-of-Use

Ease-of-use of any system, according to David et al. is defined as, "*the degree to which a person believes that using a particular system would be free of effort*" [53, 54]. Utmost priority was given in the design and development of the proposed AMC to ensure its ease-of-use. However, this can only be verified by the stakeholders of this device from their first-hand interaction with it. We will verify this aspect of the device in details in **section 4.3, "*Usability Analysis of the Assistive Mouse Controller (AMC)*"**, **section 4.4, "*User Satisfaction Analysis of the Assistive Mouse Controller (AMC)*"**, and **section 4.5, "*User Acceptability Analysis of the Assistive Mouse Controller (AMC)*"**. To summarize, the users who had interacted with the AMC, were satisfied with its ease-of-use.

3.1.3.3 Aesthetics and Fashion

Aesthetics of a wearable device concerns the level of attraction that a user possesses towards it. It may be due to its physical appearance or functionality for the intended use case [19, 38]. *Fashion*, on the other hand, affects user perception of comfort or desirability of the wearable device [38]. In the context of this study, comfort, functionality, and physical appearance of the AMC were sequentially prioritized, which we believed will enhance the desirability of the device. We will analyze the desirability or acceptance of the device leveraging the Technology Acceptance Model (TAM) [53, 54, 69] in details later, in **section 4.5, "*User Acceptability Analysis of the Assistive Mouse Controller (AMC)*"**.

3.2 Prototype Development

Considering the design principles related to the *accessibility*, *interaction*, and *usability* of wearable assistive technologies, as discussed in **section 3.1, "*Associated Design Principles*"**, we have fabricated a working prototype of the proposed head-mounted AMC, as shown in **Fig. 3.3a**. The prototype is shaped after a helmet, with a visor-like arch that can be rotated up and down. The main purpose of the visor is to house the IR sensor adjustment mechanism, as shown in **Fig. 3.3a** and **Fig. 3.3b**, and to make it easier for the user to wear the AMC. The prototype of the proposed Assistive Mouse Controller (AMC) comprises three separate entities, as outlined in **Fig. 3.3**, such as – 1) a transmitter unit, 2) a receiver unit, and 3) a device driver software. The transmitter unit, shaped as a helmet, is basically the wearable part of the AMC, which contains all the sensors, microcontroller, wireless communication module, power source and is responsible for sensor data acquisition, processing, and wireless transmission to a PC via the receiver unit. The form-factor of human head varies across humans. Therefore, to ensure wearability of the AMC by people with varying head sizes, adjustable head straps have been facilitated. An inherent challenge with actuating mouse clicks with cheek muscle twitches is that the cheek shape varies from person to person as well, resulting in different patterns of cheek muscle movements. So, to ensure proper actuation of mouse clicks, the IR sensors have also been made adjustable to make the AMC usable by people with different cheek shape, as depicted in **Fig. 3.3b**.

The receiver unit connects to a PC and is responsible for retrieving data from the transmitter unit, wirelessly. These data are then mapped to appropriate system calls with the help of a custom device driver software, enabling mouse control.

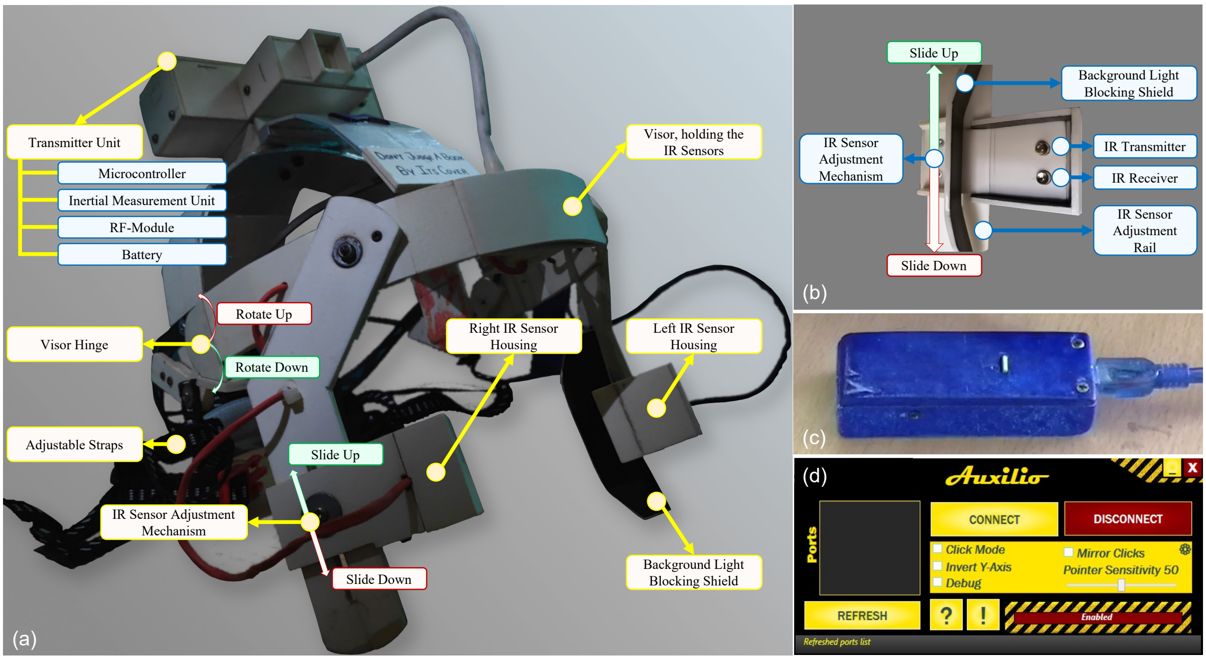


Figure 3.3: The constituent elements of the proposed Assistive Mouse Controller (AMC). (a) The wearable transmitter unit, for sensor data acquisition and transmission, (b) IR sensor housing and adjustable mechanism, (c) the receiver unit, for wireless retrieval of sensor data and forwarding those to the device driver software, and (d) the custom device driver software for mapping sensor data to system calls for mouse control.

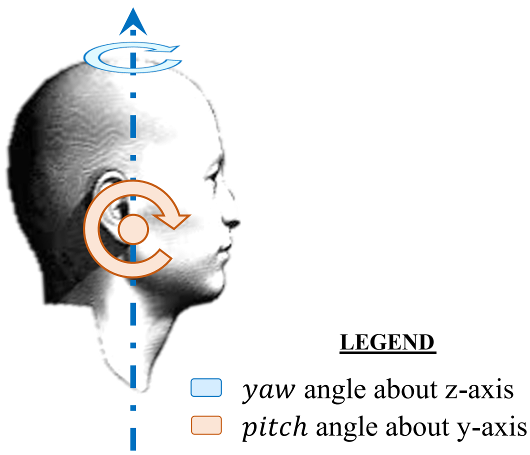


Figure 3.4: Yaw and pitch movements of the human head.

Two types of sensors, each for a different purpose, were used in the proposed AMC. First, the Inertial Measurement Unit (IMU), featuring an MPU9250 (a combination of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer). Second, one pair of IR sensors (transmitter and receiver) per cheek (left and right), to detect cheek muscle twitches for mouse click actuation. The purpose of the IMU is to measure the yaw (horizontal rotation of head about the z-axis) and the pitch (vertical rotation of head about the y-axis) angles of head rotation, as shown in **Fig. 3.4**, facilitating horizontal and vertical movements of the mouse cursor on the screen, respectively. A user can ensure full screen coverage of the cursor by rotating his/her head by only $\pm 15°$ both horizontally and vertically, which according to experts is well within the ergonomic range of motion of the human head [106, 107].

3.3 System Design and Implementation

In this section, we provide a walkthrough of the sequence of steps involved in processing various sensor data to facilitate mouse control using our proposed AMC.

3.3.1 Transmitter Unit: Sensor Data Acquisition and Processing

For generating the yaw and pitch angles of head rotation, the raw readings from the accelerometer, the gyroscope, and the magnetometer, must be passed through an orientation filter based on a sensor fusion algorithm. In connection to this, we have used the popular, robust, and computationally inexpensive orientation filter for IMUs, known as the Madgwick filter [108, 109], which prevents accumulation of angular measurement errors over time, while having insignificant ($< 5°$) instantaneous measurement errors. Furthermore, the mouse cursor movement on the screen, is mapped to the absolute rather than relative movement of the head to prevent error accumulation overtime. Madgwick filter internally handles the calculations using quaternions which prevents Gimbal lock [108, 109].

The *yaw* and *pitch* angles are measured relative to a reference *zero* point. This point is considered as the orientation of the user's head at device startup, while focusing on the screen at its center. The corresponding measurements at this stage are measured as the offset angles, yaw_{offset} and $pitch_{offset}$. Therefore, at startup, the proposed AMC goes through a calibration phase ($8 - 10\,seconds$), during which the user orients his/her head towards the middle of the screen and holds position until they hear 3 consecutive beeps. The reference values, yaw_{offset}, $pitch_{offset}$, are calculated as the means of *yaw* and *pitch* angles, obtained during the calibration phase, following **Eq. 3.1** and **Eq. 3.2**, respectively, where n is the number of observations of each of these angles during this phase.

$$yaw_{offset} = \frac{1}{n}\sum_{i=0}^{n} yaw_i \tag{3.1}$$

$$pitch_{offset} = \frac{1}{n}\sum_{i=0}^{n} pitch_i \tag{3.2}$$

Finally, to get the offset adjusted yaw and pitch angles, $yaw^{'}$ and $pitch^{'}$, relative to the reference zero point, the offset values, yaw_{offset} and $pitch_{offset}$, are subtracted from the raw yaw and $pitch$ angles, as shown in **Eq. 3.3** and **Eq. 3.4**, respectively.

$$yaw^{'} = yaw - yaw_{offset} \tag{3.3}$$

$$pitch^{'} = pitch - pitch_{offset} \tag{3.4}$$

Analogous to measuring head rotation angles, mouse clicks are actuated when the differences between the left and right IR sensor readings, IR_{Left} and IR_{Right}, and the respective reference values, IR_{Left}^{Ref} and IR_{Right}^{Ref}, exceed an empirically determined threshold. The values of IR_{Left}^{Ref} and IR_{Right}^{Ref} are measured as the means of the respective values, IR_{Left} and IR_{Right}, obtained during the calibration phase, following **Eq. 3.5** and **Eq. 3.6**, respectively, while the cheek muscles of the user are in relaxed state.

$$IR_{Left}^{Ref} = \frac{1}{n}\sum_{i=0}^{n} IR_{Left} \tag{3.5}$$

$$IR_{Right}^{Ref} = \frac{1}{n}\sum_{i=0}^{n} IR_{Right} \tag{3.6}$$

The third beep at the end of the calibration phase indicates that the device has been calibrated, and the user is free to move his/her head or twitch cheek muscles for controlling the mouse. After that the values $yaw^{'}$, $pitch^{'}$, IR_{Left}, IR_{Right}, IR_{Left}^{Ref}, and IR_{Right}^{Ref} are transmitted to the receiver unit, connected with the PC, for further processing. Considering the design principles, *obtrusiveness*, and *overload*, two gesture controls, one for *enabling* and the other for *disabling* the mouse functionality of the AMC have been incorporated. For disabling the mouse, a user has to rotate his/her head down to about 35° and twitch both cheek muscles, after which they can easily interact with their surroundings. During this time, no data will be transmitted to the receiver unit. For re-enabling the mouse, the user has to rotate his head up to about 35° and twitch both cheek muscles, after which data transmission will be re-initiated, and the mouse can be controlled as before.

3.3.2 Receiver Unit: Processed Data Retrieval

Upon receiving the processed values from the transmitter unit, the values $yaw^{'}$, $pitch^{'}$, IR_{Left}, and IR_{Right}, are passed through a smoothing filter, which calculates the weighted averages of the respective current and previous values of these readings for noise removal. Once smoothened, the $yaw^{'}$ and $pitch^{'}$ angles are converted to a value between 0 and 1 through min-max normalization for generating the screen coordinates ($screen_x$ and $screen_y$), later in the device driver software. These data are then transferred to the device driver software via serial communication for invoking appropriate system functions, which give the user control over the computer mouse.

3.3.3 Device Driver Software: System Function Invocation

The min-max normalized values of the $yaw^{'}$ and $pitch^{'}$ angles, received via serial communication from the receiver unit, are converted into screen coordinates ($screen_x$ and $screen_y$) by multiplying with the screen resolution, fetched from the operating system, as shown in **Eq. 3.7** and **Eq. 3.8**, respectively. These coordinates are then used by the driver software for moving the mouse cursor to the desired location on the screen.

$$screen_x = minmax(yaw^{'}) \times screen_{width} \tag{3.7}$$

$$screen_y = minmax(pitch^{'}) \times screen_{height} \tag{3.8}$$

As mentioned earlier, mouse clicks are actuated if the difference between IR sensor reading and its reference value, due to cheek muscle twitches, exceeds a certain threshold value. In such cases, the system function that simulates a "*mouse button press*" event, is invoked. Otherwise, the system function that simulates a "*mouse button release*" event, is invoked. A workflow diagram showing the different steps of sensor data acquisition, processing, screen coordinate generation, and mouse click actuation, distributed across the 3 different entities of the proposed AMC, is outlined in **Fig. 3.5**. In the next section, we will elaborate on our experimental procedures, where we investigate different aspects of the proposed Assistive Mouse Controller (AMC), such as – performance in pointing and typing tasks, usability analysis, user satisfaction analysis, and device acceptability analysis.

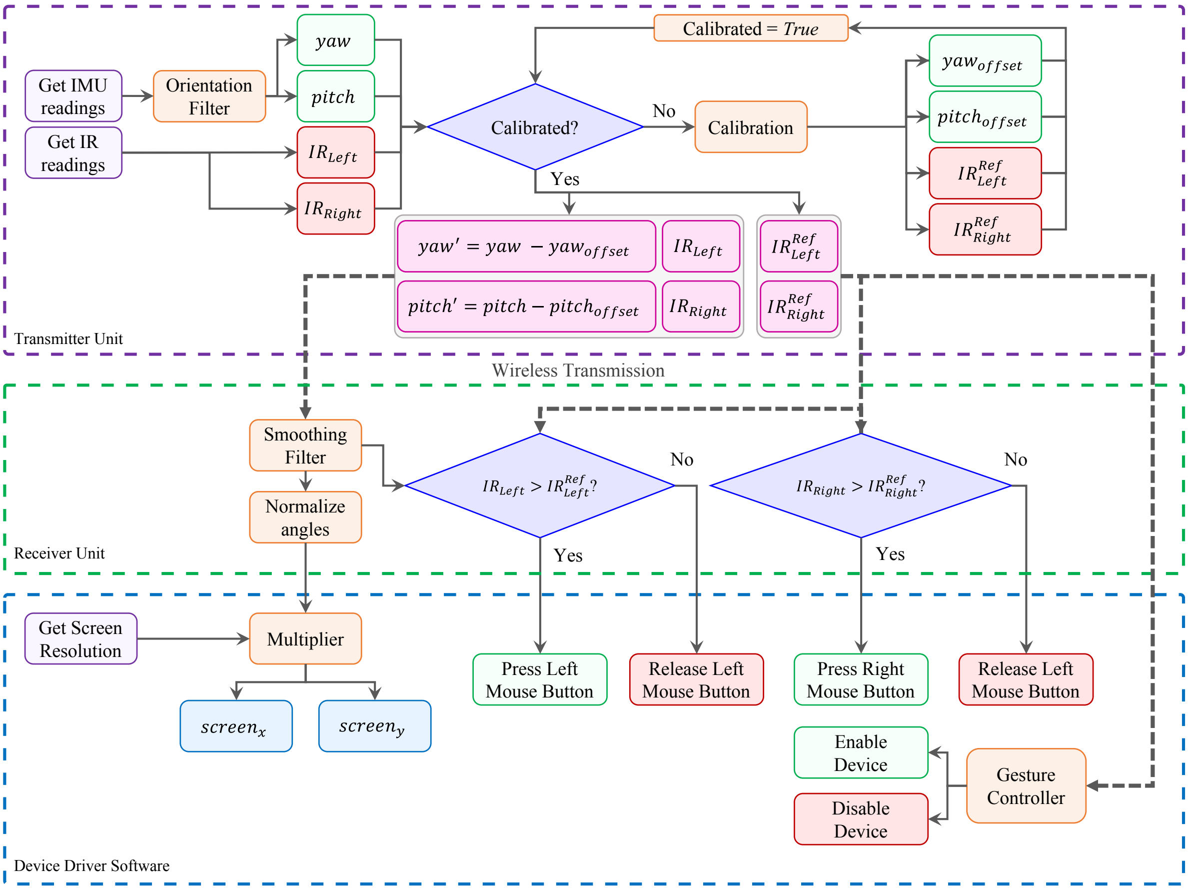


Figure 3.5: A workflow diagram of sensor data acquisition, processing, and mouse control signal generation using the proposed Assistive Mouse Controller (AMC).

Chapter 4

Experimental Design and Result Analysis

In this section, we elaborate on the suite of experiments that have been conducted for analyzing the *performance*, the *usability*, the *user satisfaction*, and the *user acceptance* of the proposed Assistive Mouse Controller (AMC).

In connection to the performance analysis of the AMC, two within subjects experiments were conducted, such as –

(a) "*Point and Click*" experiment, where a user is required to move the cursor over a specific on-screen target and click on it by twitching their cheek muscles.

(b) "*Typing*" experiment, where a user is required to type in certain sentences with the help of a virtual keyboard.

For analyzing the performance of the AMC in these two tasks, real-life individuals with upper limb disability were recruited for first-hand interaction with a computer using the AMC only. Furthermore, healthy individuals were also recruited for performing the same two tasks in a within subject arrangement, with an optical mouse only, such that a comparative performance analysis of the AMC and an optical mouse in similar tasks could be accommodated, involving physically challenged and healthy individuals, respectively. The screen resolution was considered as a control variable while conducting these analyses.

Next, for analyzing perceived usability and satisfaction of the physically challenged individuals from their first-hand experience with the AMC, the System Usability Scale (SUS) [60, 61] and the Quebec User Evaluation of Satisfaction with Assistive Technology 2.0 (QUEST 2.0) [66] framework.

Finally, user acceptance of the AMC was analyzed with the help of a survey questionnaire, leveraging the Technology Acceptance Model (TAM) [53, 54, 69]. However, due to the outbreak of COVID-19 at the time of the analysis, first-hand interaction with the AMC could not be accommodated, and therefore, the survey had to be conducted online on a different user base with upper limb disability. A detailed walkthrough of these analyses is provided in the subsequent sections.

4.1 Point and Click Experiment

In the domain of Human-Computer Interaction (HCI), a pointing task is considered as the user interaction for selecting any element on a user interface with any pointing device such as mouse, stylus, trackpad, finger, or any other wearable devices. The purpose of this experiment is to get an understanding of users' performance while interacting with different user interfaces using the proposed Assistive Mouse Controller (AMC), considering interface elements (*windows, icons, menus*, etc.) of different shapes and sizes in terms of, the time required to complete a pointing task and its perceived difficulty. Shannon's Index of Difficulty (ID), reputable for quantifying the perceived difficulty of pointing tasks as a logarithmic relationship between movement-amplitude (A) and target-width (W), is used for modelling the corresponding observed movement-times (MT_O) in such tasks in *controlled* experimental setup. However, real-life pointing tasks are both spatially and temporally *uncontrolled*, being influenced by factors, such as – human aspects, subjective behavior, the context of interaction, the inherent speed-accuracy trade-off where, emphasizing accuracy compromises speed of interaction and vice versa, and so on. Effective target-width (W_e) is considered as spatial adjustment for compensating accuracy. However, no significant adjustment exists in the literature for compensating speed in different contexts of interaction in these tasks. As a result, without any temporal adjustment, the true difficulty of an *uncontrolled* pointing task may be inaccurately quantified using Shannon's ID. In this section, we verify this by proposing ANTASID (*A Novel Temporal Adjustment to Shannon's ID*) formulation with detailed performance analysis. This section begins with a discussion on the relevant theoretical background, followed by a brief literature review, and our proposed approach. Finally, details of our experimental methodology, involving a generic mouse and our proposed AMC, result analysis, and research implications have been discussed.

4.1.1 Theoretical Background

In the domain of Human-Computer Interaction (HCI), a pointing task is considered as the user interaction for selecting any element on a user interface with any pointing device such as *mouse, stylus, trackpad, finger*, or any other wearable devices. Shannon's Index of Difficulty (ID) [110], as shown in **Eq. 4.1**, is reputable for quantifying the perceived difficulty of such a task. It is expressed as a logarithmic relation between movement-amplitude (A) and target-width (W), where A is defined as the distance between the starting location of the cursor and the target's center. Applying Fitts's law, the movement-time (MT) of any pointing task can be modeled as a linear function of ID, as shown in **Eq. 4.2**, where the constants a and b are empirically defined from a regression analysis of experimental data. The ideology of ID is that the difficulty of a task increases, as A increases and/or W decreases. However, it fails to address the speed-accuracy trade-off in pointing tasks [111]. The basic idea of this trade-off is that if users prefer to be efficient in terms of speed, the observed movement-time (MT_O) will be shorter and if the focus is shifted to accuracy, it will be longer. To account for the variability in accuracy, researchers have formulated a Spatially Adjusted (SA) variant of ID, as shown in **Eq. 4.3**, by replacing the nominal target-width, W with the effective target-width, W_e [110, 112, 113]. W_e can be calculated either using the standard deviation method, given the endpoint coordinates are recorded, as shown in **Eq. 4.4**, or using the discrete-error method given the error-rates of pointing are recorded [110].

$$ID = \log_2\left(\frac{A}{W} + 1)\right) \tag{4.1}$$

$$MT = a + b \times ID \tag{4.2}$$

$$ID_{SA} = \log_2\left(\frac{A}{W_e} + 1\right) \tag{4.3}$$

$$W_e = 4.133 \times SD_x \tag{4.4}$$

The index of performance, also known as throughput (TP), as shown in **Eq. 4.5**, is defined as the average of the ratio of ID and MT_O over n pointing tasks [110, 114], where TP increases proportionally with ID.

$$TP = \frac{1}{n}\sum_{i=1}^{n}\frac{I_{D_i}}{MT_{O_i}} \tag{4.5}$$

In most studies related to Fitts's law [111, 114–120], *controlled* experiments are conducted in a lab setup with either subjective or parametric (manipulating A or W), or operational constraints (*extremely accurate, accurate, neutral, fast*, and *extremely fast*). In *uncontrolled* experiments, however, no such constraints are imposed. The objective of *controlled* experiments is to understand the effect of manipulating a variable on other variables of interest. This is often preferred while exploring new aspects of HCI. As stated in literature [121], although these studies may have high internal validity, they are at a risk of low external validity. In other words, findings of these studies may not hold for a different experimental setup. Moreover, factors that are difficult to manipulate in *controlled* experiments, makes this issue even more complex [111]. Therefore, it is imperative to conduct *uncontrolled* experiments to understand the extent of validity of any theories or formulations. It is logical to consider pointing tasks in real-life as part of *uncontrolled* experiments as they are both spatially and temporally unconstrained and biased due to human factors such as physical inability, distraction, fatigue, excitement, cognition time, etc., thereby, introducing context of interaction.

To comprehend the speed-accuracy trade-off in real-life pointing tasks, let us consider a user in two different contexts of submitting an online exam script: 1) well ahead of deadline and 2) at the verge of deadline, with the click of a "*Submit*" button. In the first scenario, the person will be in a relaxed state of mind, naturally, s/he will not emphasize speed of interaction over accuracy. However, in the second scenario, the person will feel tensed, emphasizing speed of interaction over accuracy to meet the submission deadline. Therefore, the time taken to complete similar pointing tasks on the same interface, may vary depending on the context.

Moreover, interaction with two similar graphical interfaces for two different applications might be different, based on the context and use cases of the applications. For example, Facebook being a "*Social Media*" platform and Google Classroom being an "*Educational*" platform, have a "*Post*" and a "*Submit*" button, respectively, for doing similar tasks, i.e., uploading contents to the platforms. However, while posting on Facebook, users are generally in a relaxed state of mind. On the contrary, while using Google Classroom as an exam script submission system, drawing from the previous example of submitting a script at the verge of deadline, the users are generally in a tensed state of mind. Therefore, in the case of Facebook, while a user will focus more on clicking the "*Post*" button accurately taking adequate time, in the other case, a user will focus more on clicking the "*Submit*" button quickly, minimizing the interaction time while emphasizing speed of interaction due to contextual differences.

It is evident from these discussions that the context of any pointing task affects the inherent speed-accuracy tradeoff, along with the corresponding task-completion time. In such scenarios of *uncontrolled* pointing tasks, concerning context of interaction and subjective behavior [111], Shannon's ID may fail to quantify the perceived difficulty of these tasks with or without spatial adjustment, justifying the need for a temporal adjustment factor (t). Although prior studies on Fitts's law conducted *controlled* experiments [111,114–120] and *uncontrolled* experiments [122–126] with various adjustments to Shannon's ID, no significant evidence was found regarding temporal adjustments to account for the context and speed-accuracy tradeoff of interaction.

In connection to this, we present a novel formulation of a temporal adjustment factor, t, as the binary logarithm of observed movement-time (MT_O) of pointing tasks to quantify the contextual information of the task in *bits*. We have augmented the unadjusted and the spatially adjusted formulation of Shannon's ID, as shown in **Eq. 4.1** and **Eq. 4.3**, respectively, with t

as a power factor of W, to form ANTASID (A Novel Temporal Adjustment to Shannon's ID) formulation for quantifying ID of such tasks. We hypothesized that Shannon's ID may not be able to accurately quantify the perceived difficulty of pointing tasks due to the subjective and contextual behavior, and speed-accuracy trade-off with or without spatial adjustment. Hence, augmenting it with t may resolve these issues and ensure a reliable quantification of ID.

In the next sections, we present a literature review on the quantification of perceived difficulty of pointing tasks, followed by an explanation of the proposed ANTASID formulation in details. We then elaborate on the user study, followed by the result analysis section and a discussion on the properties of ANTASID formulation. Finally, we summarize our observations and give a direction on future works.

4.1.2 Literature Review

Researchers have been trying to understand the impact of speed-accuracy trade-off in pointing tasks based on Fitts's law for quite a while. The correct formulation of ID given the nature and constraints of pointing tasks is still an active research area.

Having analyzed the impact of speed-accuracy trade-off in pointing tasks in [111], the authors have proposed a modified spatial adjustment factor, W_m, as shown in **Eq. 4.6**, where α is a power factor expressing a nonlinear relation between A and W_m. ID was formulated using this modified spatial adjustment factor W_m, as shown in **Eq. 4.7**. The value of α was empirically determined and cannot be generalized for other datasets. The authors imposed *five* operational constraints (*extremely accurate, accurate, neutral, fast*, and *extremely fast*) in their experiment. In our experiment, however, we did not impose any such operational constraints to get an understanding of how Fitts's law performs in *uncontrolled* experiments using the classical as well as the proposed formulation of ID.

$$W_m = W \times \left(\frac{4.133 \times SD_x}{W}\right)^{\alpha} \tag{4.6}$$

$$ID = log_2\left(\frac{A}{W_m} + 1\right) \tag{4.7}$$

A human motor behavioral model in distal pointing tasks [115] has been explored that formulates ID as a function of angular amplitude (α), angular target width (ω) and an empirically defined constant (k), as shown in **Eq. 4.8**. The authors considered k as a power of, ω due to the nonlinear relationship between α and ω. However, they did not provide any mathematical derivation of k. As a result, R^2-value of the regression model varied for different values of k. Using their proposed formulation of ID, they achieved a R^2-value of 0.961 for $k = 3$ in a *controlled* study.

$$ID = \left[log_2\left(\frac{\alpha}{\omega^k} + 1\right)\right]^2 \tag{4.8}$$

Researchers have also studied the effect of screen size variations on ID in *controlled* experimental conditions [116]. Their findings revealed that the ratio of A and W in ID, fails to capture the true perceived difficulty in pointing tasks. They proposed modifications in the formulation of ID for larger and smaller screen sizes, as shown in **Eq. 4.9** and **Eq. 4.10**, respectively. The terms α and β were empirically determined. Motivated by their work, we have defined the temporal adjustment factor (t) as a power of W. However, rather than quantifying an experiment-specific value of t, we have defined it as a function of MT_O of each pointing task for better quantification of ID in any experimental setup.

$$ID = log_2\left(\frac{A^\alpha}{W} + 1\right), \alpha > 1 \tag{4.9}$$

$$ID = log_2\left(\frac{A}{W^\beta} + 1\right), \beta > 1 \tag{4.10}$$

A predictive error model was derived in [117] by manipulating parameters of Fitts's law such as, W, A, and MT_O. The authors reported that W has a greater influence on error-rate than A. They also reported a logarithmic speed-accuracy trade-off described by Fitts's law.

In [118], the authors have analyzed the speed-accuracy phenomenon of Fitts's law in trajectory-based tasks with temporal constraints. They reported that in spatially constrained tasks, lateral deviation of the trajectory was affected by W and subjective bias. On the other hand, in temporally constrained tasks, it was affected by W and average steering speed.

Researchers in [119] reported that temporal constraint influences the speed-accuracy trade-off in aimed hand movements. Furthermore, the SH-model for pointing tasks was introduced based on the temporal distribution of successful hits and general principles of information theory [120]. The performance of this model was validated with the help of AIC (Akaike's Information Criterion) [127][.

A new derivation of Fitts's law was also proposed based on velocity profile in pointing tasks [122]. The authors have compared their model's performance with widely accepted models. They conducted both *controlled* and *uncontrolled* experiments using *homogeneous* targets (the same value of W for a group of targets) and *heterogeneous* targets (different value of W for each target).

Considering maximum entropy, researchers have also explored an exponentially modified Gaussian model to estimate a linear bound of linear regression in the presence of outliers [124].

According to their work, data from such tasks have high variance and positive skewness, resulting in a very poor fit of the classical linear regression models. Considering their observations, we conducted experiments involving *uncontrolled* pointing tasks and analyzed the performance of various ID formulations on the experimental data.

Considering *uncontrolled* aimed movements in Graphical User Interfaces (GUI), a real-life "*in the wild*" or in other words, an *uncontrolled* scenario of pointing tasks was analyzed by logging mouse cursor trajectories without imposing any constraints on user interaction [126]. The authors have introduced a spatial adjustment factor Length Distance Index (LDI), as shown in **Eq. 4.11**, in the formulation of ID where, L is the amplitude of movement and D is the straight-line distance between the *starting* and the *end* points of the movement. Apart from the studies mentioned above, a formal information theoretic approach of resolving speed-accuracy tradeoff has also been explored [125].

$$LDI = \left(\frac{L}{D} - 1\right)^{\frac{1}{4}} \tag{4.11}$$

It is evident from the literature review that the relative weights of movement-amplitude (A) and target-width (W) have been adjusted by a power factor while quantifying ID, minimizing the inherent non-linearity between the two parameters. However, all these factors were empirically defined, and cannot be generalized for other experiments. In the next section, we discuss the proposed ANTASID formulation, where we define the temporal adjustment factor (t) for analyzing the perceived difficulty of real-life pointing tasks applying Fitts's law.

4.1.3 ANTASID Formulation

ANTASID formulation introduces a temporal adjustment factor (t) to ID as a power factor of W. The Path Efficiency (PE) of a pointing task is defined as the ratio of Straight Line Distance (SLD) between the cursor position at the beginning of a task and the target's center to the movement-amplitude (A) [128], quantifying the corresponding spatial efficiency. Analogous to PE, our proposed adjustment factor, t, for a particular pointing task is based on the Temporal Efficiency (TE) of that task.

Taking the influence of external factors, such as- *context of interaction, biased human behavior, speed-accuracy trade-off, human factors*, and so on [111, 114–123] into account, if there are n pointing tasks in an experiment, we define the TE of the i^{th} pointing task (TE_i), as shown in **Eq. 4.12**, as the ratio of the average observed movement-time ($\overline{MT_O}$) over the n pointing tasks to the observed movement-time (MT_O^i) of that task.

$$TE_i = \frac{\overline{MT_O}}{MT_O^i},\, where\, 1 \leq i \leq n \tag{4.12}$$

To comprehend the significance of the temporal adjustment factor (t), we have conducted two *uncontrolled* experiments through a pointing-task-based game (developed in-house) using an optical mouse and our proposed Assistive Mouse Controller (AMC) as pointing devices. We have defined *uncontrolled* pointing tasks as those, where – 1) no operational constraints are imposed and 2) no manipulation of A occurs. We have constructed *two* Internal Datasets with the *uncontrolled* user-interaction data from this game. The authors in [122] proposed a new derivation of Fitts's Law and conducted both *controlled* and *uncontrolled* experiments on pointing tasks. Datasets of both of their experiments [123] are publicly available. In addition to the data from the *uncontrolled* experiments of the Benchmark [123] and the Internal Datasets, we have leveraged the data from the *controlled* experiments of the Benchmark Dataset to verify the external validity of ANTASID formulation in *controlled* scenarios of pointing tasks as well.

From the data of our *uncontrolled* pointing task experiment using a mouse, and that of the *controlled* and *uncontrolled* pointing experiments in the Benchmark Dataset [123], the value of $\overline{MT_O}$ was found to be $0.8875, 0.7628$, and $0.8618\, seconds$ for $n = 6469, n = 8345$, and $n = 39050$ pointing tasks, respectively. Based on this empirical data, we considered the value of $\overline{MT_O}$ as $1\, second$ for mathematical convenience. Since ID is expressed in bits, we defined t_i of the i^{th} pointing task as the binary logarithm of TE_i, as shown in **Eq. 4.13**, quantifying the temporal information of that task in bits. As $\overline{MT_O} = 1\, second$, the expression t_i, as shown in **Eq. 4.13**, reduces to the negative binary logarithm of MT_O^i, as shown in **Eq. 4.14**, as $log_2 1 = 0$. However, in case of different experiments, for instance, analysis of Fitts's law in pointing tasks using a wearable pointing device, if the value of $\overline{MT_O}$ deviates far from $1\, second$, the actual value of $\overline{MT_O}$ might produce better quantification of ID, subject to further investigation. In other words, the expression of t_i, as shown in **Eq. 4.13**, may be a better fit in this case.

$$t_i = \log_2\left(\frac{\overline{MT_O}}{MT_O^i}\right),\, where\, 1 \leq i \leq n \tag{4.13}$$

$$t_i = -\log_2\left(MT_O^i\right),\, where\, \overline{MT_O} = 1\, second\, and\, 1 \leq i \leq n \tag{4.14}$$

Shannon's ID in its original form, as shown in **Eq. 4.1**, is neither spatially nor temporally adjusted. From this point onward, we will refer to it as ID_{NA}, following **Eq. 4.15**. The spatially adjusted ID, as shown in **Eq. 4.3**, will be referred to as ID_{SA}, following **Eq. 4.16**. To address the nonlinear relationship between A and W, most studies have adjusted W with a power factor [111, 115]. Furthermore, as the movement time for any pointing task depends on two sub-movements [117, 118], such as - 1) Initial Ballistic Phase and 2) Optional Correction Phase, it is intuitive that for a target with smaller W, more time will be spent on the latter. Based on this intuition and evidence from the literature, our proposed ANTASID formulation augments ID_{NA} and ID_{SA} with t as a power factor of W to formulate ID_{TA} and ID_{TSA}, as shown in **Eq. 4.17** and **Eq. 4.18**, respectively, where ID_{TA} is only temporally adjusted and ID_{TSA} is both temporally and spatially adjusted.

$$ID_{NA} = \log_2\left(\frac{A}{W} + 1\right) \tag{4.15}$$

$$ID_{SA} = \log_2\left(\frac{A}{W_e} + 1\right) \tag{4.16}$$

$$ID_{NA} = \log_2\left(\frac{A}{W^t} + 1\right) \tag{4.17}$$

$$ID_{SA} = \log_2\left(\frac{A}{W_e^t} + 1\right) \tag{4.18}$$

Due to the speed-accuracy trade-off phenomenon accompanied by context of interaction and subjective behavior, by definition, the value of t will be different for each of the $i \in n$ tasks and participants, resulting in a realistic value of ID. An overview of the context and method of ANTASID formulation, is depicted in **Fig. 4.1**. In the next section, we discuss our experimental design and data analysis to investigate the validity of our formulation.

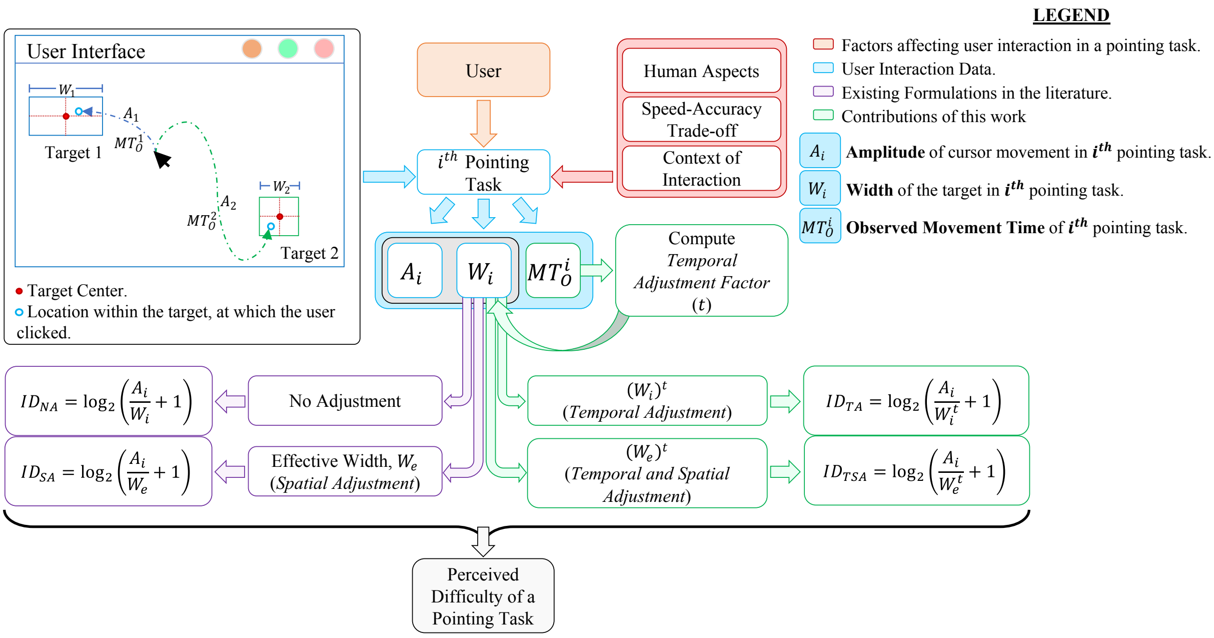


Figure 4.1: Overview of the context and the proposed ANTASID formulation.

4.1.4 Methodology

To investigate the significance of ANTASID formulation in accurately quantifying ID in *uncontrolled* pointing tasks, we conducted two separate *uncontrolled* within-subject experiments, featuring a balloon popping game, "*Popper*" (implemented in-house using *python*) with an optical mouse and our proposed AMC as pointing devices. We have constructed *two* Internal Datasets with the *uncontrolled* user-interaction data from this game, where *one* dataset contains interaction data of healthy individuals using an optical mouse, and the other contains interaction data of individuals with upper limb disability using our proposed Assistive Mouse Controller (AMC). We also analyzed the data from the *controlled* and the *uncontrolled* experiments of the Benchmark Dataset [123]. After analyzing all the associated datasets, we have gained valuable insights of the performance of ANTASID formulation in both scenarios of pointing tasks using two different devices.

To validate the significance of the temporal adjustment factor, t, in quantifying ID of pointing tasks in both *controlled* and *uncontrolled* scenarios and to verify how accurately the classical formulation of Shannon's ID can quantify the perceived difficulty of these tasks, we analyzed MT from $four$ different regression models, considering spatial and/or temporal adjustments to Shannon's ID, such as- neither spatially nor temporally adjusted (ID_{NA}), only temporally adjusted (ID_{TA}), only spatially adjusted (ID_{SA}), and both temporally and spatially adjusted (ID_{TSA}). We state our null hypothesis, H_0, as -

> H_0: "*Temporally adjusted Shannon's ID might not accurately quantify the perceived difficulty of pointing tasks in both controlled and uncontrolled scenarios.*"

To be able to reject H_0, we need to verify whether ID_{TA} and ID_{TSA} provide a better model fit and are statistically significant over ID_{NA} and ID_{SA} in both *controlled* and *uncontrolled* scenarios through statistical analyses of data using one-way ANOVA, one-way F-test, followed by a post-hoc test. The level of significance (α) of the statistical analysis was considered as $\alpha = 0.05$.

As mentioned in **section 4.1.3**, **"*ANTASID Formulation*"**, whether the expression of the temporal adjustment factor (t), following **Eq. 4.13**, quantifies the perceived difficulty of *uncontrolled* pointing tasks better than that in **Eq. 4.14**, for the proposed wearable AMC, has been tested as well. Therefore, considering both expressions of t, we have conducted the same suite of regression and statistical analyses on the internal dataset containing *uncontrolled* user-interaction data of the game "*Popper*" with the proposed AMC.

To summarize, all the formulations of Shannon's ID considered in this study, were analyzed on – 1) *three* datasets featuring *uncontrolled* experiments [*two* Internal Datasets (6469 and 666 pointing tasks using an optical mouse and the proposed AMC, respectively) and *one* Benchmark Dataset (39050 pointing tasks)] and 2) *one* dataset featuring *controlled* experiments [Benchmark (8345 pointing tasks)].

4.1.4.1 Participants

The target users for this experiment were individuals with or without any form of upper limb disability. However, all of them were required to have basic computing knowledge. For the experimental studies with an optical mouse and our proposed AMC, 25 right-handed healthy volunteers [16 males (64%, Mean Age: 24.19 ± 1.47 years), 9 females (36%, Mean Age: 21.33 ± 1.89 years); Mean Age: 23.20 ± 2.14 years], and 15 individuals with upper limb disability [9 males (60%, Mean Age: 26.57 ± 4.39 years), 6 females (40%, Mean Age: 24.33 ± 4.96 years)], respectively, were recruited. All of them had adequate experience and knowledge of operating a computer. The healthy participants were recruited from known acquaintances and via email, while the individuals with upper limb disability were recruited from known acquaintances, local rehabilitation centers, and local NGOs. Each of the participants provided a verbal consent prior to their participation in this study.

4.1.4.2 Experimental Design

The healthy participants were asked to play the entire game 3 times on a laptop with a screen resolution of 1920×1080 pixels using a generic computer mouse as a pointing device, while the individuals with upper limb disability were asked to play the game just once using the proposed AMC in the same setup. We allotted 15 minutes per participant during which they were briefed about the semantics of the game, had a few trial runs followed by the actual experiment. Data for each play of the game were automatically uploaded to our server. The participants were notified about the automated data collection prior to their participation and were assured of no invasion of privacy from our part.

Since this work is focused specifically on *uncontrolled* pointing tasks, unlike the authors in [111], we did not impose any constraints such as – *extremely accurate, accurate, neutral, fast*, and *extremely fast* on their interaction with the game. The participants had to pop balloons of 4 different widths, W (32 px, 64 px, 96 px, and 128 px) as targets, only one at a time, appearing at random locations on the screen. The game was designed to be run in full-screen mode, ensuring full utilization of the screen resolution. The game featured *two* types of levels, *homogeneous* level (all targets in a level have the same width) and *heterogeneous* level (targets in a level are of different widths). There were a total of *five* levels in the game, with *four* *homogeneous* levels and only *one* *heterogeneous* level.

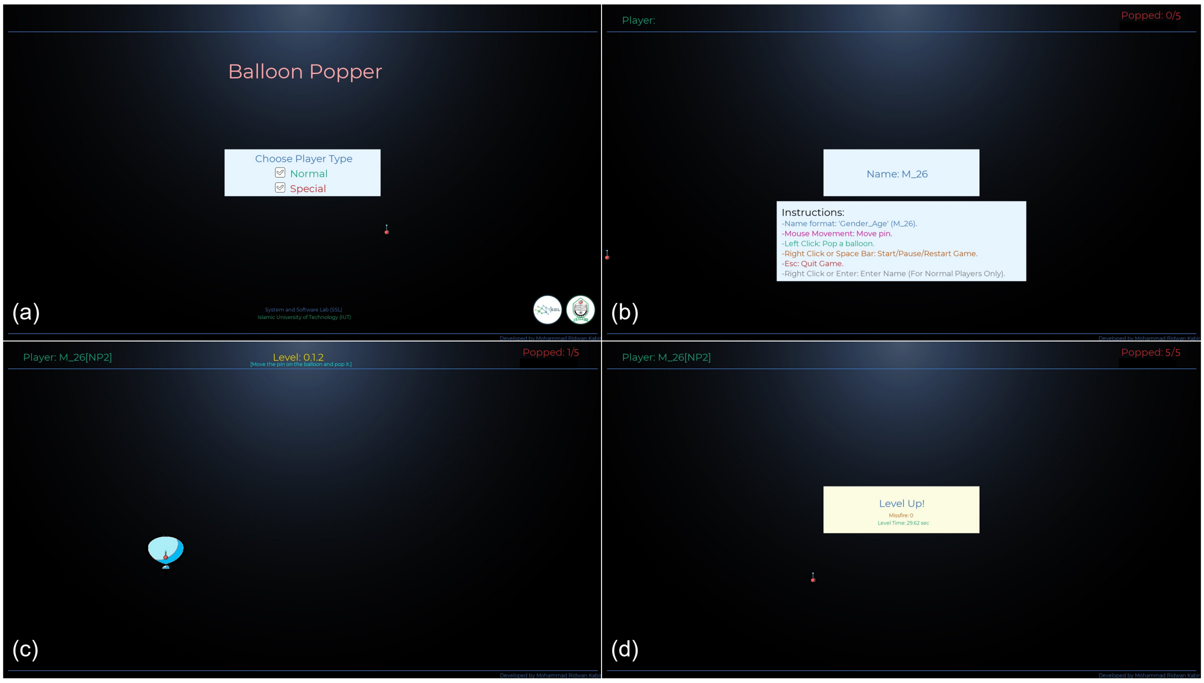


Figure 4.2: Snapshots of the game "*Popper*" – (a) Selection of Player Type, (b) Player registration and game instruction screen, (c) A particular level with a balloon of size 128px, and (d) Resting period in the form of a reward screen between levels for reducing fatigue.

For the healthy participants, there were 15 targets per *homogeneous* level and 30 targets in the *heterogeneous* level. Therefore, a total of 60 sequential *homogeneous* targets and 30 sequential *heterogeneous* targets were presented to a healthy participant. For the participants with upper limb disability on the other hand, there were 9 targets per *homogeneous* level and 12 targets in the *heterogeneous* level, presenting, a total of 36 sequential *homogeneous* targets and 12 sequential *heterogeneous* targets to them. A brief resting period was allocated after each level in the form of a reward screen to reduce fatigue. The game ended when all the targets had been popped by a participant, and the data was uploaded to our server for further analysis. Few snapshots of the game have been provided in **Fig. 4.2** and the quantitative and qualitative summaries of the game levels are provided in **Table 4.1**.

Table 4.1: Qualitative and quantitative summary of the game "Popper".

Level Type	**Level Serial**	**Target Width, $w_i \in W$ (pixels)**	**Total Targets (Healthy Participants)**	**Total Targets (ULD Participants)** [a]
Homogeneous	1	128	15	9
	2	96	15	9
	3	64	15	9
	4	32	15	9
Heterogeneous	5	Random [32/64/96/128]	30	12
		Total Targets	**90**	**48**

[a] Upper Limb Disabled (ULD).

In our experiment, we define the popping of a target as a *trial*. A *trial* began with the appearance of a target and ended when a participant clicked inside a target. Clicks outside the target boundary were recorded as miss-clicks. *Trials* with miss-clicks were not rejected as artifacts. The screen coordinate of the cursor at the beginning and at the end of a *trial* were considered as the starting and the ending coordinates, respectively. However, a participant could move the cursor around the screen freely, before a target appeared and after it was clicked. Therefore, there was no fixed starting coordinate for the mouse cursor in any trial, rather the cursor coordinates at the time of appearance of a new target was considered as the starting coordinate. Due to this arrangement, it is intuitive that the movement-amplitude, A will vary, ensuring no spatial constraint is imposed. The movement-amplitude (A) was calculated as the sum of the Euclidean Distances (EDs) between two consecutive coordinates in the cursor trajectory, and the observed movement-time (MT_O) was recorded as the duration of a *trial*. After 3 plays of the game, "*Popper*", from 25 healthy participants, about 6750 *trials* [4500 *homogeneous* (66.67%), 2250 *heterogeneous* (33.33%)], and from 15 participants with upper limb disability after 1 play of the game, about 720 *trials* [540 *homogeneous* (75%), 180 *heterogeneous* (25%)], were registered. A descriptive summary of the parameters that were recorded per trial is summarized in **Table 4.2**.

Table 4.2: Descriptive summary of parameters, recorded per trial, for the game "*Popper*".

Parameter	Unit	Interpretation
Level Serial	x	Level number (1 – 5).
Target-Width (W)	32, 64, 96, and 128 (pixels)	Target-width (W) in pixels.
Starting Coordinate	(x, y)	Coordinate of the cursor at the time of target appearance.
Ending Coordinate	(x, y)	Coordinate of the cursor at the time of clicking inside the target.
Target Center	(x, y)	Coordinate of the center of a target.
Movement Time (MT_O)	Time in seconds	Time required to click on a target from the moment it appeared on the screen.
Number of miss-clicks	x	Number of clicks outside the target boundary.
Coordinates of cursor trajectory	$[(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)]$	List of coordinates in the cursor trajectory from the Starting Coordinate to the Ending Coordinate. Used in the calculation of movement-amplitude (A).

4.1.4.3 Data Processing

Data analysis was carried out using *python*. Prior to analysis, trials with erroneous parameter values (e.g., $MT_O = 0\,seconds$) due to system issues, were removed from the Internal Datasets. This cleanup is required to avoid erroneous calculation of t, following **Eq. 4.14**. For example, for any trial i, if $MT_O^i = 0$ (due to system error), then $t_i = -log_2 0$ is undefined. Furthermore, trials having MT_O beyond 3 Standard Deviations (SD) of the mean observed movement-time ($\overline{MT_O}$) were removed from this dataset, which we term as the L_1 cleanup. A summary of data distribution for both healthy and disabled participants after each cleanup is depicted in **Table 4.3**. A remarkable insight from this two-level cleanup on each of the *two* Internal Datasets is the relatively constant ratio of *homogeneous* and *heterogeneous* trials at each level of cleanup.

Table 4.3: Distribution summary of trials in the Internal Dataset at different levels of cleanup.

Participant Type	Nature of Experiment	Cleanup Type	Number of Trials Before Cleanup	Accept/Reject Ratio of Trials after Cleanup				Ratio of Trial Type after Cleanup			
				Accepted [a]		*Rejected*		*Homogeneous*		*Heterogeneous*	
				N	%	N	%	N	%	N	%
Healthy	Uncontrolled	Erroneous Data Removal	6750	6505	96.37	245	3.63	4319	66.40	2186	33.60
		L_1	6505	6469	99.45	36	0.55	4291	66.33	2178	33.67
ULD [b]		Erroneous Data Removal	720	677	94.03	43	5.97	445	65.73	232	34.27
		L_1	677	666	98.38	11	1.62	436	65.47	230	34.53

[a] Trials within $3\,SD$ of $\overline{MT_O}$.

[b] Upper Limb Disabled (ULD).

As mentioned earlier, the Benchmark Dataset [123] contained data from both *controlled* and *uncontrolled* experiments, featuring *homogeneous* and *heterogeneous* targets. However, in the experiments with *homogeneous* targets, the authors manipulated both the movement-amplitude and the target-width, which goes against our experimental design. Therefore, in our analysis, we considered data from both experiments featuring *heterogeneous* targets only. Although the authors had already removed trial data with MT_O beyond 3 SD of $\overline{MT_O}$ from this dataset [8350 *controlled* and 39050 *uncontrolled* trials post-cleanup], we further removed trials with erroneous parameter values (e.g., $MT_O = 0\,seconds$) from this dataset, obtaining 8345 *controlled* and 39050 *uncontrolled* trials.

For the Internal Dataset, we calculated W_e following the standard deviation method in **Eq. 4.4** [110]. However, one shortcoming of the Benchmark Dataset is that neither the coordinates of target selection and its center nor the percentage of errors were recorded. Therefore, W_e cannot be calculated using the standard deviation method. However, the discrete-error method of determining W_e [110] can be applied by approximating a reasonable error-rate $\epsilon\%$, where for error-rates less than $\epsilon\%$, $W_e < W$ and vice versa and for error-rates equal to $\epsilon\%$, $W_e = W$. Therefore, for the Benchmark Dataset, we approximated $\epsilon = 3.883\%$ and calculated the average effective target-width ($\overline{W_e}$), such that $\overline{W_e} = \overline{W}$, as shown in **Eq. 4.19**, where n is the number of trials, W_i is the target-width for trial i, and z is the Z-score at the corresponding error-rate. ID_{SA} and ID_{TSA} were calculated for this dataset using the values of $\overline{W_e}$ as shown in **Table 4.4**.

$$\overline{W_e} = \frac{1}{n}\sum_{i=1}^{n}\frac{2.066}{z} \times W_i \tag{4.19}$$

Table 4.4: Comparison of Average effective target-width ($\overline{W_e}$) at the approximated error-rate (ϵ) and the average target-width ($\overline{W}$) in the Benchmark Dataset.

Nature of Experiment	$\overline{W}$ (pixels)	Approximation of $\overline{W_e}$ (pixels) ($\epsilon = 3.883\%$) [a]
Controlled	30.1780	30.1782
Uncontrolled	30.2105	30.2108

[a] ϵ is the approximated error-rate.

4.1.5 Results

As mentioned earlier, we have used regression analysis for predicting MT using the different formulations of ID (ID_{NA},ID_{SA},ID_{TA}, and ID_{TSA}). We conducted a one-way ANOVA, followed by a paired F-test for analyzing the corresponding statistical significance of the quantification of ID using classical and ANTASID formulations. Furthermore, to avoid the risk of Type-I errors, we conducted the Tukey's HSD post-hoc test [129] on our formulations. We did not perform any comparative performance analysis of our models with that of the Benchmark Dataset [123] because of the differences in the formulation of ID. We have used Shannon's ID and proposed adjustments to it, while they have used the Square-Root Variant of Fitts's law. The result analysis of this study is divided into *two* categories, such as – 1) *controlled* and *uncontrolled* experiments using an Optical Mouse, and 2) *uncontrolled* experiment using the proposed AMC.

4.1.5.1 Controlled and Uncontrolled Experiments using Optical Mouse

In this section, results from the analysis of the Internal Dataset, obtained from the user-interaction of the game "*Popper*" with an optical mouse in *uncontrolled* setup, and the Benchmark Dataset, featuring both *controlled* and *uncontrolled* experiments are discussed. From the regression analysis of the Internal Dataset, as shown in **Fig. 4.3**, it is evident that ANTASID formulation provides a reasonable fit (R^2-value) of the model, with ($R^2_{TSA} = 0.8405$) or without ($R^2_{TA} = 0.8177$) spatial adjustment, as shown in **Fig. 4.3d** and **Fig. 4.3b**, respectively. For the Benchmark dataset, at the approximated error-rate of $\epsilon = 3.883\%$, similar results were observed for both the *controlled* experiment ($R^2_{TSA} = 0.9095$, $R^2_{TA} = 0.8521$), as shown in **Fig. 4.4d** and **Fig. 4.4b**, respectively, and the *uncontrolled* experiment ($R^2_{TSA} = 0.8953$, $R^2_{TA} = 0.8308$), as shown in **Fig. 4.5d** and **Fig. 4.5b**, respectively. Evidently, ID_{TSA} consistently follows a normal distribution, as shown in **Fig. 4.6d**, **Fig. 4.6h**, and **Fig. 4.6l**. From one-way ANOVA, it was observed that ANTASID formulations had significantly higher F-statistics at $p < 0.001$ in all the datasets compared to ID_{NA} and ID_{SA}. The parameters of regression analysis of the four formulations on different datasets along with the corresponding results of ANOVA test are summarized in **Table 4.5**.

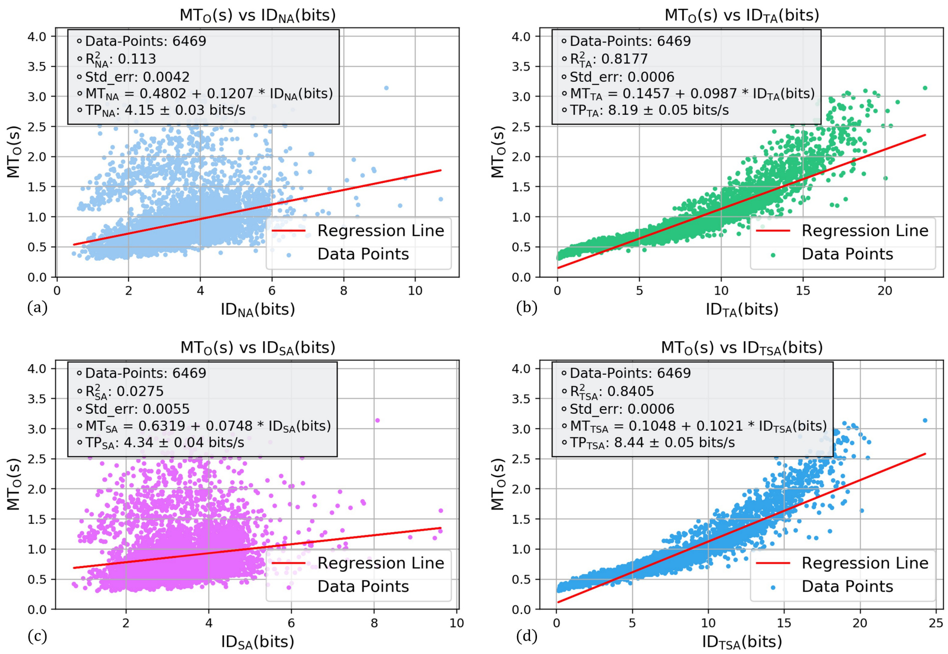


Figure 4.3: Regression Analysis of the Internal Dataset (*Uncontrolled* Experiment) with an Optical Mouse, using – (a) ID_{NA}, (b) ID_{TA}, (c) ID_{SA}, and (d) ID_{TSA}.

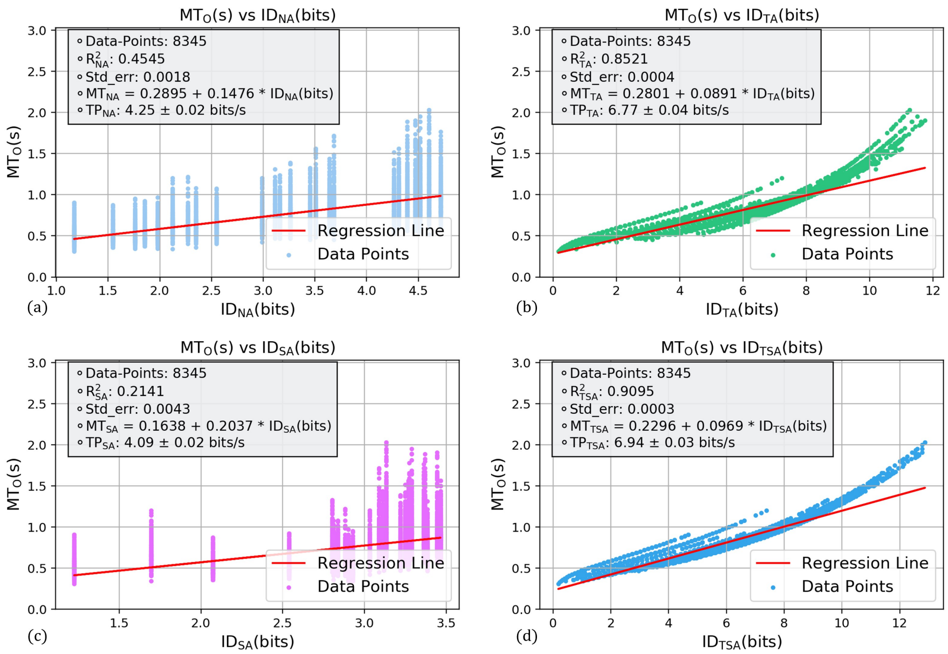


Figure 4.4: Regression Analysis of the Benchmark Dataset (*Controlled* Experiment) with an Optical Mouse, using – (a) ID_{NA}, (b) ID_{TA}, (c) ID_{SA}, and (d) ID_{TSA}.

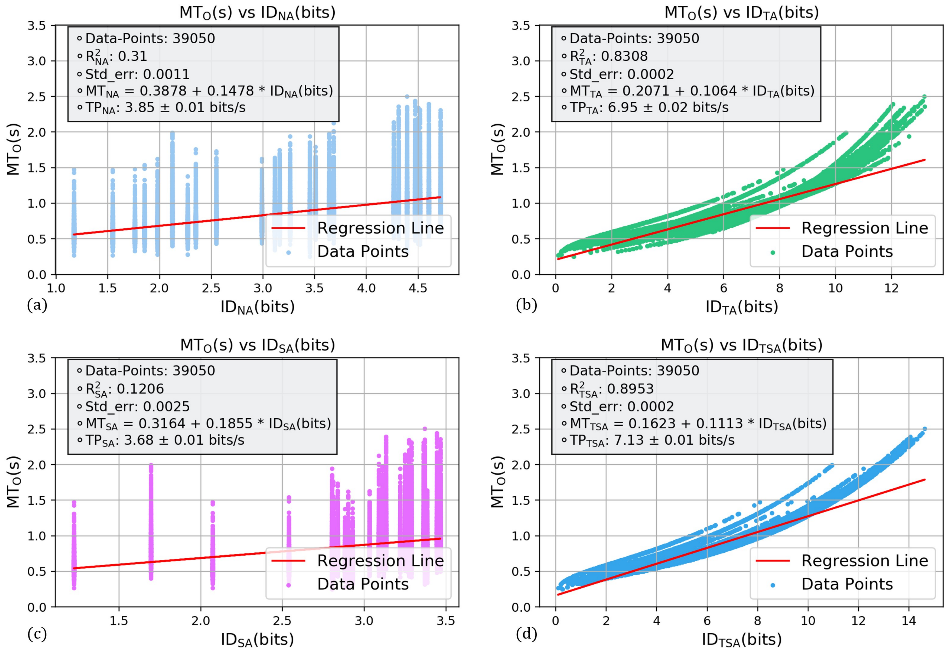


Figure 4.5: Regression Analysis of the Benchmark Dataset (*Uncontrolled* Experiment) with an Optical Mouse, using – (a) ID_{NA}, (b) ID_{TA}, (c) ID_{SA}, and (d) ID_{TSA}.

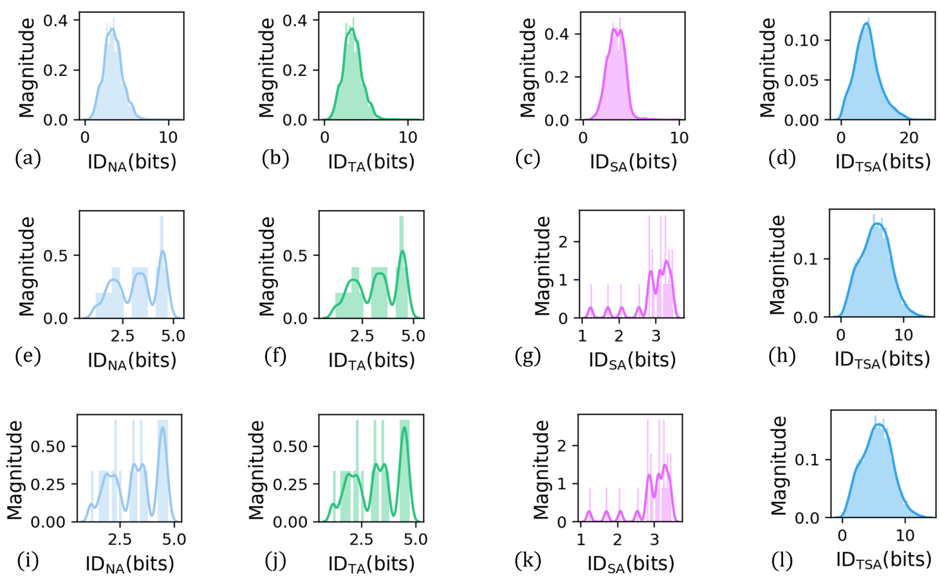


Figure 4.6: Using an Optical Mouse, the distribution of different formulations of ID – (a, b, c, d) *Uncontrolled* Experiment of the Internal Dataset, (e, f, g, h) *Controlled* Experiment of the Benchmark Dataset, and (i, j, k, l) *Uncontrolled* Experiment of the Benchmark Dataset.

Table 4.5: Regression model parameters of Fitts's Law, TP and ANOVA test results for Optical Mouse as a pointing device.

Dataset (Experiment type) [Pointing Device]	**Formulation Type**	ID	R^2 **value**	**Std. Error** (SE)	$TP\pm$ **95%CI**	ANOVA *DOF*	ANOVA *F-stat*	ANOVA *p-value* [a]
Internal Dataset (Uncontrolled) [Optical Mouse]	Classical	ID_{NA}	0.1130	0.0042	4.15±(0.03)	(1, 6467)	824.12	<0.001
		ID_{SA}	0.0275	0.0055	4.34±(0.04)	(1, 6467)	182.78	<0.001
	ANTASID	ID_{TA}	0.8177	0.0006	8.19±(0.05)	(1, 6467)	29010.66	<0.001
		ID_{TSA}	0.8405	0.0006	8.44±(0.05)	(1, 6467)	34087.95	<0.001
Benchmark Dataset (Uncontrolled) [Optical Mouse] (ϵ=3.883%) [b]	Classical	ID_{NA}	0.3100	0.0011	3.85±(0.01)	(1, 39048)	17541.32	<0.001
		ID_{SA}	0.1206	0.0025	3.68±(0.01)	(1, 39048)	5356.10	<0.001
	ANTASID	ID_{TA}	0.8308	0.0002	6.95±(0.02)	(1, 39048)	191728.50	<0.001
		ID_{TSA}	0.8953	0.0002	7.13±(0.01)	(1, 39048)	334025.21	<0.001
Benchmark Dataset (Controlled) [Optical Mouse] (ϵ=3.883%) [b]	Classical	ID_{NA}	0.4545	0.0018	4.25±(0.02)	(1, 8343)	6950.55	<0.001
		ID_{SA}	0.2141	0.0043	4.09±(0.02)	(1, 8343)	2273.19	<0.001
	ANTASID	ID_{TA}	0.8521	0.0004	6.77±(0.04)	(1, 8343)	48051.61	<0.001
		ID_{TSA}	0.9095	0.0003	6.94±(0.03)	(1, 8343)	83876.01	<0.001

[a] p-values were computed at a significance level of, α=0.05.
[b] ϵ is the approximate error-rate.

Given all the datasets, ID_{TSA} has the best average model fit ($\overline{R^2} = 0.8818$) along with the least average standard error, $\overline{SE} = 0.0004$. A summary of the average performance of the models across all the datasets in **Table 4.6** suggests that the mean throughput ($\overline{TP}$) almost doubles with ANTASID formulations compared to the classical ones. This is because, TP increases continuously and proportionally with ID_{TSA} and ID_{TA}, which can be visualized from the scatter plots of TP vs ID of the Internal Dataset, as shown in **Fig. 4.7**. Pairwise F-test, as shown in **Table 4.7**, revealed the superiority of ANTASID formulation over both ID_{NA} and ID_{SA} at the desired level of significance ($\alpha = 0.05$), with a p-value < 0.001, in all the datasets considered in this study. The post-hoc test using Tukey's HSD [129] method also validated the same, having an adjusted p-value of 0.001.

Table 4.6: Average performance of the regression models across all the datasets for interaction data obtained with an Optical Mouse.

Formulation Type	ID	$\overline{R^2}$ (±95%) **CI** [a]	$\overline{SE}$ (±95%) **CI** [a]	$\overline{TP}$ (±95%) **CI** [a]
Classical	ID_{NA}	**0.2925** (±0.1227)	**0.0024** (±0.0012)	**4.08** (±0.15)
	ID_{SA}	**0.1207** (±0.0668)	**0.0041** (±0.0011)	**3.03** (±0.24)
ANTASID	ID_{TA}	**0.8335** (±0.0124)	**0.0004** (±0.0001)	**7.30** (±0.55)
	ID_{TSA}	**0.8818** (±0.0261)	**0.0004** (±0.0001)	**7.50** (±0.48)

[a] CI: Confidence Interval

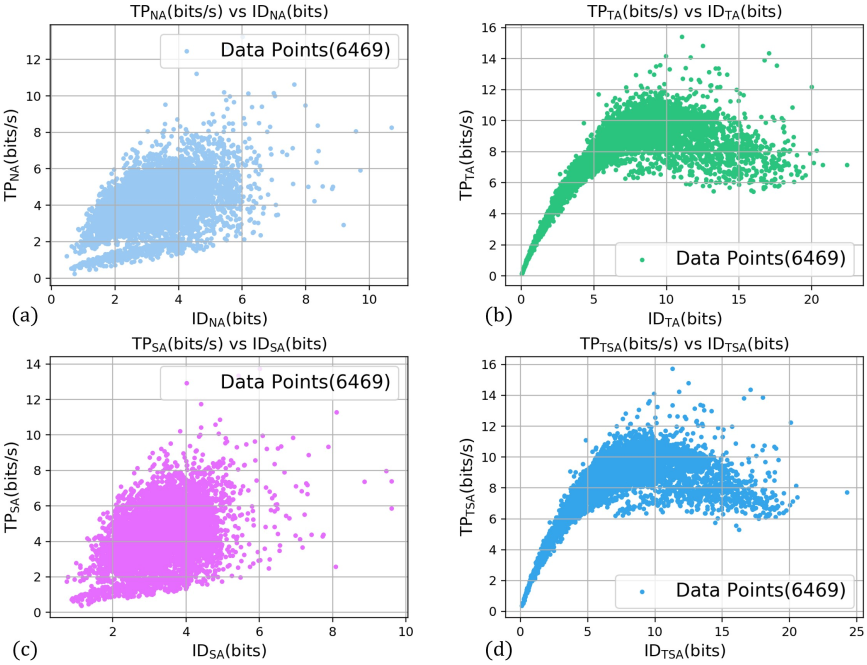


Figure 4.7: Analysis of the Throughput, TP, using - (a, c) the classical and (b, d) ANTASID formulations of Shannon's Index of Difficulty, ID, for the Internal Dataset, featuring *Uncontrolled* Experiment with an Optical Mouse.

Table 4.7: Pairwise F-test results for interaction data obtained with an Optical Mouse.

ID $(\sigma_A^2 > \sigma_B^2)$ [a]		**Internal Dataset (Uncontrolled Experiment)**		**Benchmark Dataset (Uncontrolled Experiment) (ϵ=3.883 %)** [b]		**Benchmark Dataset (Controlled Experiment) (ϵ=3.883 %)** [b]	
A	B	*F-stat*	*p-value* [c]	*F-stat*	*p-value* [c]	*F-stat*	*p-value* [c]
ID_{TSA}	ID_{NA}	7.4409	<0.001	2.8881	<0.001	2.0025	<0.001
ID_{TSA}	ID_{SA}	30.6092	<0.001	7.4203	<0.001	4.2527	<0.001
ID_{TA}	ID_{NA}	7.2310	<0.001	2.6807	<0.001	1.8744	<0.001
ID_{TA}	ID_{NA}	29.7458	<0.001	6.8873	<0.001	3.9807	<0.001

[a] Variance (σ_i^2) of ID, where $i \in \{A, B\}$.
[b] ϵ is the approximated error-rate.
[c] p-values were computed at a level of significance, α=0.05.

4.1.5.2 Uncontrolled Experiment using the proposed AMC

In this section, results from the analysis of the Internal Dataset, obtained from the user-interaction of the game "*Popper*" with the proposed AMC, featuring *uncontrolled* experiment. The performances of ANTASID formulation using the *two* different representations of the temporal adjustment factor (t), following **Eq. 4.13** and **Eq. 4.14**, are also elaborated.

From the regression analysis of the user-interaction data in **Fig. 4.8**, it is evident that the classical formulations of Shannon's ID (ID_{NA}, ID_{SA}) provide a poor fit of the data ($R^2_{NA} = 0.4316$, $R^2_{SA} = 0.3167$), as shown in **Fig. 4.8a** and **Fig. 4.8b**, respectively, with a very low throughput (TP) ($TP_{NA} = 0.58 \pm 0.02$ bits/s, $TP_{SA} = 0.60 \pm 0.02$ bits/s). On the contrary, using ANTASID formulation (ID_{TA}, ID_{TSA}), following the expression of t in **Eq. 4.14**, where the value of $\overline{MT_O}$ is approximated to $1\,second$, both R^2-values and TP exhibit an increase in magnitude ($R^2_{TA} = 0.6590$, $TP_{NA} = 4.22 \pm 0.12$ bits/s, $R^2_{TSA} = 0.8151$, $TP_{SA} = 4.20 \pm 0.11$ bits/s), as shown in **Fig. 4.8c** and **Fig. 4.8d**, respectively. Compared to the classical formulation, on an average, the throughput of the system increases by approximately 7.14 times in this case. Again, following the expression of t in **Eq. 4.13**, where the value of $\overline{MT_O}$ is the actual average of the observed movement times across all the pointing tasks using the proposed AMC, the R^2 values ($R^2_{TA} = 0.8581$, $R^2_{TSA} = 0.8885$) increase even more, as shown in **Fig. 4.8e** and **Fig. 4.8f**. However, throughput of the system, as shown in **Fig. 4.8e** and **Fig. 4.8f**, plummeted compared to that, as shown in **Fig. 4.8c** and **Fig. 4.8d**. On an average, the throughput of the system, in this case, increases by approximately 1.57 times, compared to the classical formulation.

Considering the proposed AMC, the results of regression analysis using ANTASID formulation, where t is quantified as per **Eq. 4.13**, is more realistic. This can be mathematically explained from the definition of TP in **Eq. 4.5**, where it is evident that with the increase of ID and/or with the decrease of MT, the value of TP will increase. Again, from the relation between MT and ID in **Eq. 4.2**, it can be inferred that the observed movement-time, MT_O, will increase with ID. Now, drawing from this relation and visualizing the TP vs ID graphs in **Fig. 4.9**, quantification of ID using ANTASID formulations with $\overline{MT_O}$ approximated to $1\,second$, as shown in **Fig. 4.9c** and **Fig. 4.9d**, fail to preserve this relation, as the majority of the TP values decrease relatively monotonically with the increase in ID. However, when ID is quantified using ANTASID formulations with $\overline{MT_O}$ equal to the actual average of the observed movement times, as shown in **Fig. 4.9e** and **Fig. 4.9f**, across all pointing tasks ($8.1619\,seconds$, in this case), the relation between TP and ID is preserved relatively better than the former one, following the same pattern as the one in **Fig. 4.7b** and **Fig. 4.7d**.

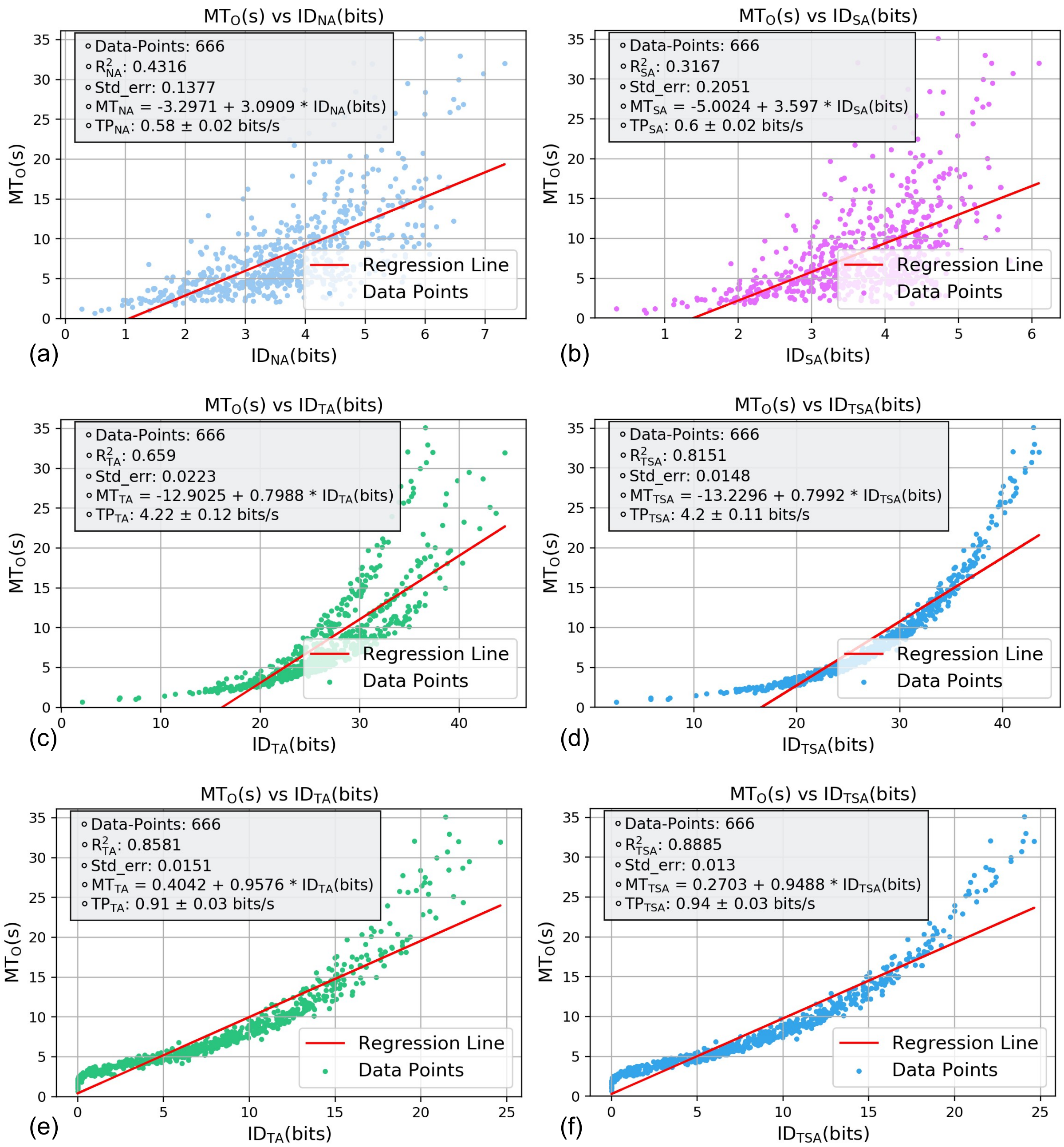


Figure 4.8: Regression Analysis of the Internal Dataset (*Uncontrolled* Experiment) with the proposed Assistive Mouse Controller (AMC), using different formulations of Shannon's Index of Difficulty (ID), such as – (a, b) the classical, (c, d) ANTASID with $\overline{MT_O}$ approximated to 1 *second*, and (e, f) ANTASID with $\overline{MT_O}$ as the actual average.

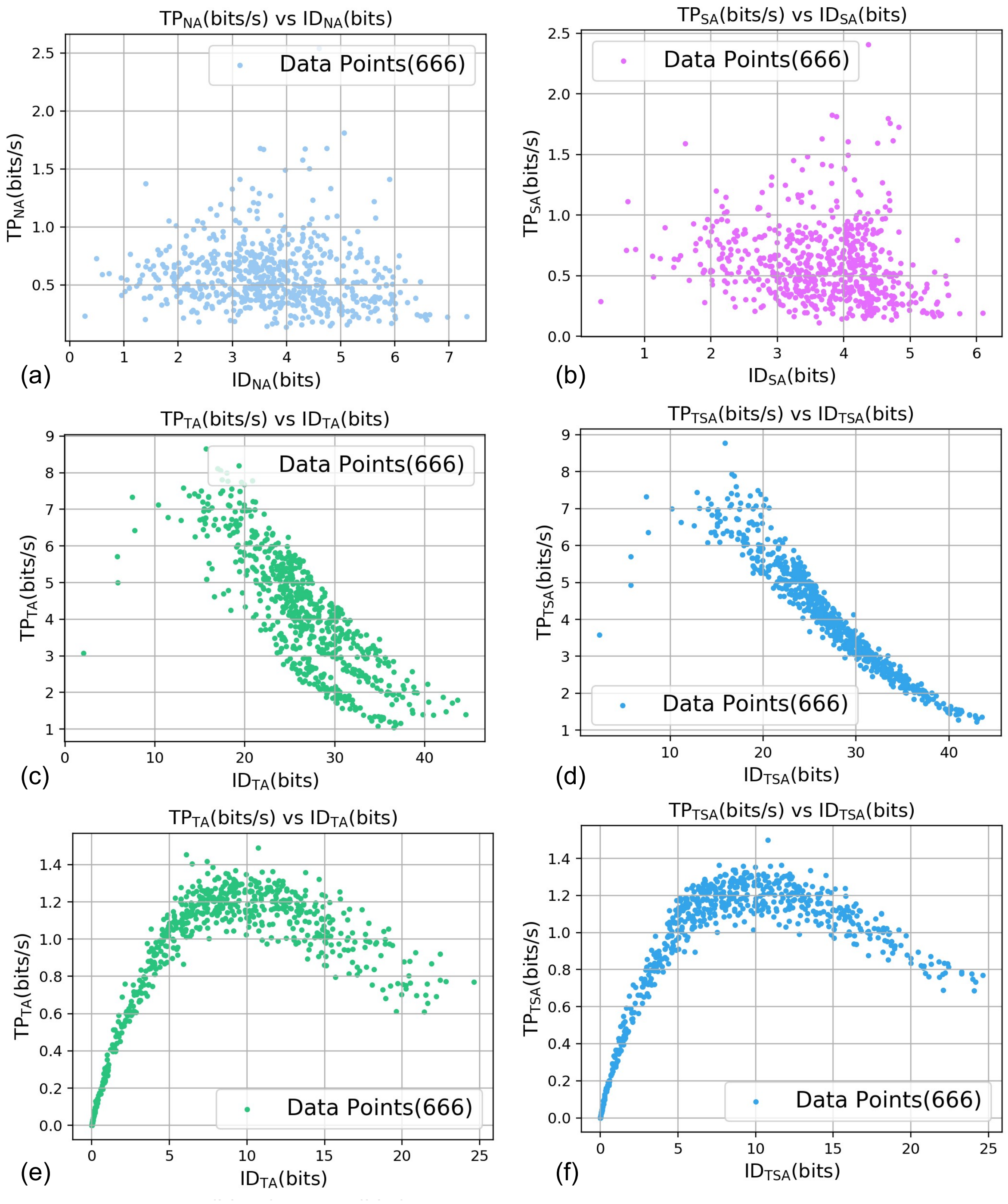


Figure 4.9: Analysis of the Throughput (TP) of the Internal Dataset (*Uncontrolled* Experiment) with the proposed Assistive Mouse Controller (AMC), using different formulations of Shannon's Index of Difficulty (ID), such as – (a, b) the classical, (c, d) ANTASID with $\overline{MT_O}$ approximated to 1 *second*, and (e, f) ANTASID with $\overline{MT_O}$ as the actual average.

For pointing tasks accomplished with the proposed AMC, the corresponding IDs, using both classical and ANTASID formulations, are normally distributed, as shown in **Fig. 4.10a** and **Fig. 4.10b**. From one-way ANOVA, it was observed that ANTASID formulations had significantly higher F-statistics at $p < 0.001$ in all the cases compared to ID_{NA} and ID_{SA}. The parameters of regression analysis of the four formulations using the proposed AMC along with the corresponding results of ANOVA test are summarized in **Table 4.8**. Pairwise F-test, as shown in **Table 4.9**, revealed the superiority of ANTASID formulation over both ID_{NA} and ID_{SA} at the desired level of significance ($\alpha = 0.05$), with a p-value < 0.001, in all the cases. The post-hoc test using Tukey's HSD [129] method also validated the same, having an adjusted p-value of 0.001. These analyses imply that we can reject the null hypothesis, H_0 and accept the alternative hypothesis -

> H_1: "*Temporally adjusted Shannon's ID may better quantify the perceived difficulty of pointing tasks in both controlled and uncontrolled scenarios.*"

The spatial adjustment on top of the temporal one makes the formulation even more robust and provides a normally distributed ID along with enhanced TP.

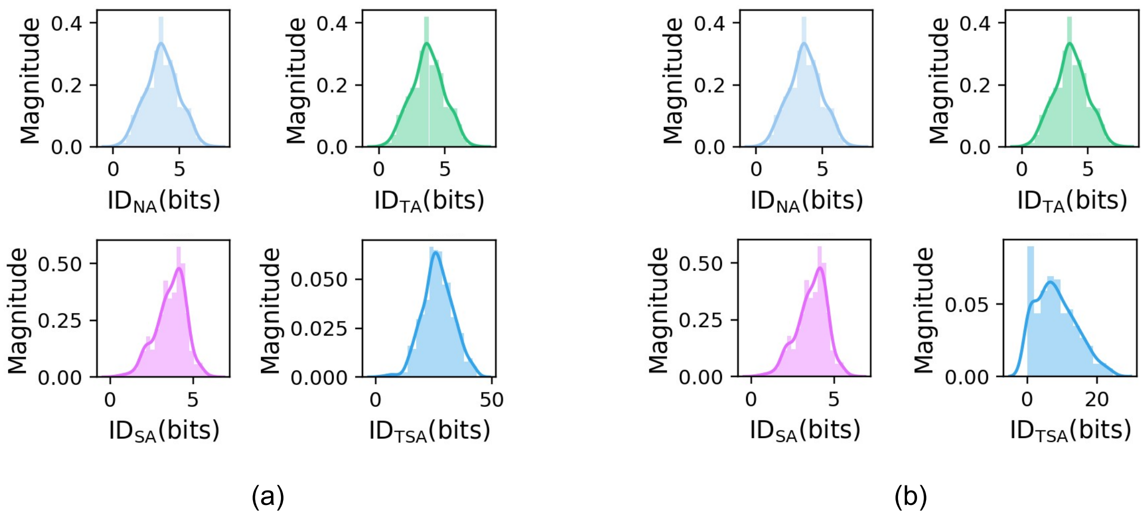


Figure 4.10: Using the proposed Assistive Mouse Controller (AMC), the distribution of different formulations of ID with the temporal adjustment factor (t) fomulated considering – (a) $\overline{MT_O}$ approximated to 1 *second* and (b) ANTASID with $\overline{MT_O}$ as the actual average.

Table 4.8: Regression model parameters of Fitts's Law, TP and ANOVA test results for the proposed AMC as a pointing device.

Dataset (Experiment type) [Pointing Device]	Formulation Type	ID	R^2 value	Std. Error (SE)	$TP\pm$ 95%CI	ANOVA DOF	ANOVA F-stat	ANOVA p-value [a]
Internal Dataset (Uncontrolled) [Proposed AMC [b]]	Classical	ID_{NA}	0.4316	0.1377	0.58±(0.02)	(1, 664)	504.21	<0.001
		ID_{SA}	0.3167	0.2051	0.60±(0.02)	(1, 664)	307.68	<0.001
	ANTASID [c]	ID_{TA}	0.6590	0.0223	4.22±(0.12)	(1, 664)	1283.11	<0.001
		ID_{TSA}	0.8151	0.0148	4.20±(0.11)	(1, 664)	2928.09	<0.001
	ANTASID [d]	ID_{TA}	0.8581	0.0151	0.91±(0.03)	(1, 664)	4016.94	<0.001
		ID_{TSA}	0.8885	0.0130	0.94±(0.03)	(1, 664)	5293.44	<0.001

[a] p-values were computed at a significance level of, α=0.05.
[b] Assistive Mouse Controller (AMC).
[c] t in the formula of ID, is quantified using the approximation, $\overline{MT_0} = 1second$ (**Eq. 4.14**).
[d] t in the formula of ID, is quantified using actual average, $\overline{MT_0}$ of the observed movement times (**Eq. 4.13**).

Table 4.9: Pairwise F-test results for interaction data obtained with the proposed AMC.

Formulation Type	ID ($\sigma_A^2 > \sigma_B^2$) [a] A	B	Internal Dataset (Uncontrolled Experiment) F-stat	p-value [b]
ANTASID [c]	ID_{TSA}	ID_{NA}	1.8885	<0.001
	ID_{TSA}	ID_{SA}	2.5742	<0.001
	ID_{TA}	ID_{NA}	1.5270	<0.001
	ID_{TA}	ID_{NA}	2.0813	<0.001
ANTASID [d]	ID_{TSA}	ID_{NA}	0.0587	<0.001
	ID_{TSA}	ID_{SA}	2.8061	<0.001
	ID_{TA}	ID_{NA}	1.9882	<0.001
	ID_{TA}	ID_{NA}	2.7100	<0.001

[a] Variance (σ_i^2) of ID, where $i \in \{A, B\}$.
[b] p-values were computed at a level of significance, α=0.05.
[c] t in the formula of ID, is quantified using the approximation, $\overline{MT_0} = 1second$ (**Eq. 4.14**).
[d] t in the formula of ID, is quantified using actual average, $\overline{MT_0}$ of the observed movement times (**Eq. 4.13**).

4.1.6 Discussion

Extensive studies have been carried out on Fitts's law over the years for understanding human performance in pointing tasks. These studies have proposed several variants of ID with the aim to develop an enhanced human interaction model. However, the perfect formulation of ID is still an active research area. In this work, we have proposed ANTASID formulation utilizing temporal efficiency of pointing tasks, reflecting the variation of perceived difficulty of pointing tasks in different contexts of interaction, and analyzed its effect alone or combined with spatial adjustment in the quantification of ID using an optical mouse and the proposed AMC. To summarize our contributions -

(a) We have formulated a temporal adjustment factor (t) for better quantification of ID by considering the context of interaction in real-life *uncontrolled* pointing tasks.

(b) We have generated *two* datasets, containing the parameters required for quantifying ID of *uncontrolled* pointing tasks using Fitts's law with an optical mouse and the proposed Assistive Mouse Controller (AMC).

(c) We have analyzed the statistical significance of ANTASID as well as the classical formulation of Shannon's ID and verified that the classical ones might not accurately quantify ID for *uncontrolled* pointing tasks based on the context of interaction.

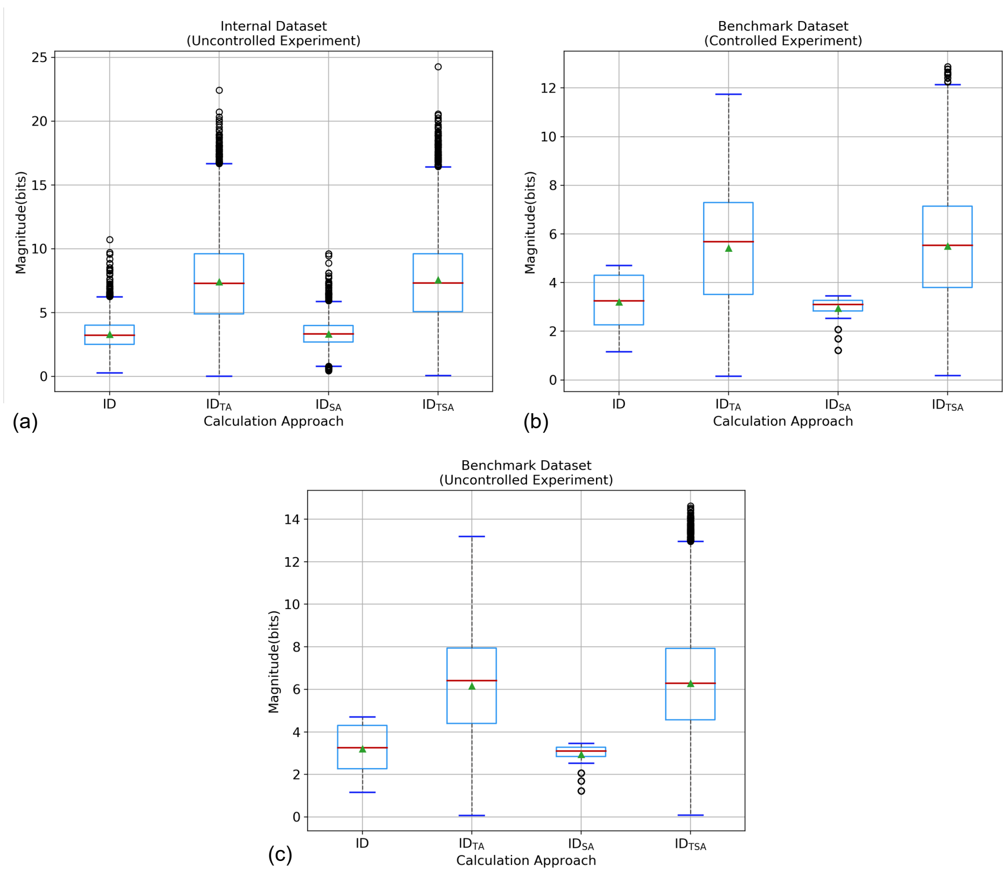


Figure 4.11: Box plot analysis of the perceived difficulty of pointing tasks ($ID_{NA}, ID_{TA}, ID_{SA}, ID_{TSA}$) using ANTASID and the classical formulations of Shannon's Index of Difficulty using an Optical Mouse, considering – (a) the *Uncontrolled* Experiment of the Internal Dataset, (b) the *Controlled*, and (c) the *Uncontrolled* Experiment of the Benchmark Dataset.

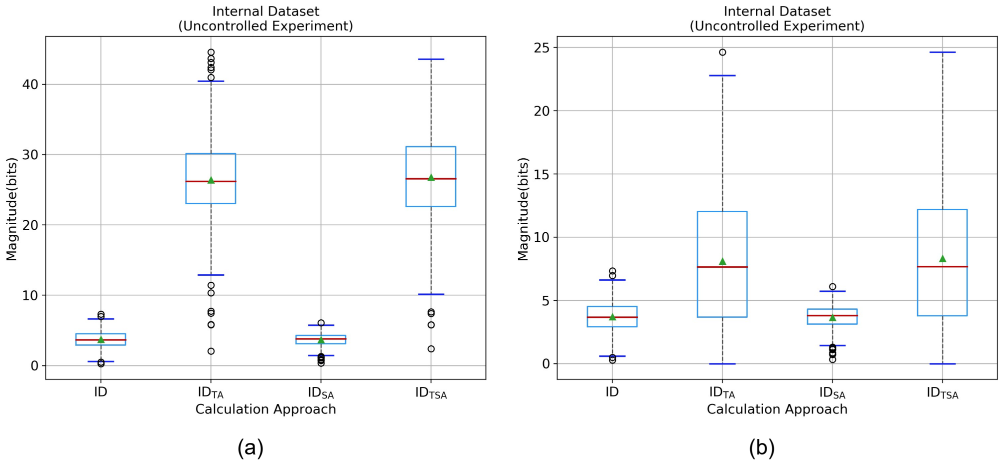


Figure 4.12: Box plot analysis of the perceived difficulty of pointing tasks ($ID_{NA}, ID_{TA}, ID_{SA}, ID_{TSA}$) using ANTASID and the classical formulations of Shannon's Index of Difficulty using the proposed AMC, featuring the *Uncontrolled* Experiment of the Internal Dataset, considering – (a) $\overline{MT_O}$ approximated to 1 *second* and (b) ($\overline{MT_O}$ as the actual average.

With respect to the experimental datasets considered in this study, the perceived difficulty of pointing tasks, quantified using ANTASID formulation (ID_{TA}, ID_{TSA}), has an enhanced interquartile range compared to the classical formulations of Shannon's ID (ID_{NA}, ID_{SA}), as shown in **Fig. 4.11** and **Fig. 4.12**. The mean of the predicted movement-times using ANTASID ($\overline{MT_{TA}}$, $\overline{MT_{TSA}}$)) and the classical formulations of Shannon's ID ($\overline{MT_{NA}}$, $\overline{MT_{SA}}$) are almost constant for both the Internal dataset, as shown in **Fig. 4.13a** and **Fig. 4.14**, and the Benchmark dataset, as shown in **Fig. 4.13b** and **Fig. 4.13c**. Both MT_{TA} and MT_{TSA} exhibit interquartile ranges closer to the observed movement-time (MT_O), compared to both MT_{NA} and MT_{SA}, as shown in **Fig. 4.13** and **Fig. 4.14**. From this analysis, we can infer that the temporal adjustment factor (t) is able to capture the speed-accuracy trade-off phenomena of pointing tasks by adjusting the relative weights of W and A through ANTASID formulations (ID_{TA}, ID_{TSA}), exploiting the temporal efficiency of the user to reflect context-based deviation of perceived difficulty of the tasks. We have found this inference to be consistent across all the datasets.

A major observation from our analyses is that even in both *controlled* and *uncontrolled* scenarios of pointing tasks, considering different pointing devices (handheld optical mouse and wearable AMC), ANTASID formulation significantly improved the fitness value of the regression model, as well as TP, compared to its classical counterparts, as seen from **Table 4.5** and **Table 4.8**. This proves the robustness of ANTASID formulation in handling the context of interaction and the speed-accuracy trade-off in real-life pointing tasks. Evidently, ANTASID formulation is versatile and significantly overcomes the risk of low external validity.

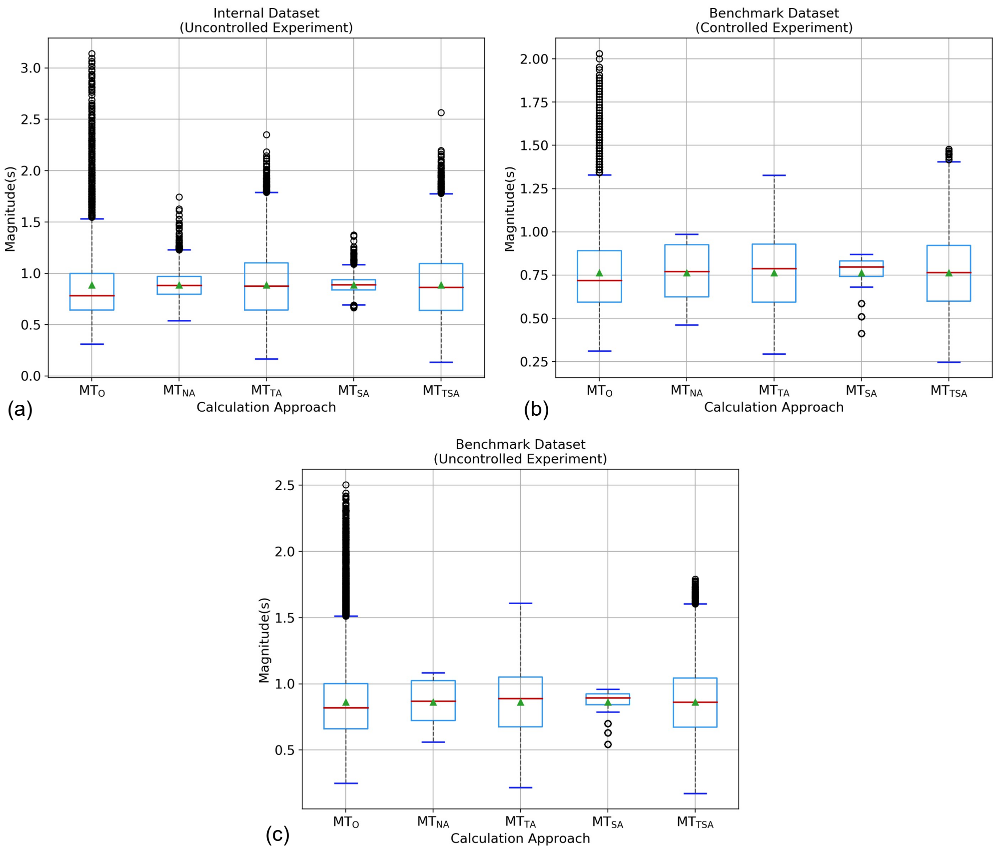


Figure 4.13: Box plot analysis of the predicted movement-times ($MT_{NA}, MT_{TA}, MT_{SA}, MT_{TSA}$) using ANTASID and the classical formulations of Shannon's Index of Difficulty compared to the observed movement-time (MT_O) using an Optical Mouse, considering – (a) the *Uncontrolled* Experiment of the Internal Dataset, (b) the *Controlled*, and (c) the *Uncontrolled* Experiment of the Benchmark Dataset.

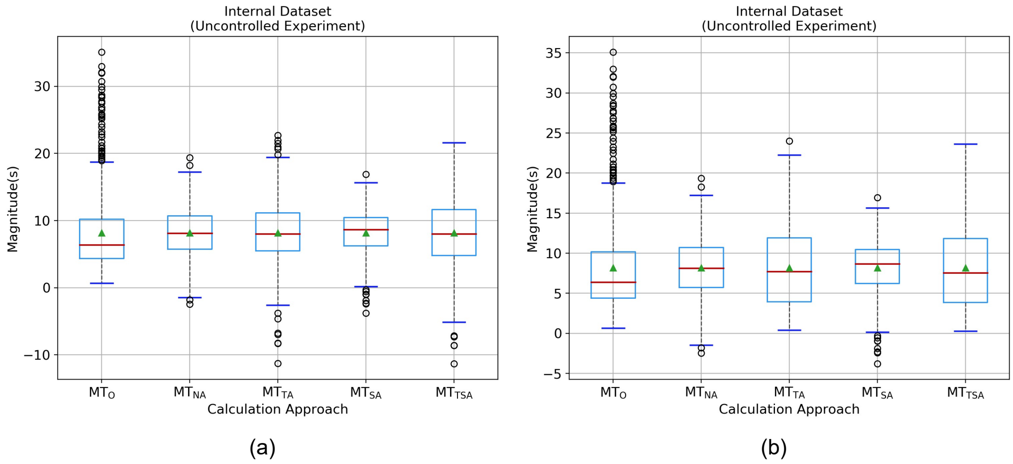


Figure 4.14: Box plot analysis of the predicted movement-times ($MT_{NA}, MT_{TA}, MT_{SA}, MT_{TSA}$) using ANTASID and the classical formulations of Shannon's Index of Difficulty compared to the observed movement-time (MT_O) using the proposed AMC, considering – (a) $\overline{MT_O}$ approximated to 1 *second* and (b) $\overline{MT_O}$ as the actual average.

4.1.6.1 Research Implications

In certain contexts, it may be necessary to design application UIs to meet a specific index of difficulty (ID). Based on the desired ID, general context of interaction, and temporal efficiency of a specific pointing task, a possible practical significance of our study may be the determination of a *lower bound* on the width (W) of targets (*windows, icons, menus*, and *navigation bars*) in the design of application UIs. This may not only help the UI designers in designing aesthetic UIs, but also enhance the throughput and efficiency of user interaction. Our proposed ANTASID formulation may be further used in testing the same UI in different circumstances. Taking context of interaction into account, the need for introducing a temporal adjustment factor (t) while quantifying the perceived difficulty of *uncontrolled* pointing tasks using Shannon's ID cannot be over-emphasized, facilitating better comprehension of the efficiency of an interface with respect to its intended use case. For instance, in a click based real-time competitive game, though the UI remains the same, considering different scenarios, a player might want to quickly perform certain interactions. For instance, in the beginning of real-time strategy games, generally the contention remains lesser than the middle or end portion of the game, where the players focus more towards quick decisions, actions and clicks. The proposed model can also be utilized in such scenarios to evaluate the perceived difficulty of real-time interaction under different contexts. We plan to carry out such research in the future, further exploring the implications of the proposed formulation.

4.1.6.2 Practical Implications

When it comes to the design and development of any device for human-computer interaction, minimal interaction time is one of the major concerns. A healthy individual can interact with a computer using a mouse with a reasonably shorter time. Their physical ability plays a significant role behind the amount of time that might be required to complete a certain task. However, the situation is not quite the same for individuals with upper limb disability. They are deprived of the ability to use an optical mouse, and therefore, are unable to accomplish basic computing tasks, in connection to which an Assistive Mouse Controller (AMC) can play a significant role. Although the task completion times using an AMC will be longer compared to an optical mouse, at least it can assist people with upper limb disability in performing tasks that were previously impossible on their part.

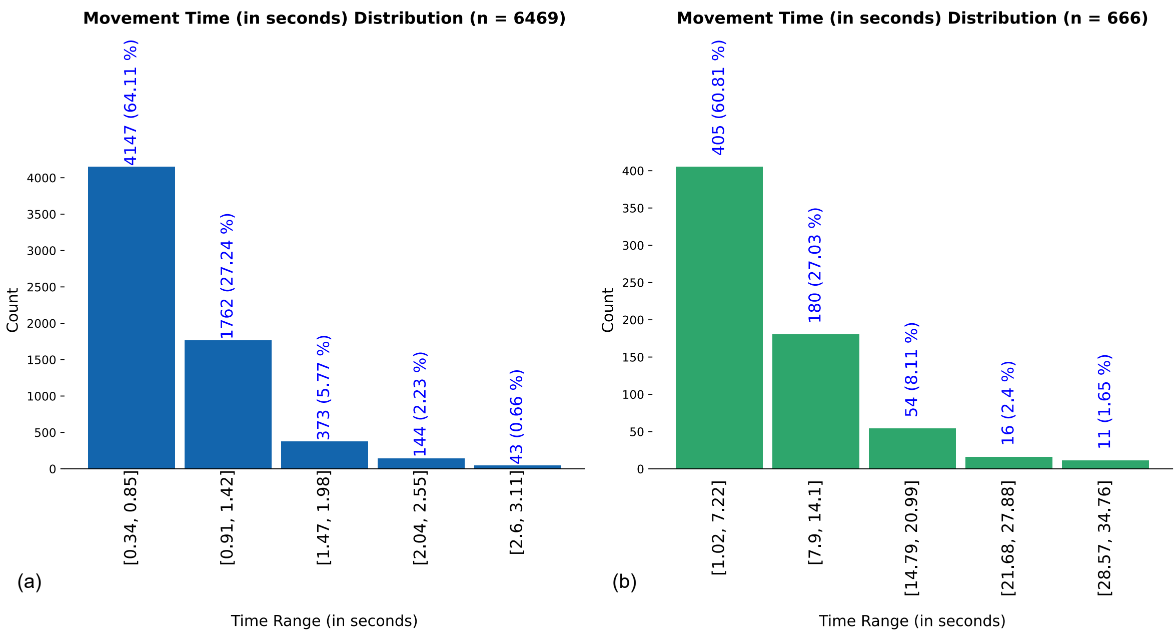


Figure 4.15: Distribution of the task completion times in the "*Point and Click*" experiment, using – (a) an optical mouse and (b) the proposed Assistive Mouse Controller (AMC).

Table 4.10: Descriptive statistics of the task completion times in the "*Point and Click*" experiment using different pointing devices.

Pointing Device	**Tasks (n)**	**Descriptive Statistics (in seconds)**						
		Mean	*SD*	*Min*	25^{th} *Percentile*	50^{th} *Percentile*	75^{th} *Percentile*	*Max*
Optical Mouse	6469	**0.8875**	0.4036	0.3120	0.6410	**0.7820**	1.0000	**3.1410**
AMC	666	**8.1619**	5.8173	0.6720	4.3785	**6.4065**	10.1880	**35.1090**

Analyzing the histograms of the task completion times using the two pointing devices in this experiment, as shown in **Fig. 4.15**, and the descriptive statistics of the same, as summarized in **Table 4.10**, it was observed for the healthy individuals that, with an optical mouse, the task completion times of about 64.11% of the tasks were within 0.34-0.85 *seconds*, with a mean completion time of 0.8875 *seconds*. About 50% of the time, 0.7820 *seconds* were required to complete a task. For the individuals with upper limb disability, the corresponding task completion times, using the proposed AMC, of about 60.81% of the tasks were within 1.02–7.22 *seconds*, with a mean of 8.1619 *seconds* and a 50^{th} percentile of 6.4065 *seconds*. From this analysis in the context of this experiment, the average task completion time using the AMC was about 9.2 times longer than that of an optical mouse. However, for individuals with upper limb disability, who could not previously accomplish the same tasks and interact with a computer like a healthy person, the average task completion time may be regarded reasonable. In the next section, we will analyze user performance in typing tasks using the AMC and an optical mouse to facilitate a comparative performance analysis between the two.

4.2 Typing Experiment

A keyboard and a mouse are considered as standard media of user input to a computer. A healthy individual without any form of upper limb disability can use a physical keyboard for providing different characters, numerals, commands, etc. as input to a computer. However, most modern operating systems feature an on-screen virtual keyboard, on which a key press event can be triggered with the help of a computer mouse as well. Individuals with upper limb disability, unlike their healthy counterparts, cannot interact with a physical keyboard. Therefore, given that they have access to a wearable Assistive Mouse Controller (AMC), the virtual keyboard in combination with the mouse cursor may serve as an alternative input modality for typing tasks. In this section, we elaborate on a typing experiment, where users were required to type 5 different sentences with a virtual keyboard through a typing game "*TypeWriter*" (implemented in-house using *python*), few snapshots of which have been provided in **Fig. 4.16**. Standard metrics, such as – MissTypes, Accuracy, Words Per Minute (WPM), and Characters Per Minute (CPM), were used for measuring user performance in this task. Both healthy individuals and those with upper limb disability were recruited for this purpose, where the healthy individuals were asked to give text input using an optical mouse only, and the physically challenged individuals were asked to do the same with the proposed AMC only through a virtual keyboard that followed the QWERTY layout. This arrangement helped us perform a comparative analysis of users' performance using the *two* interaction devices. We have constructed two datasets with the user-interaction data from this game, where one dataset contains interaction data of healthy individuals using an optical mouse, and the other contains interaction data of individuals with upper limb disability using our proposed AMC. It was hypothesized that the typing performance of the healthy individuals with the optical mouse might be better compared to their physically challenged counterparts, who used the proposed AMC for similar purpose. However, it is to be noted that, the purpose of this study is not to determine the superiority of an optical mouse over the proposed AMC, rather its purpose is to establish the contribution of the proposed AMC in facilitating human-computer interaction for the people with upper limb disability, otherwise impossible. This section begins with the details of our experimental methodology, involving a generic mouse and our proposed AMC, followed by results analysis, and discussion sections.

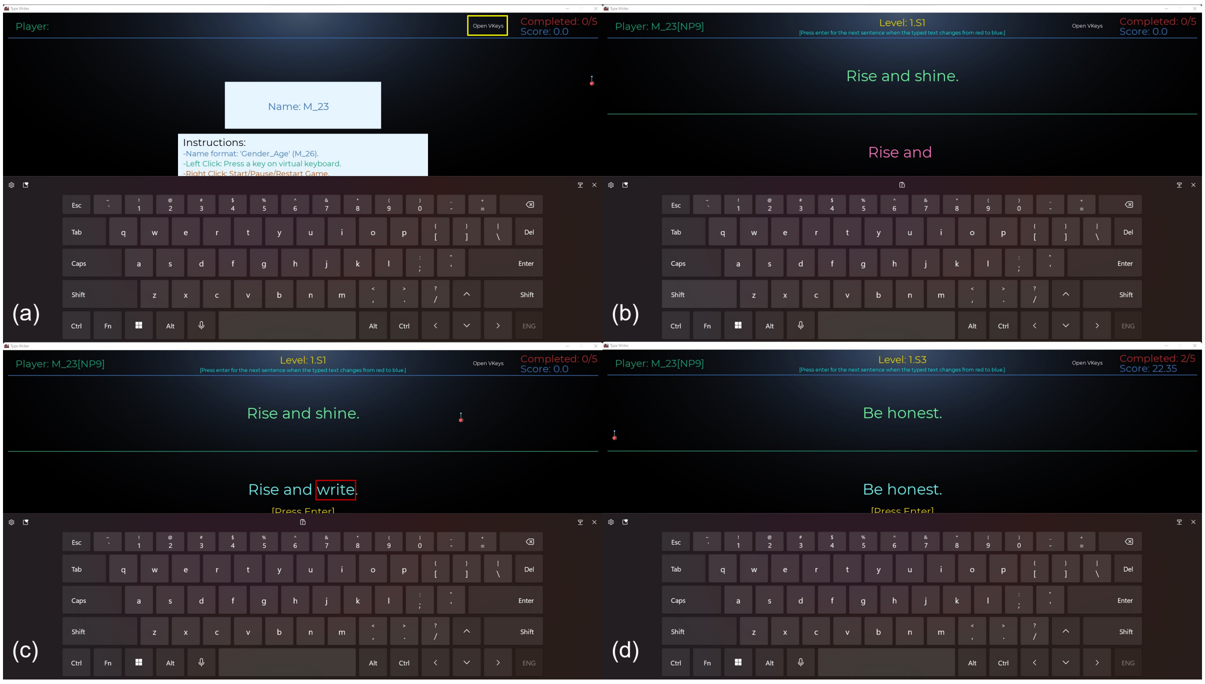


Figure 4.16: Snapshots of the game "*TypeWriter*" – (a) Player registration and game instruction screen, (b) Target sentence shown in *green*, and user written sentence in *red*. (c) Sentence completed (in *cyan*) with errors (in *red* rectangle), and (d) Sentence completed (in *cyan*) without error.

4.2.1 Methodology

4.2.1.1 Participants

The target users for this experiment were individuals with or without any form of upper limb disability. However, all of them were required to have basic computing knowledge. For the experimental study with an optical mouse, the same 25 healthy participants [16 males (64%, Mean Age: 24.19 ± 1.47 years), 9 females (36%, Mean Age: 21.33 ± 1.89 years); Mean Age: 23.20 ± 2.14 years] of the "*Point and Click*" experiment in **section 4.1**, **"*Point and Click Experiment*"**, were recruited. Although the same 15 participants with upper limb disability of the "*Point and Click*" experiment were initially recruited for this experiment using our proposed AMC, 6 of them could not attend the experiment sessions due to personal reasons, leaving 9 individuals [6 males (66.67%, Mean Age: 26.83 ± 3.89 years), 3 females (33.33%, Mean Age: 25.33 ± 1.70 years)] with upper limb disability. Each of the participants provided a verbal consent prior to their participation in this study.

4.2.1.2 Experimental Design

Both healthy participants and those with upper limb disability were asked to play the entire game once on a laptop with a screen resolution of 1920×1080 pixels using a generic computer mouse and the proposed AMC as pointing devices, respectively. We allotted 15 minutes per participant during which they were briefed about the semantics of the game, had a few trial runs, followed by the actual experiment. Data for each play of the game were automatically uploaded to our server. The participants were notified about the automated data collection prior to their participation and were assured of no invasion of privacy from our part.

Each of the participants had to write 5 sentences, distributed in 5 levels of the game, using their respective pointing devices and a virtual keyboard that followed the QWERTY layout. The sentences that had to be written were displayed on the top half of the screen in *green*, while the characters that were typed in, were shown on the bottom half in *red*, as depicted in as shown in **Fig. 4.16b**, **Fig. 4.16c**, and **Fig. 4.16d**. Once a sentence was complete, it turned into *cyan*, and a prompt, "*Press Enter*", appeared below the sentence to allow the participant to move to the next sentence with the press of the "*Enter*" button, as depicted in **Fig. 4.16c** and **Fig. 4.16d**. The *backspace* key was intentionally disabled in the game to correctly quantify some performance metrics. To facilitate opening the virtual keyboard, from within the game, a button, "*Open VKeys*" was provided in the top right corner of the screen, as shown in **Fig. 4.16a**. The game ended when all the sentences had been typed in by a participant, and the data was uploaded to our server for further analysis. The user-interaction data, recorded while playing the game, were – Typed String (TS), Player Keystrokes (PK), First Acquired Time (FAT), and Sentence Completion Time (SCT). PK was measured as the total number of keystrokes required by a player to complete a sentence. FAT was quantified as the elapsed time from the appearance of a sentence on screen to the typing of the first character of a sentence, while SCT was quantified as the elapsed time from typing the first character to the press of the "*Enter*" button [130–132]. After one play of the game, "*TypeWriter*", from 25 healthy participants, about 125 instances, 25 instance/sentence, and from 9 participants with upper limb disability, about 45 instances, 9 instance/sentence, were registered.

A qualitative and quantitative summary of the 5 sentences featured in this game is provided in **Table 4.11** and a descriptive summary of the parameters that were recorded per sentence is summarized in **Table 4.12**.

Table 4.11: Qualitative and quantitative summary of the game "*TypeWriter*".

Level	Sentence	Uppercase Letter(s)	Lowercase Letter(s)	Special Character(s)	Length	Ideal Number of Strokes Required [a]
1	Rise and shine.	1	11	3	15	16
2	Nothing lasts forever.	1	18	3	22	23
3	Be honest.	1	7	2	10	11
4	Respect the elders.	1	15	3	19	20
5	Follow your heart.	1	14	3	18	19
	Total	5	65	14	84	89

[a] Ideal number of keystrokes is greater than the number of characters by 1, due to pressing of the "*shift*" key for typing the uppercase letter.

Table 4.12: Descriptive summary of parameters, recorded per sentence, for the game "*TypeWriter*".

Parameter	Unit	Interpretation
Level Serial	x	Level number (1 – 5).
Typed String (TS)	string	User-typed sentence.
Player Keystrokes (PK)	x	Number of keystrokes required by a participant to complete a sentence.
First Acquired Time (FAT)	Time in seconds	Time required from appearance of sentence to first keystroke.
Sentence Completion Time (SCT)	Time in seconds	Time required to complete a sentence.

4.2.1.3 Data Processing

Data analysis was carried out using *python*. Prior to analysis, the data set was cleaned off of erroneous data to avoid erroneous calculation. In this study, typing performance was measured using various standard metrics, such as – *MissTypes*, *Accuracy*, *Words Per Minute* (WPM), and *Characters Per Minute* (CPM), adopted from prior studies [130–132]. As the backspace key was intentionally disabled for this game, it was computationally convenient to count the number of wrong characters typed in by the user by simple string-matching technique, quantifying the metric, *MissTypes*, in the process. For the metric Accuracy, the ratio of the number of correctly typed in characters to the length of the sentence was considered, as shown in **Eq. 4.1**. The formula for quantifying WPM, as shown in **Eq. 4.2**, was adopted from prior studies [130–132], where the length of a word is considered to be 5 characters long [132], while CPM was measured as the ratio of the length of a user-typed string to SCT, as shown in **Eq. 4.3**. a descriptive summary of the performance metrics that were considered for this study is summarized in **Table 4.13**. A pairwise F-test for variances was conducted on the performance metrics to analyze whether the variances in performance across differently abled users, using different interaction devices, were significant. In any case, once the performance metrics for the respective pointing devices were generated, they were visualized for better clarity and to get an idea of variances in user performance, considering differences in physical ability.

$$Accuracy = \frac{number of correctly typed characters}{length of the displayed string} \tag{4.1}$$

$$WPM = \left| \frac{length of user - typed string}{SCT} - 1 \right| \times 60 \times \frac{1}{5} \tag{4.2}$$

$$CPM = \frac{length of user - typed string}{SCT} \times 60 \tag{4.3}$$

Table 4.13: Descriptive summary of the metrics, considered in this study, for quantifying typing performance.

Metric	Unit	Interpretation
MissTypes	x	Number of mismatches between user-typed and displayed sentences.
Accuracy	percentage	Ratio of the correctly typed characters and length of the displayed sentence.
Words Per Minute (WPM)	words / minute	Estimate of speed of typing a 5-character long word.
Characters Per Minute (CPM)	chars / minute	Estimate of characters per minute, considering SCT.

4.2.2 Results

The results of the typing performance analysis are shown in **Fig. 4.17**. The average WPM using the proposed AMC was found to be around 2.05, which is about 8 times lesser than that of the optical mouse, around 16.72 WPM. Similar ratio is carried over to CPM as well, with optical mouse having a value of 89.29 and AMC having 10.92, signifying the consistency of the experiment. Moreover, the same ratio of 8 times, is inversely carried over to SCT as well, with the optical mouse requiring almost 8 times less than the AMC to complete a sentence. Another important thing to notice is the value of FAT, where using the AMC, it took around 4 times longer to hit the first character after the appearance of a sentence than the optical mouse. Optical mouse also demonstrates better performance in terms of MissTypes and Accuracy, the first one being almost 4 times less than that of the AMC. Accuracy is subject to speed-accuracy trade-off [114, 125] and though less than that of an optical mouse (81.72% percent of that of the optical mouse), the accuracy of the AMC is not equivalently less, as the other parameters discussed before. From the analysis and visualization of the other parameters, it can be deduced that the participants were trading off WPM and CPM, or in other term speed, in the case of AMC to acquire comparatively better accuracy. The standard error of mean in most of the parameters are quite small or consistent. However, in cases of SCT and CPM, the variations of standard error of mean are noticeably different, comparing the ones of the optical mouse and the AMC.

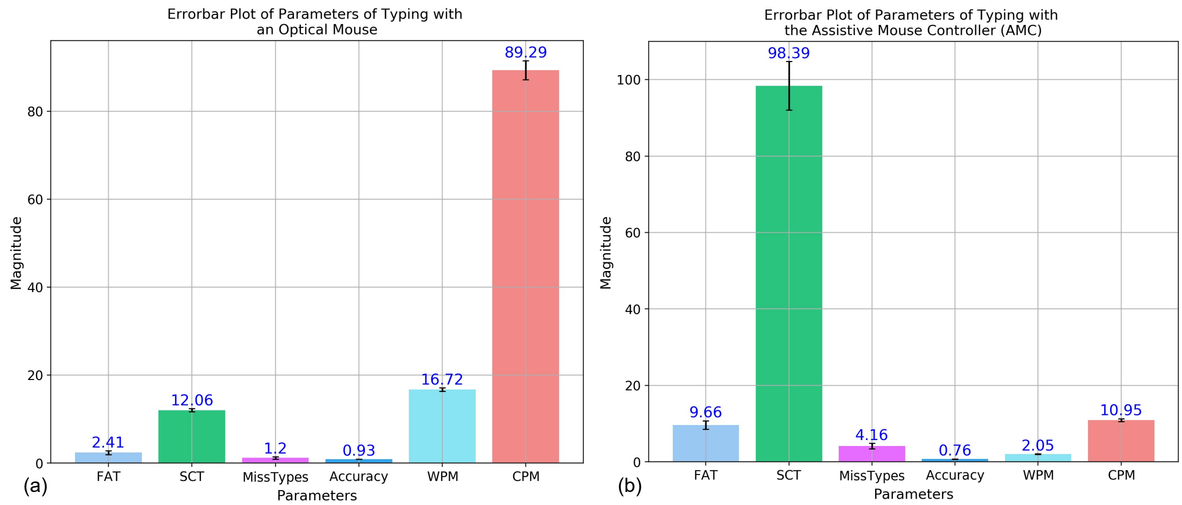


Figure 4.17: Visualization of typing performance metrics using – (a) an optical mouse and (b) the proposed Assistive Mouse Controller (AMC). **FAT**: First Acquired Time, **SCT**: Sentence Completion Time, **WPM**: Words Per Minute, **CPM**: Characters Per Minute.

Furthermore, from the summary of means of the performance metrics per sentence, as shown in **Table 4.14**, a decreasing trend can be observed in the value of FAT for the AMC, which is not the case for the optical mouse. This trend is an indication that with time, users of the proposed AMC may demonstrate enhanced control of their interaction with a computer, thereby, reducing interaction time in the process. The results of a pairwise F-test for variances on the performance metrics, summarized in **Table 4.15**, suggest that the performance of the healthy individuals, with the optical mouse was significantly better than that of the individuals with upper limb disability, using the AMC.

Table 4.14: Summary of means of the performance metrics per sentence of the game "*TypeWriter*".

Level	Sentence	Mean FAT		Mean SCT		Mean MissTypes		Mean Accuracy		Mean WPM	
		Optical Mouse	*AMC*	*Optical Mouse*	*AMC*	*Optical Mouse*	*AMC*	*Optical Mouse*	*AMC*	*Optical Mouse*	*AMC*
1	Rise and shine.	4.2338	12.1407	12.7990	91.1267	0.7391	5.1111	0.9500	0.6600	14.0370	1.9256
2	Nothing lasts forever.	1.5568	11.7847	15.4589	118.0624	2.9600	6.0000	0.8636	0.7256	17.4888	2.1822
3	Be honest.	1.7468	8.6648	7.4531	57.3056	0.4000	1.8889	0.9600	0.8111	16.2004	1.9633
4	Respect the elders.	3.2318	8.5381	12.4513	116.5487	0.9200	4.4444	0.9520	0.7667	18.2612	2.0733
5	Follow your heart.	2.1651	7.1614	11.7892	108.9044	1.3896	3.3333	0.9271	0.8144	17.2762	2.1089

Table 4.15: Summary of the results of pairwise F-test for variance for the performance metrics.

Interaction Device ($\sigma_A^2 > \sigma_B^2$) [a]		FAT		SCT		MissTypes		Accuracy		WPM	
A	*B*	*F-stat*	*p-value* [b]	*F-stat*	*p-value* [b]	*F-stat*	*p-value* [b]	*F-stat*	*p-value* [b]	*F-stat*	*p-value* [b]
Optical Mouse	**AMC**	-	-	-	-	-	-	-	-	**99.1391**	<0.001
AMC	**Optical Mouse**	**2.3921**	<0.001	**108.6828**	<0.001	**2.8648**	<0.001	**4.0345**	<0.001	-	-

[a] Variance (σ_i^2) of performance metrics for device i, where $i \in A, B$.
[b] p-values were computed at a level of significance, α =0.05.

4.2.3 Discussion

This experiment investigated the performance of users with upper limb disability using the proposed AMC compared to that of healthy individuals with an optical mouse, in typing tasks through the game "*TypeWriter*" (implemented in-house in *python*). Various standard performance metrics, such as – MissTypes, Accuracy, Words Per Minute (WPM), and Characters Per Minute (CPM), were adopted from prior studies [130–132] to juxtapose their respective performances in typing tasks. It was hypothesized that the performance of the healthy individuals might be better compared to their physically challenged counterparts. Also, the goal of the study was not to establish the superiority of one device over the other, rather it was to understand how the proposed AMC might assist physically challenged individuals to perform typing tasks using an alternative input modality.

From our result analysis, we found that the performance of the healthy individuals was significantly better than their physically challenged counterparts, supporting our hypothesis in the process. Furthermore, we have also shown that using the proposed AMC, individuals with upper limb disability can participate in typing tasks like their healthy counterparts. Although their performance is not so high as the healthy participants, who used an optical mouse for typing, it may provide a good starting point for future research, where the interaction of the AMC may be optimized for enhancing user performance. In connection to this, future works may include design and development of a keyboard layout for people with upper limb disability, specifically suited for typing tasks using the proposed AMC. In the next section, we will implement the System Usability Scale (SUS) [61] to obtain valuable and relevant insights of the device usability.

4.3 Usability Analysis of the Assistive Mouse Controller (AMC)

The purpose of assistive technologies is to help physically challenged individuals with different activities, allowing them to participate equally in all forms of interaction like their healthy counterparts. In this regard, usability of the device is a very important aspect, which primarily encapsulates the idea of how easily a user can adapt to a particular assistive technology. Usability of any assistive technology enhances user's appeal for that technology. Therefore, usability analysis of the proposed Assistive Mouse Controller (AMC) is a crucial part of this study. In this section, we analyze the usability of the AMC, according to the System Usability Scale (SUS) [61]. The section begins with a discussion on the theoretical background of SUS, followed by its application in relation to this study.

4.3.1 Theoretical Background

According to ISO $9241-11$, usability of any system or device is defined as, "*the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use*" [64]. The System Usability Scale (SUS) [60, 61] is one of the most popular and easy to use methods that employs a closed-questionnaire based approach to quantify the subjective assessments of usability of any system or device. It is a 10-item questionnaire, based on a 5-point Likert scale, corresponding to the basic issues that a user might run into while using any system. The 10-items of SUS as proposed by J. Brooke [60] have been summarized in **Table 4.16**.

Table 4.16: The 10 items of the System Usability Scale (SUS) as proposed by J. Brooke in 1996 [60].

Item	Description
SUS 1	I think that I would like to use this system frequently.
SUS 2	I found the system unnecessarily complex.
SUS 3	I thought the system was easy to use.
SUS 4	I think that I would need the support of a technical person to be able to use this system.
SUS 5	I found the various functions in this system were well integrated.
SUS 6	I thought there was too much inconsistency in this system.
SUS 7	I would imagine that most people would learn to use this system very quickly.
SUS 8	I found the system very cumbersome to use.
SUS 9	I felt very confident using the system.
SUS 10	I needed to learn a lot of things before I could get going with this system.

SUS can be used for evaluating the usability of any device or system, only when the respondents of the questionnaire have used it first-hand. The *even* numbered items in the questionnaire are *negative* sounding, while the *odd* ones are *positive* sounding, allowing identification of valid responses. For example, if a user's response to the item, "*I found the system unnecessarily complex*", is *low*, then his/her response to the item, "*I thought the system was easy to use*", logically must be *high*. However, if this is not the case, the response may be ignored.

The SUS score, as specified by J. Brooke [60], is a single number between 0 and 100, representing a composite measure of the overall usability of the system under evaluation. However, before calculating this score, the scale contribution of each item, which is a number between 0 and 4, needs to be calculated. For the *even* numbered items, the respective score contribution is calculated as 5 minus the scale value (1 5), while for the *odd* numbered items, it is calculated as the scale value (1 5) minus 1. Next, the sum of the score contributions of the *even* and the *odd* numbered items are calculated as Y_O and X_O, respectively. Finally, the SUS score for the system or device under evaluation is calculated as $(X_O + Y_O) \times 2.5$, generating a number between 0 and 100. The process of calculating SUS scores is depicted in **Fig. 4.18**.

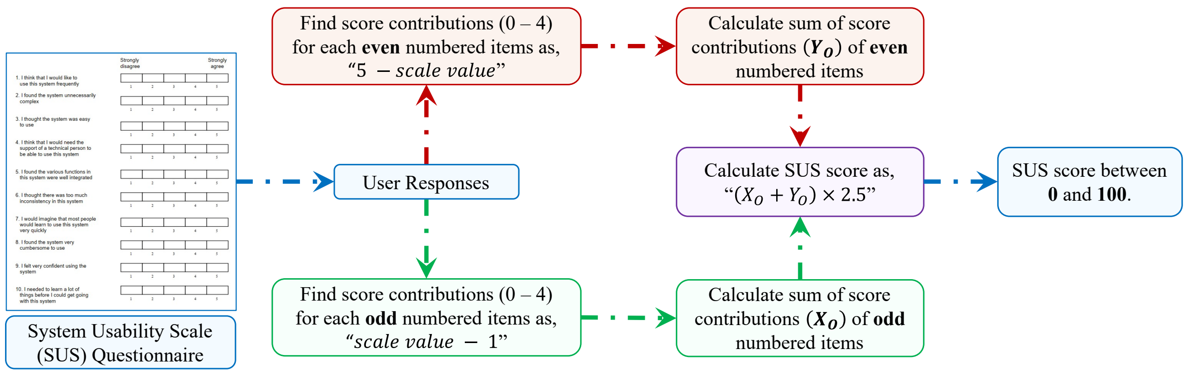


Figure 4.18: Workflow diagram of calculating the System Usability Scale (SUS) score.

The SUS score itself does not represent whether the usability of a system or a device is *poor* or *good*. Therefore, to facilitate some form of interpretation of the SUS score, researchers have assigned letter grades ($A+, A, A-$, etc.) to this score, based on empirical evaluation of various studies related to SUS [133, 134]. For example, Bangor et al. [134] developed a SUS score grading scale, where scores below 60 were assigned as "*F*", between 60 and 69 as "*D*", between 70 and 79 as "*C*", between 80 and 89 as "*B*", and 90 and above as "*A*". To provide more granularity of interpretation, Lewis et al. [133], subdivided the letter grades "*A*", "*B*", and "*C*" in to 3 categories, such as – "$A+$", "A", "$A-$", "$B+$", "B", "$B-$", etc. A summary of the letter grade assignment to SUS scores, by Lewis et al. [133], is provided in **Table 4.17**. In the next section, we elaborate on our methodology, followed by results analysis and discussion.

Table 4.17: Letter grade assignment to System Usability Scale (SUS) scores by Lewis et al. [133] for better interpretation of usability.

SUS Score	Percentile Range	Letter Grade
84.10 - 100.00	96 - 100	*A+*
80.80 - 84.00	90 - 95	*A*
78.90 - 80.70	85 - 89	*A−*
77.20 - 78.80	80 - 84	*B+*
74.10 - 77.10	70 - 79	*B*
72.60 - 74.00	65 - 69	*B−*
71.10 - 72.50	60 - 64	*C+*
65.00 - 71.00	41 - 59	*C*
62.70 - 64.90	35 - 40	*C−*
51.70 - 62.60	15 - 34	*D*
0.00 - 51.60	0 - 14	*F*

4.3.2 Methodology

4.3.2.1 Participants

The target users for this experiment were individuals with upper limb disability, who had first-hand experience with the proposed AMC. In our case, the same 15 individuals with upper limb disability [9 males (60%, Mean Age: 26.57 ± 4.39 years), 6 females (40%, Mean Age: 24.33 ± 4.96 years)] who participated in the "*Point and Click*" experiment in **section 4.1**, "***Point and Click Experiment***", were also recruited for this online survey. Each of the participants provided a verbal consent prior to their participation in this study. The age distribution of the 15 respondents is depicted in **Fig. 4.19**.

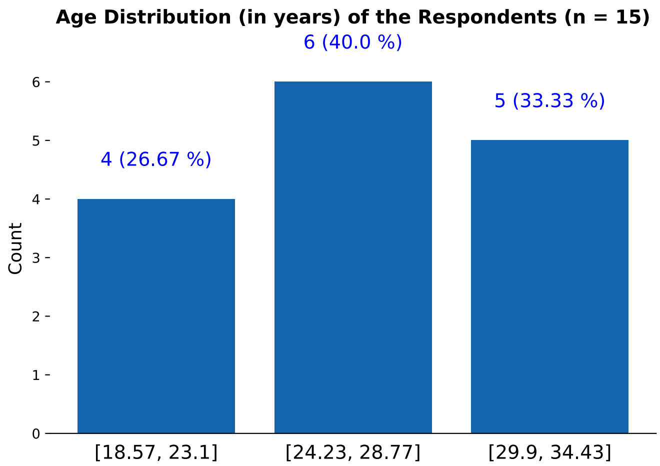


Figure 4.19: Age distribution of the 15 respondents, who participated in the survey.

4.3.2.2 Experimental Design

Once the participants completed the "*Point and Click*" and the "*Typing*" experiments with the proposed AMC, they were invited to take an online survey for rating different usability aspects of the AMC. The survey questionnaire comprised of the same 10-items, as proposed by J. Brooke [60], measuring different usability aspects of the proposed AMC on a 5-point Likert scale with ratings, such as – 1 – *Strongly Disagree*, 2 – *Disagree*, 3 – *Neutral*, 4 – *Agree*, and 5 – *Strongly Agree*.

4.3.2.3 Data Processing

In this study, data analysis was done in *python*. Once the user responses to the survey items were recorded, the mean and Standard Deviation (SD) of the scores, corresponding to each item, were calculated. The SUS score of the AMC per respondent and its equivalent letter grades were then calculated, following the process outlined in **Figure 23** and the grading scheme summarized in **Table 17**, respectively. Then, the mean of all SUS scores and the corresponding letter grade were calculated to get an overall interpretation of the usability of the proposed AMC. Finally, pairwise F-tests were carried out on the user ratings of different pairs of SUS items, to verify whether they varied significantly, which in theory, should not.

4.3.3 Results

From the user ratings of this study, summarized in **Table 4.18**, it was observed that the SUS scores of the AMC ranged between 70.00 and 97.50, with a mean score of 84.17 ($\pm$8.05). The *minimum*, the *maximum*, and the *mean* letter grades obtained, were C, $A+$, and $A+$, respectively. The percentage of user ratings of the overall usability of the AMC, in terms of the letter grades, $A+$, A, $A-$, $C+$, and C, were 60%, 6.67%, 13.33%, 13.33%, and 6.67%, respectively. Considering the different SUS items, about 73.33% of the participants strongly disagreed on their interaction with the AMC as being unnecessarily complex, with a mean rating of 4.20 ($\pm$0.56). Considering the items SUS2, SUS3, and SUS8, where the *first* item concerns about system complexity, the *second* about its ease-of-use, and the *last* about its cumbersomeness, the user ratings should not vary significantly. Intuitively, if the rating for SUS3 is high, then the corresponding ratings for SUS2 and SUS8 should be low. To verify whether the variances were significantly different, pairwise F-tests were carried out for all possible combinations of the group of items SUS2, SUS3, and SUS8. For the SUS item pairs, (SUS2, SUS3), (SUS2, SUS8), and (SUS3, SUS8) the pairwise F-test results were ($F_{14,14} = 1.9545, p = 0.1111$), ($F_{14,14} = 1.9545, p = 0.1111$), and ($F_{14,14} = 1.0000, p = 0.5000$), respectively, indicating the ratings did not vary significantly. Interestingly, the percentage of users, who strongly agreed on the AMC to be easy to use, was equal to that of those, who strongly disagreed on its cumbersomeness, which is about 53.33%. For the same *two* items, similar proportions for the ratings, *agreed-disagreed* (40.00%) and neutral (6.67%), were observed as well. Similar consistency in variance of user ratings, in theory, should exist between the items SUS5 and SUS6, which was confirmed by a pairwise F-test on these *two* items ($F_{14,14} = 1.3488, p = 0.2915$). For better visualization, box plots of user-ratings for the 10-items of the SUS questionnaire are outlined in **Fig. 4.20**.

Table 4.18: Results of usability analysis of the proposed Assistive Mouse Controller (AMC) using the System Usability Scale (SUS).

Respondent	SUS 1	SUS 2	SUS 3	SUS 4	SUS 5	SUS 6	SUS 7	SUS 8	SUS 9	SUS 10	SUS Score	Letter Grade [a]
R1	4	1	5	1	5	1	4	1	4	1	92.50	*A+*
R2	4	2	4	2	5	1	5	1	4	3	82.50	*A*
R3	4	1	4	2	3	2	3	2	3	1	72.50	*C+*
R4	4	1	5	2	5	1	4	2	5	1	90.00	*A+*
R5	4	1	5	1	5	1	4	1	4	1	92.50	*A+*
R6	5	2	4	2	5	1	4	1	5	1	90.00	*A+*
R7	5	1	5	2	5	1	5	1	5	1	97.50	*A+*
R8	4	2	5	4	4	2	5	2	3	2	72.50	*C+*
R9	4	1	3	2	4	2	3	2	3	2	70.00	*C*
R10	3	1	5	1	4	2	4	2	3	1	80.00	*A−*
R11	4	1	4	3	5	1	4	1	5	1	87.50	*A+*
R12	4	1	4	1	5	3	5	2	2	1	80.00	*A−*
R13	4	1	5	2	4	2	5	3	5	1	85.00	*A+*
R14	5	2	4	2	5	1	5	1	4	3	85.00	*A+*
R15	5	1	5	2	3	2	4	1	4	1	85.00	*A+*
Mean	4.20	1.27	4.47	1.93	4.47	1.53	4.27	1.53	3.93	1.40	84.17	*A+*
SD	0.56	0.46	0.64	0.80	0.74	0.64	0.70	0.64	0.96	0.74	8.05	

[a] Letter Grades were adopted from [133].

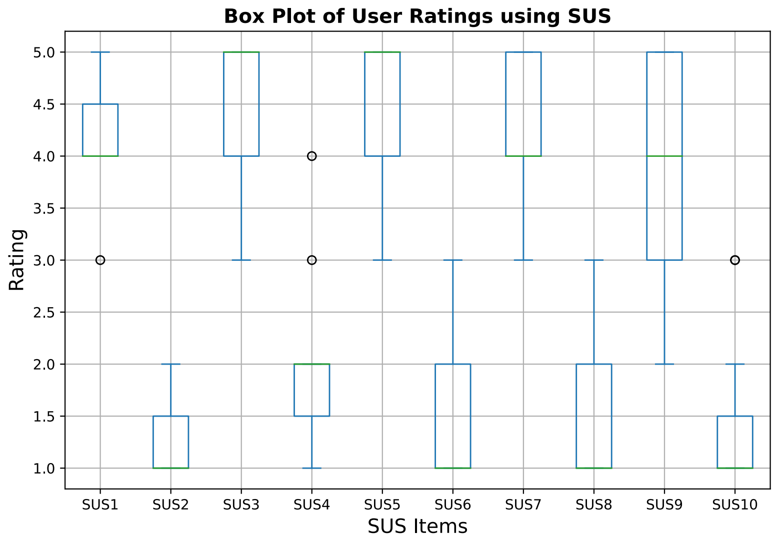


Figure 4.20: Box plot of user ratings of the proposed Assistive Mouse Controller (AMC) using the System Usability Scale (SUS).

4.3.4 Discussion

This experiment investigated the users' standpoint on the usability of the proposed AMC, leveraging the System Usability Scale (SUS). From the result analysis of this experiment, the user ratings were found to vary insignificantly, while maintaining consistency between the ratings of different pairs of positive and negative sounding SUS items. In terms of usability, the mean SUS score of the device was about 84.17 out of 100, achieving an overall rating of $A+$. This rating, according to the letter grade assignment of SUS scores for better interpretation of system usability by Lewis et al. [133], falls in the highest order of the usability scale ($96 - 100$ percentile range). The *lowest* and the *highest* SUS scores of the device were 70.00 and 97.50, respectively. Although some usability ratings were between the 41^{st} and the 64^{th} percentile, following **Table 17**, such as the ratings $C+$ and C, respectively, it is an indication that the perception of device usability is subjective, and therefore, not every user will perceive its usability in the same way. However, the proportions of such ratings are smaller than that of $A+$ rating. These findings further raise the need to investigate users' satisfaction with the device in connection to their perceived level of device usability, which will be analyzed using the Quebec User Evaluation of Satisfaction with Assistive Technology 2.0 (QUEST 2.0) framework in the following section.

4.4 User Satisfaction Analysis of the Assistive Mouse Controller (AMC)

From the perspective of physically challenged users, evaluating their perceived satisfaction with any assistive technology is an important psychological phenomenon that significantly determines whether it will be accepted or rejected by them for further use. In this regard, the most popular tool is the Quebec User Evaluation of Satisfaction with Assistive Technology 2.0 (QUEST 2.0) framework [66], which is a 12-item outcome measure that measures user satisfaction from two perspectives, such as *device* and *services*. In this section, a discussion on the theoretical background of QUEST 2.0, followed by our approach for analyzing users' satisfaction of the proposed Assistive Mouse Controller (AMC) has been provided.

4.4.1 Theoretical Background

The Quebec User Evaluation of Satisfaction with Assistive Technology (QUEST) was developed to fill up the gap between theoretical knowledge and the factors that influence user satisfaction with assistive technologies [66]. The initial version of QUEST was a 24-item outcome measurement tool, where each item quantified users' level of satisfaction based on a 5-point Likert scale. Over the course of time, research [67, 68] had been carried out that aimed to validate and analyze the reliability of the QUEST model, leading to the development of the QUEST 2.0, a generic 12-item questionnaire with the same objective as its predecessor. Among these 12-items, 8 items are intended to analyze user satisfaction from device perspective, while the rest from service perspective. In any case, the analyst has the flexibility to add any other items, which they considered important [66]. Apart from these 12-items, a user is also asked to identify *three* of the most important factors associated with the assistive technology under consideration. From the analysis of user responses, *three* types of scores are generated, such as – *device*, *services*, and *total QUEST*. These scores are calculated as the average of the valid responses per item [66]. In the next section, we elaborate on our methodology, followed by results analysis and discussion.

4.4.2 Methodology

4.4.2.1 Participants

The target users for this experiment were individuals with upper limb disability, who had first-hand experience with the proposed AMC. In our case, the same 15 individuals with upper limb disability [9 males (60%, Mean Age: 26.57 ± 4.39 years), 6 females (40%, Mean Age: 24.33 ± 4.96 years)] who participated in the "*Point and Click*" experiment in **section 4.1, "*Point and Click Experiment*"**, were also recruited for this survey. Each of the participants provided a verbal consent prior to their participation in this study.

4.4.2.2 Experimental Design

Since in the context of this study, a working prototype of a wearable Assistive Mouse Controller (AMC) has been developed, the AMC is not yet available to the mass, and therefore, there is no concept of follow-up user services at present. In other words, user satisfaction with the AMC could not be analyzed from a *service* perspective. Therefore, in this study, users' satisfaction with the AMC has been analyzed from *device* perspective only.

A total of 10 items, corresponding to different aspects of the AMC, were considered for analyzing user satisfaction with the AMC from device perspective. Some of these items were *adopted* directly, some were *adapted* from prior studies [68] to suit the context of this study, while some were *newly developed* specifically for this study. A 5-point Likert scale was used to quantify users' responses to the items with ratings, such as – 1 – *Very Unsatisfactory*, 2 – *Unsatisfactory*, 3 – *More or Less Satisfactory*, 4 – *Satisfactory*, and 5 – *Very Satisfactory*. Furthermore, an additional question was considered where the users were asked to choose the *three* most important aspects of the AMC from the 10 items. The entire survey was conducted online. The items corresponding to the analysis of user satisfaction, with references to prior studies, from which they were either *adopted*, *adapted*, or *newly developed*, are summarized in **Table 4.19**.

Table 4.19: Questionnaire items corresponding to QUEST 2.0 framework for analyzing user satisfaction, adapted from [68].

Item	Description
Item 1	How satisfied were you with, the **dimensions (size, height, length, or width)** of the Assistive Mouse Controller (AMC)?
Item 2	How satisfied were you with, the **weight** of the Assistive Mouse Controller (AMC)?
Item 3	How satisfied were you with, the **adjustability (fixing, fastening)** of the Assistive Mouse Controller (AMC)?
Item 4	How satisfied were you with, the **safety** of the Assistive Mouse Controller (AMC)?
Item 5	How satisfied were you with, the **durability (endurance, resistance to wear)** of the Assistive Mouse Controller (AMC)?
Item 6	How satisfied were you with, the **ease-of-use** of the Assistive Mouse Controller (AMC)?
Item 7	How satisfied were you with, the **comfortability** of the Assistive Mouse Controller (AMC)?
Item 8	How satisfied were you with, the **mouse cursor precision** of the Assistive Mouse Controller (AMC)?
Item 9	How satisfied were you with, the **mouse click accuracy** of the Assistive Mouse Controller (AMC)?
Item 10	How satisfied were you with, the **battery life** of the Assistive Mouse Controller (AMC)?
Multiple Choice	Considering different aspects of the AMC, such as - *Dimensions, Weight, Adjustability, Safety, Durability, Ease of Use, Comfortability, Mouse Cursor Precision, Mouse Click Accuracy*, and *Battery Life*, please select the **three** most important ones, in your opinion.

4.4.2.3 Data Processing

In this study, data analysis was done in *python*. Once the user responses to the survey items were recorded, the reliability of the questionnaire was measured using the Cronbach's Alpha (α) (CA) test, where $\alpha > 0.7$ is recommended for acceptable reliability [73, 135]. The mean and standard deviation of the scores, corresponding to each item, were calculated. Since the users' satisfaction with the AMC has been analyzed from device perspective only, for reasons mentioned earlier, there was no scope of calculating satisfaction scores from *service* perspective. Therefore, the total QUEST 2.0 score was equivalent to the mean sub-score from a *device* perspective. Furthermore, the responses were analyzed to identify the *three* most important aspects of the proposed AMC, in terms of usability.

4.4.3 Results

Table 4.20 outlines the means of users' satisfaction scores with the proposed AMC from *device* perspective. The α value of questionnaire reliability, obtained using the CA test, was found to be 0.7801, indicating acceptable reliability. The mean satisfaction scores of the users across different aspects of the AMC ranged between 3.8667 and 4.8667, which in terms of percentage is between 77.33% and 97.33%. The overall mean satisfaction score was found to be 4.3867. In other words, the users were able to achieve an overall satisfaction of 87.73% while using the device. The *three* most important aspects of the AMC, according to the users, were found to be *mouse cursor precision*, *ease-of-use*, and *adjustability*. The importance of different aspects of the AMC, according to the users, is outlined in descending order in **Fig. 4.21**.

Table 4.20: Mean of satisfaction scores of users ($n = 15$) with the Assistive Mouse Controller (AMC) from device perspective.

Device Aspects	User Satisfaction Scores		
	Mean	%	*SD*
Dimension	4.3333	86.67	1.1751
Weight	4.6000	92.00	1.0556
Adjustability	4.6667	93.33	0.8997
Safety	4.8667	97.33	0.5164
Durability	4.2000	84.00	1.2071
Ease of Use	4.3333	86.67	1.1751
Comfortability	4.2667	85.33	1.0998
Mouse Cursor Precision	3.8667	77.33	1.3558
Mouse Click Accuracy	3.9333	78.67	1.4376
Battery Life	4.8000	96.00	0.7746
Overall Mean Score	4.3867	87.73	1.0697

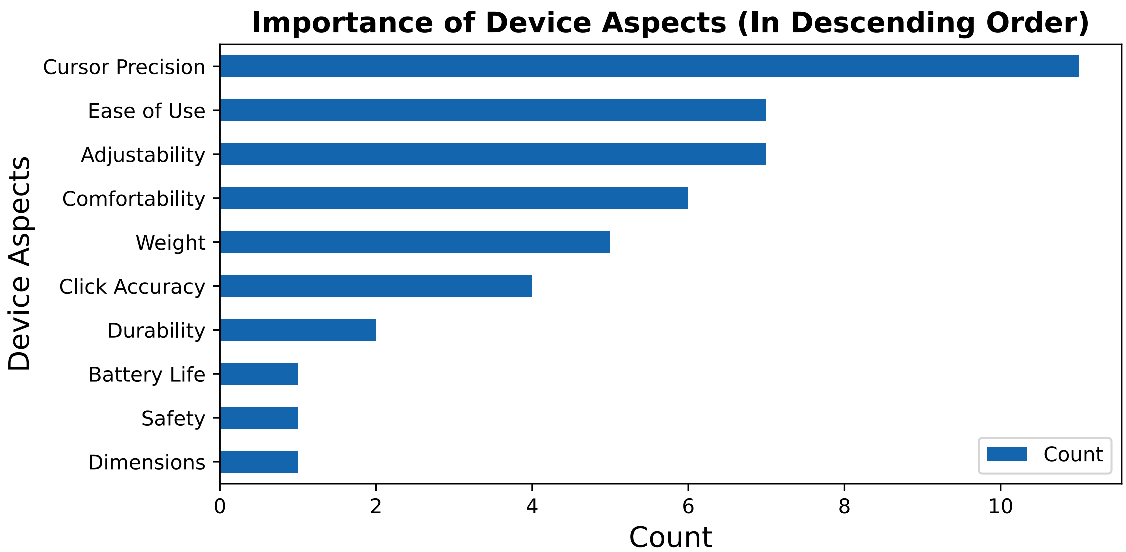


Figure 4.21: The importance of different aspects of the proposed Assistive Mouse Controller (AMC) from users' perspective.

4.4.4 Discussion

This experiment investigated the users' satisfaction with different aspects of the proposed AMC, leveraging the QUEST 2.0 framework. From the result analysis of this experiment, *cursor movement precision* was found to be the most important aspect. This is expected, as the main purpose of this device is to control a mouse and if the cursor movement is not smooth and precise, it will compromise human-computer interaction and all the other relevant aspects. The user ratings for *ease-of-use* and *adjustability* were similar, which turned out to be the *second* and the *third* most important aspects, respectively. *Comfortability* turned out to be the *fourth* important aspect from the users' perspective. From this analysis, it may be inferred that ease-of-use of the device encompasses most of the other aspects of the device, not in the top *three*, which influence user interaction with a computer. To conclude, the proposed AMC demonstrated a high level of user satisfaction (about 87.73%), which leads us to further analyze users' perspective on whether they will accept this technology as an AMC for human-computer interaction. In connection to this, users' acceptability of the proposed AMC will be analyzed using the Technology Acceptance Model (TAM), in the following section.

4.5 User Acceptability Analysis of the Assistive Mouse Controller (AMC)

Users' acceptance of a particular technology is driven by various psychological constructs, such as ease-of-use, perceived usefulness, confidence while using it, etc. The Technology Acceptance Model (TAM) is used in this regard to analyze the influence of these constructs on users' attitude towards that technology and their intention of adopting it as part of their lifestyle [53, 54, 69]. Prior studies [70, 72–74, 136–147] have utilized the TAM in this regard, pointing out key factors and their relationship that influence acceptance of a technology. However, few of the studies were related to the acceptance of wearable technologies in general. To the best of our knowledge, no significant work has been reported on the analysis of the acceptance of a wireless head-mounted Assistive Mouse Controller (AMC) for people with upper limb disability using the TAM. In this section, a discussion on the theoretical background of TAM, followed by a brief literature review, and our approach for analyzing the acceptance of the proposed AMC has been provided.

4.5.1 Theoretical Background

The development of newer wearable technologies, while solving various real-life scenarios, has led to the research on numerous theoretical models for analyzing users' acceptance of those technologies. From a psychological perspective, any technology which is perceived as easy-to-use, will be considered useful, generating a positive attitude towards its usage, thereby, increasing its chances of being accepted by the users as a part of their lifestyle. The Technology Acceptance Model (TAM), as proposed initially by Davis et al. [53, 54] in 1989, and later extended by Venkatesh et al. [69] in 2000, has been widely used for analyzing users' acceptance of different technologies. Venkatesh and Davis [69], in their proposal of the TAM, primarily explained the influence of different psychological constructs, such as -

- **Perceived Usefulness (PU)**: "*The degree to which a person believes that using a particular system would enhance his or her job performance*" [53, 54].
- **Perceived Ease of Use (PEU)**: "*The degree to which a person believes that using a particular system would be free of effort*" [53, 54].
- **Subjective Norm (SN)**: "*The person's perception that most people who are important to him or her think s/he should or should not perform the behavior in question*" [53, 54].

- **Attitude Towards Usage (ATU)**: "*An individual's positive or negative feelings (evaluative affect) about performing the target behavior*" [53, 54].
- **Behavioral Intention (BI)**: "*A measure of the strength of one's intention to perform a specified behavior*" [53, 54].

The constructs, PU and PEU affect a user's ATU and BI towards the acceptance of a technology [53,54]. In the subsequent theoretical extension of the TAM, proposed by Venkatesh [69] and referred to as the TAM2, the influence of various external variables, such as – experience, output quality, job relevance, result demonstrability, etc. on the psychological constructs, PU and PEU, of the original TAM model had also been considered. To generalize, for any technology, the external variables directly or indirectly influence PEU and PU of a technology. Increased PEU will enhance PU, generating positive ATU of that technology among the users. These psychological constructs (PU and ATU) then influence the user's BI to accept the technology. An outline of the TAM2 model is depicted in **Fig. 4.22**.

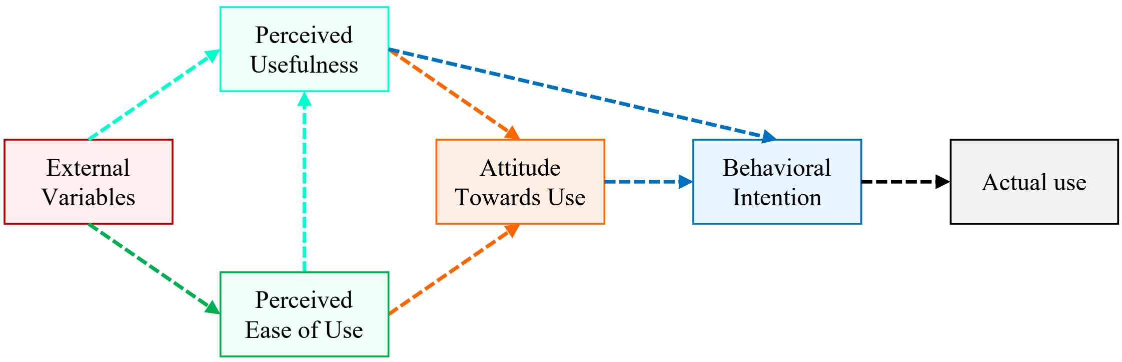


Figure 4.22: Outline of the Technology Acceptance Model 2 (TAM2).

The analysis of users' acceptance of a technology using the TAM or the TAM2 framework typically involves a self-administered, closed-ended, n-point ($n = 4, 5, 6$ or 7) Likert scale-based survey questionnaire, which is divided into sections that represent different psychological constructs (e.g., PU, PEU, SN, etc.) [69, 73, 146, 148, 149]. Each question corresponding to a particular construct is normally referred to as a measurement *item*. Based on a theoretical analysis of possible influence of one construct over another, alternative hypotheses are postulated [69,72,135,150] and tested (*rejected* or *accepted*) later during data analysis. In studies related to technology acceptance, involving TAM or TAM2 [70,72–74,135,141,150], data analysis typically involves *two* steps, such as – 1) developing a measurement model and 2) developing a Structural Equation Model (SEM) [73, 135, 137].

4.5.1.1 Measurement Model

The measurement model is generally developed through Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA) [73, 135, 151–153]. Detailed descriptions of EFA and CFA are beyond the scope of this study, and the reader is requested to refer to the work of Noora Shrestha [153] for better comprehension. However, before either EFA or CFA could be conducted for developing the measurement model, it is necessary to check whether the dataset under consideration is adequate for factor analysis. The adequacy test involves both Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy [152, 153]. Bartlett's test of sphericity is intended to test whether the items in the questionnaire are correlated enough, such that the correlation matrix does not become an identity matrix. This can be verified if the value of p, obtained from this test is less than 0.05, given that 95% confidence interval is considered [153]. The KMO measure on the other hand is used to determine whether the sample size is large enough for factor analysis. The KMO value ranges between 0 and 1, where values between 0.8 and 1.0, 0.7 and 0.79, and 0.6 and 0.69 indicate the sample size is "*adequate*", "*middling*", and "*mediocre*", respectively [153]. KMO values less than 0.6 is considered inadequate for factor analysis, in which case, the sample size needs to be increased [153]. The measurement model is developed with the aim to test the following properties –

(a) **Overall reliability of the questionnaire**: Measured using the Cronbach's Alpha (α) (CA) test, where $\alpha > 0.7$ is recommended for acceptable reliability [73, 135].

(b) **Internal consistency of the constructs**: Generally measured using their respective Composite Reliability (CR) [73, 135, 137, 151, 154, 155], where the typical value of CR should be greater than 0.7 [73, 151]. However, CR$>$ 0.6 and CR$\leq$ 0.7 is also acceptable [135, 155].

(c) **Individual item reliability**: Measured using factor loadings (λ), where factors are defined as latent or unobserved variables that affect a particular construct [72, 73, 137, 151, 152, 155]. Only the factors whose eigenvalues are greater than 1 are considered for analysis [152, 153]. Although the typical value of λ should be greater than 0.7, values between 0.5 and 0.7 are also acceptable [72, 151].

(d) **Convergent Validity (CV) of a construct**: An indicator of high correlation between the items that are thought to be theoretically related. Alternatively, CV ensures that the items intended for measuring a construct are indeed measuring that construct. For ensuring CV of a construct, both CR and Average Variance Extracted (AVE) of that construct are considered. Previous studies suggest that CR>0.7 and AVE>0.5 combined, are indicators of good convergent validity [73, 153, 155–158]. However, if AVE<0.5, but CR>0.6, the CV of the construct is still considered to be adequate [155].

(e) **Discriminant Validity (DV) of a construct**: Ensures that the constructs that should not be related are, in fact, not related. In other words, DV is used to ensure that the items of a particular construct are not measuring a different construct [73, 151]. DV can be ensured if the squared root of AVE for a construct (usually placed on the diagonal of the construct correlation matrix) is greater than its correlation coefficients with other constructs [70, 135, 137, 151, 152, 155, 159]. This approach of testing DV is also known as the Fornell and Larcker criterion [159].

A summary of the constraints on different test parameters of the measurement model is given in **Table 4.21**.

4.5.1.2 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is used to examine the hypotheses, postulated earlier during the theoretical analysis of possible influence of one construct over another, relevant to the acceptance of a technology [70, 72–74, 135, 141, 150, 151]. For example, if we consider *two* constructs, $CONS_1$ and $CONS_2$, where $CONS_1$ is hypothesized to have an influence on $CONS_2$; the influence is represented with an arrow, termed as a *path*, from $CONS_1$ to $CONS_2$. The magnitude of the influence, otherwise known as path coefficient, is the standardized β coefficient, which is estimated using any one of the following methods – Partial Least Square (PLS) [73, 135], Maximum Likelihood [141, 151, 160], Unweighted Least Squares (ULS) [161–163], Generalized Least Squares (GLS) [162]. The statistical significance of the path coefficient (β) is determined using bootstrapping [137, 151, 164] or t-tests [135], most commonly at a significance level of 0.05, i.e., $p < 0.05$. Thus, from this explanation, the influence of $CONS_1$ on $CONS_2$ can be written as $CONS_2 = \beta \times CONS_1$, which implies that a 1 unit change in $CONS_1$ will have β units of change in $CONS_2$ and the change would be significant if $p < 0.05$ [72]. After investigating all the hypotheses in this manner, the results are combined to generate a path model as an outcome of SEM, which summarizes the following [73, 74, 135, 137, 139, 141, 147, 150–153, 160, 164, 165] –

(a) The paths that exist between constructs.

(b) The corresponding path-coefficients and their significance.

(c) The factor loadings of different items of each construct.

Although the path model gives an overview of the influences (*significant* or *insignificant*) of one construct over another, it is important to investigate the relative fit of the data to the model. For this purpose, many studies have recommended the following fit indices – the ratio of chi-square to degrees of freedom (χ^2/df), the Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Normed Fit Index (NFI), and Root-Mean-Square Error of Approximation (RMSEA) [72, 150, 152, 166, 167]. Detailed descriptions of these indices are beyond the scope of this study and the reader is requested to refer to prior studies [72, 150, 166, 168–176], from which the recommended values of these indices have been summarized in **Table 4.22**.

Table 4.21: Summary of the constraints on different test parameters of the measurement model.

Property	Metric(s)	Condition	Remark
Adequacy Testing of Sample Size for Factor Analysis	Bartlett's test of Sphericity [152, 153]	Large χ^2 value at $p < 0.05$	Inter-construct correlation matrix is not an identity matrix
	Kaiser-Meyer-Olkin (KMO) measure of sample size adequacy [152, 153]	$0.80 \leq KMO < 1.00$	Adequate
		$0.70 \leq KMO < 0.79$	Middling
		$0.60 \leq KMO < 0.69$	Mediocre
		$KMO < 0.60$	Inadequate
Reliability of the Questionnaire	Cronbach's Alpha (α) [73, 135]	$0.90 \leq \alpha$	Excellent
		$0.80 \leq \alpha < 0.90$	Good
		$0.70 \leq \alpha < 0.80$	Acceptable
		$0.60 \leq \alpha < 0.70$	Questionable
		$0.50 \leq \alpha < 0.60$	Poor
		$\alpha < 0.50$	Unacceptable
Internal Consistency of the Constructs	Composite Reliability (CR) [73, 135, 137, 151, 154, 155]	$CR \geq 0.70$	Good
		$0.60 \leq CR < 0.70$	Acceptable
Individual Item Reliability	Factor Loading (λ) [72, 73, 137, 151, 152, 155]	$\lambda \geq 0.70$	Good
		$0.50 \leq \lambda < 0.70$	Acceptable
Convergent Validity (CV)	CR, Average Variance Extracted (AVE) [73, 153, 155–158]	$CR \geq 0.70$ and $AVE \geq 0.50$	Good
		$CR > 0.60$ and $AVE < 0.50$	Acceptable
Discriminant Validity (DV)	Average Variance Extracted (AVE) [70, 73, 135, 137, 151, 152, 155]	AVE of each construct should be greater than its correlation coefficient with all other constructs	Good

Table 4.22: Recommended values of model fit indices in Structural Equation Modelling (SEM).

Fit Indices	Recommended Value
χ^2/df	$\leq$3.00
Goodness-of-Fit Index (GFI)	$\geq$0.90
Adjusted GFI (AGFI)	$\geq$0.80
Comparative Fit Index (CFI)	$\geq$0.90
Tucker-Lewis Index (TLI)	$\geq$0.90
Normed Fit Index (NFI)	$\geq$0.90
Root-Mean-Square Error of Approximation (RMSEA)	$\leq$0.08

4.5.2 Literature Review

Till date, several researchers have leveraged TAM for analyzing how the different psychological constructs, under the influence of external variables, affect user's acceptance of different technologies. In this section, however, considering the relevance to this study, we elaborate on studies related to TAM analysis of wearable technologies only.

In addition to the traditional components of TAM, Tsai et al. [73] conducted a study with 31 older patients with cardiovascular diseases and 81 older adults in general, to understand the behavioral effects of TA, Perceived Ubiquity (PUB), and Resistance to Change (RC), on the adoption of a wearable cardiac warming system in older adults. Their research findings state that TA has negative effects on PEU and PUB, while PUB affects both PU and PEU of cardiac warming system. On top of these, PU was found to have an indirect effect on BI through ATU. Felea et al. [135] analyzed the influence of factors, such as – Perceived Enjoyment (PE), defined as, "*the level to which using a specific technology or service is seen as enjoyable*", and Visual Attractiveness (VA), defined as, "*an aesthetic product design expressed through shapes, colors, and materials and user interfaces such as device menus and the mobile applications of wearable devices*", on the adoption of wearable technologies among 192 Romanian students using the TAM. Their analysis revealed that apart from the relation between the original constructs of the TAM, VA positively affects PE and ATU, while PE positively affects PU, ATU, and BI when it comes to adoption of wearable technologies. Ashfaq et al. [72] analyzed external factors, such as – Perceived Irreplaceability, Perceived Credibility, Compatibility, etc., that might influence elderly diabetic peoples' intention to continue using digital health wearables through a survey from 223 diabetic patients, aged 60 years and above. The findings of their study revealed that all the factors mentioned above, had positive influence on the intention to continue using digital health wearables. Lin et al. [70], have developed an instrumented wearable vest for monitoring the quality of posture among elderly people. They identified Technology Anxiety (TA) as a common psychological trait among elderly people when acceptance of new technology is of concern. About 50 elderly people were recruited for their study and leveraging TAM, they have analyzed the ATU and BI of their proposed technology under the influence of the psychological constructs – TA, PU, and PEU. Hong et al. [140], Chuah et al. [141] and Kim et al. [150], through a survey involving 276, 226 and 363 participants, respectively, utilized TAM to empirically identify potential external factors, such as – Visibility (VIS), Affective Quality (AQ), Relative Advantage (RA), Mobility (MB), Availability (AV), Subcultural Appeal (SA), Consumer Innovativeness (CI), etc. that might influence adoption of smartwatches. The results of these studies suggest that the variables AQ and RA influenced PU, while MB and AV influence PEU, and the variables, CI, SA and VIS, were found to be significant indicators of ATU and BI of smartwatch adoption. Lunney et al. [74] deployed the TAM for gaining insights into a user's perception of Wearable Fitness Technologies (WFT) and to analyze the relation between perceived health benefits and use of WFTs. From their analysis, it may be stated that WFTs that have enhanced PU and PEU, are more likely to instigate increased positive ATU and BI towards their adoption.

It is evident from the above discussion, while analyzing the factors that affect acceptance of a technology by a user base, the extended TAM, or in other words the TAM2 has been widely used by researchers, where the effect of various external variables on the generic constructs of TAM, such as – PU, PEU, ATU, and BI [53, 54, 69], have been analyzed. Motivated by prior studies, this research also aims to exploit the TAM2 for analyzing whether the proposed, wireless head-mounted Assistive Mouse Controller (AMC), will be an acceptable technology to the people with upper limb disabilities for human-computer interaction. In this regard, we elaborate on the constructs and the associated hypotheses in the following section.

4.5.3 Hypothesis Development and Conceptual Framework

In this section, in addition to the original psychological constructs of the TAM2 (PU, PEU, ATU, SN, and BI), we discuss some external constructs, such as – Personal Innovativeness (PI), Technology Anxiety (TA), and Perceived Behavioral Control (PBC), that may influence the acceptance of the proposed AMC technology by people with upper limb disability. Furthermore, we also state our hypotheses regarding how each of the constructs may influence other constructs, thereby, proposing our conceptual framework for validation.

4.5.3.1 Perceived Usefulness (PU)

Perceived Usefulness (PU) of a technology, according to the original proposal of TAM [53, 54] and TAM2 [69], is considered as the extent to which an individual believes it will enhance his/her performance. Given that an individual with upper limb disability is deprived of human-computer interaction, a wearable head-mounted Assistive Mouse Controller (AMC), facilitating such interaction, may improve their productivity, work-efficiency, etc., thereby, allowing them to realize its PU. The consequences of such realization may have a positive impact on their ATU and BI. TAM theorizes a direct positive effect of PU on the constructs ATU and BI [69].

Furthermore, prior studies have also analyzed similar influences in the adoption of wearable technologies, such as – smartwatches [140,141,150], wearable fitness technologies [72,74,145,159], wearable posture monitoring vest [70], wearable cardiac warming systems [73], etc. However, we have identified a gap in the literature regarding the analysis of how PU affects the ATU and BI of users with upper limb disability in the adoption of a wearable AMC, which leads to the postulation of the following hypotheses –

- **H1**: *Perceived Usefulness (PU) has a significant influence on the Attitude Towards Usage (ATU) of wearable Assistive Mouse Controllers (AMCs).*
- **H2**: *Perceived Usefulness (PU) has a significant influence on the Behavioral Intention (BI) of wearable Assistive Mouse Controllers (AMCs).*

4.5.3.2 Technology Anxiety (TA)

Technology Anxiety (TA) as proposed by Lin et al. [70] and Tsai et al. [73], is the perceived fear involved with any technology. It may analogously be termed as perceived risk. It is intuitive that any technology, whose adoption poses threat to its users, will make its usage difficult [73]. For the proposed wearable AMC technology, potential risks or anxiety factors could be the device ergonomics, complexity of interaction techniques, hygiene issues. Although overlooked most of the time, TA, if not taken into consideration, may have detrimental effects on users' PEU of a technology [70, 73]. Alternatively stating, increased TA will compromise the PEU of that technology, i.e., logically, TA should be negatively correlated with PU [70, 73]. Therefore, to investigate the nature of the relation of TA with PEU for the proposed wearable AMC, the following hypothesis is stated –

- **H3**: *Technology Anxiety (TA) has a significant negative influence on the Perceived Ease of Use (PEU) of wearable Assistive Mouse Controllers (AMCs).*

4.5.3.3 Subjective Norm (SN)

As mentioned earlier, Subjective Norm (SN) is the measure of a person's perception that his/her demonstration of a particular behavior is dependent on the approval of people who are important to him/her [69]. SN is considered to have a direct impact on the BI to accept a particular technology, which is rational, as sometimes people may exhibit certain behavioral traits under the influence of their peers even if that behavior is unfavorable for them, or they are unaware of the possible consequences. SN has been shown to have varying effects on different psychological constructs. For example, some have found SN to have positive influence on PU [147, 164], whereas some have found it to be insignificant [148, 177]. Davis et al. [54] reported an insignificant influence of SN on BI. Again, some studies suggest that SN is a determinant factor for user acceptance when it comes to computer radiography systems [148] and wearable fitness technologies [74]. However, to the best of our knowledge, the effect of SN on the acceptance of a wearable Assistive Mouse Controller (AMC) has not been studied before, and therefore, we state the following hypotheses –

- **H4**: *Subjective Norm (SN) has a significant influence on the Perceived Usefulness (PU) of wearable Assistive Mouse Controllers (AMCs).*
- **H5**: *Subjective Norm (SN) has a significant influence on the Perceived Ease of Use (PEU) of wearable Assistive Mouse Controllers (AMCs).*
- **H6**: *Subjective Norm (SN) has a significant influence on the Attitude Towards Usage (ATU) of wearable Assistive Mouse Controllers (AMCs).*
- **H7**: *Subjective Norm (SN) has a significant influence on the Behavioral Intention (BI) of adopting wearable Assistive Mouse Controllers (AMCs).*

4.5.3.4 Perceived Behavioral Control (PBC)

Perceived Behavioral Control (PBC) may be defined as, "*the confidence concerning someone's ability to perform a special activity that highly influences that person's behavior*" [53, 54, 69]. As reported by previous studies [142, 144, 146, 164], the confidence while performing any task may be considered as an important factor that may have a direct or indirect positive impact on the constructs of TAM in different contexts such as adoption of e-Government, learning with wearables, use of social media for innovation process, etc. However, to the best of our knowledge, there are insignificant references of PBC in the context of users' acceptability of wearable Assistive Mouse Controllers (AMCs). Therefore, we state the following hypotheses for investigating the influence of PBC in this regard –

- **H8**: *Perceived Behavioral Control (PBC) has a significant influence on the Attitude Towards Usage (ATU) of wearable Assistive Mouse Controllers (AMCs).*
- **H9**: *Perceived Behavioral Control (PBC) has a significant influence on the Behavioral Intention (BI) of adopting wearable Assistive Mouse Controllers (AMCs).*

4.5.3.5 Perceived Ease of Use (PEU)

Intuitively, any technology or system that is easy to interact with, motivates an individual to adopt it for further use [54]. In other words, for any technology, the psychological construct Perceived Ease of Use (PEU) has an intrinsic positive effect on the PU and ATU of that technology [53, 54, 69, 70]. In case of wearable interacting devices, ergonomics, simple interaction techniques, etc., play a vital role [19, 38, 52, 141]. The proposed Assistive Mouse Controller (AMC) incorporates minimal head rotations for mouse cursor movement and cheek muscle twitches for mouse click actuation, which are intuitive and easy-to-understand interacting mechanisms. Furthermore, an easy-to-use technology, will have greater influence on the confidence of using that technology, in other words, the associated PBC [142]. Therefore, according to TAM, there should be a significant positive influence of PEU on PU, PBC and ATU, to verify which, the following hypothesis have been postulated –

- **H10**: *Perceived Ease of Use (PEU) has a significant influence on the Perceived Usefulness (PU) of wearable Assistive Mouse Controllers (AMCs).*

- **H11**: *Perceived Ease of Use (PEU) has a significant influence on the Perceived Behavioral Control (PBC) while using wearable Assistive Mouse Controllers (AMCs).*

- **H12**: *Perceived Ease of Use (PEU) has a significant influence on the Attitude Towards Usage (ATU) of wearable Assistive Mouse Controllers (AMCs).*

4.5.3.6 Personal Innovativeness (PI)

From the perspective of technology acceptance, Personal Innovativeness (PI) may be defined as, "*the presence of characteristics, such as – willingness, curiosity, search for novelty, creativity, etc. in an individual for adopting a technology*" [136, 145, 159]. Highly innovative individuals tend to be confident, enthusiastic, and therefore, require shorter time to accept a particular technology [136, 137, 178]. Such individuals can realize the potential advantages or the PU of adopting a novel technology, earlier than others, and therefore, gradually develop a sense of increased positive ATU [137, 145, 147, 159]. This increase in ATU may have a consequent positive impact on their BI to accept that technology [145]. Although researchers [179, 180] have assumed PI to be a potential factor that governs users' acceptance of a novel technology under specific circumstances, the conclusions of these works suggest that such effect of PI on different psychological constructs of the TAM in different contexts, requires further investigation.

In the context of this study, the proposed wireless head-mounted AMC may be considered as a technological innovation for people with upper limb disability. Although there have been significant works regarding the influence of PI on the psychological constructs – PU, ATU, and BI, while adopting technologies, such as – fitness wearables [136, 145, 159], smartwatches [140], smart meter systems [137], etc., to the best of our knowledge, the references of studies that summarize the same, when it comes to the adoption of wearable AMCs, are insignificant. Thus, there is a scope of analyzing whether the influence of PI on the adoption of the proposed wearable AMCs is significantly positive, which leads to the postulation of the following hypotheses –

- **H13**: *Personal Innovativeness (PI) has a significant influence on the Perceived Usefulness (PU) of wearable Assistive Mouse Controllers (AMCs).*
- **H14**: *Personal Innovativeness (PI) has a significant influence on the Perceived Ease of Use (PEU) of wearable Assistive Mouse Controllers (AMCs).*
- **H15**: *Personal Innovativeness (PI) has a significant influence on the Perceived Behavioral Control (PBC) while using wearable Assistive Mouse Controllers (AMCs).*
- **H16**: *Personal Innovativeness (PI) has a significant influence on the Attitude Towards Usage (ATU) of wearable Assistive Mouse Controllers (AMCs).*
- **H17**: *Personal Innovativeness (PI) has a significant influence on the Behavioral Intention (BI) of adopting wearable Assistive Mouse Controllers (AMCs).*

4.5.3.7 Attitude Towards Usage (ATU)

Attitude Towards Usage (ATU), defined as the positive or the negative feeling that an individual possesses while performing a certain behavior [144], is characterized by the constructs PU, PEU, PBC, PI, and SN. The need for analyzing users' ATU of an Assistive Mouse Controller (AMC), which consequently affects their BI of adopting the technology, is significant. Some evidence of the influence of positive ATU on users' BI to adopt different technologies exist in the literature [54, 69, 70, 136, 141, 144, 150]. However, to the best of our knowledge, analysis of the influence of ATU on the acceptance of wearable AMC have not been explored. Therefore, with the intention to explore such influence using our proposed wearable AMC, we postulate the following hypothesis –

- **H18**: *Attitude Towards Usage (ATU) has a significant influence on the Behavioral Intention (BI) of adopting wearable Assistive Mouse Controllers (AMCs).*

4.5.3.8 Behavioral Intention (BI)

The ultimate objective of the Technology Acceptance Model (TAM) is to identify potential factors that affect the users' intention or willingness to accept a particular technology. The constructs, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Subjective Norm (SN), Personal Innovativeness (PI), Technology Anxiety (TA), Perceived Behavioral Control (PBC), and Attitude Towards Usage (ATU), as described earlier, are considered as the antecedents of Behavioral Intention (BI), whereas BI is considered as the antecedent of actual system or technology usage [53, 54, 69]. In other words, all the psychological constructs of TAM converge on users' BI, identifying the dependencies of the constructs in the process.

4.5.3.9 Research Model

Eighteen hypotheses (**H1-H18**), as presented in **section 4.5.3, "*Hypothesis Development and Conceptual Framework*"**, have been postulated for verifying the relationship among *eight* psychological constructs of the Technology Acceptance Model 2 (TAM2), such as – Perceived Usefulness (PU), Perceived Ease of Use (PEU), Subjective Norm (SN), Personal Innovativeness (PI), Technology Anxiety (TA), Perceived Behavioral Control (PBC), Attitude Towards Usage (ATU), and Behavioral Intention (BI), concerning the acceptance of the proposed Assistive Mouse Controller (AMC). Based on the description of these constructs and the postulated hypotheses, a TAM2-based research model, specific to the adoption of the proposed AMC, is presented in **Fig. 4.23**. The validity of these hypotheses will be analyzed next, to identify the factors that are significant in determining users' acceptability in the context of this study.

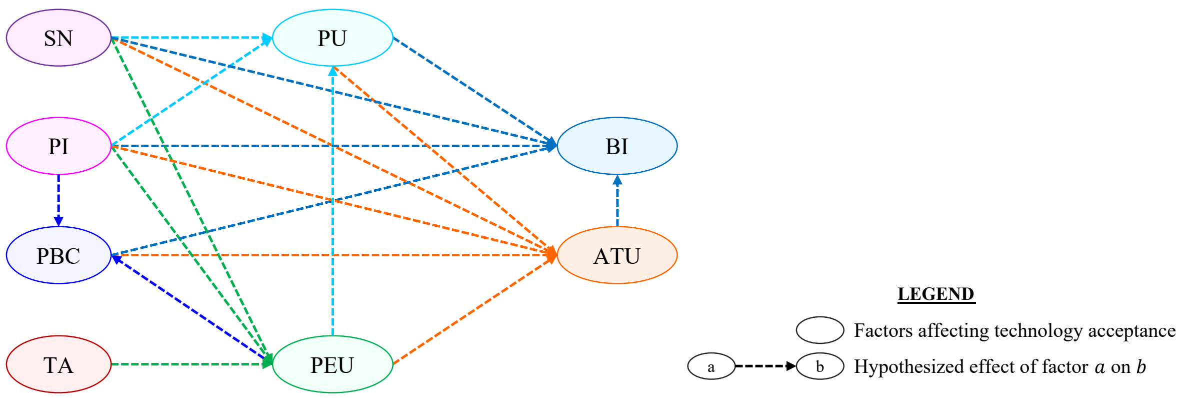


Figure 4.23: Modified Technology Acceptance Model (TAM) of the proposed Assistive Mouse Controller (AMC). **PU**: Perceived Usefulness, **PEU**: Perceived Ease of Use, **SN**: Subjective Norm, **PI**: Personal Innovativeness, **TA**: Technology Anxiety, **PBC**: Perceived Behavioral Control, **ATU**: Attitude Towards Usage, and **BI**: Behavioral Intention.

4.5.4 Methodology

4.5.4.1 Participants

The target respondents of this survey were individuals who possess basic computing knowledge and have any form of upper limb disability. The survey was conducted online, and the corresponding questionnaire was circulated among the respondents via email or social networking sites. All the 15 participants from the previous experiments responded to the survey. However, only 15 responses were insufficient for analyzing user acceptance using TAM. Furthermore, due to the outbreak of COVID-19 at the time of this analysis and impending deadlines, it was not possible to physically recruit more participants to ensure first-hand interaction with the AMC. Therefore, as an alternative, a comprehensive explanation of the purpose of this study and the different aspects of the AMC along with a video demonstration of interaction was accommodated in the questionnaire. As a result, more participants were recruited online from known acquaintances, local rehabilitation centers, and local NGOs. Along with the 15 individuals from prior experiments, a total of 150 individuals with upper limb disability responded to the survey, among which 107 were Male (71.33%, Mean Age: 33.13 ± 5.38 years) and 43 were Female (28.67%, Mean Age: 34.49 ± 4.12 years). The age distribution of the respondents is depicted in **Fig. 4.24**.

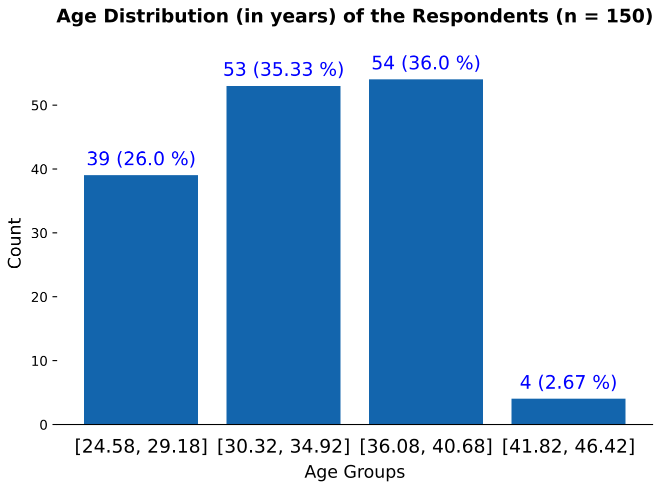


Figure 4.24: Age distribution of the 150 respondents, who participated in the survey.

4.5.4.2 Experimental Design

The survey questionnaire developed for this study consisted of *eleven* sections, where *eight* sections addressed items corresponding to the different psychological constructs of the proposed research model, as shown in **Fig. 4.23**, such as – Perceived Usefulness (PU), Perceived Ease of Use (PEU), Subjective Norm (SN), Personal Innovativeness (PI), Technology Anxiety (TA), Perceived Behavioral Control (PBC), Attitude Towards Usage (ATU), and Behavioral Intention (BI). *Two* of the remaining *three* sections were developed for presenting a brief description on the prospects of the proposed Assistive Mouse Controller (AMC) and for collecting demographic data (*name, age*, and *gender*) of the respondents. However, as mentioned earlier, due to the outbreak of COVID-19 at the time of this analysis and impending deadlines, it was not possible to ensure first-hand interaction with the AMC for all the respondents of this survey. Therefore, a short video was incorporated in the remaining one section to demonstrate the interaction with the proposed AMC by real-life upper limb disabled people, facilitating a comprehensive description of the AMC. The organization of the 11 sections of the questionnaire is depicted in **Fig. 4.25**.

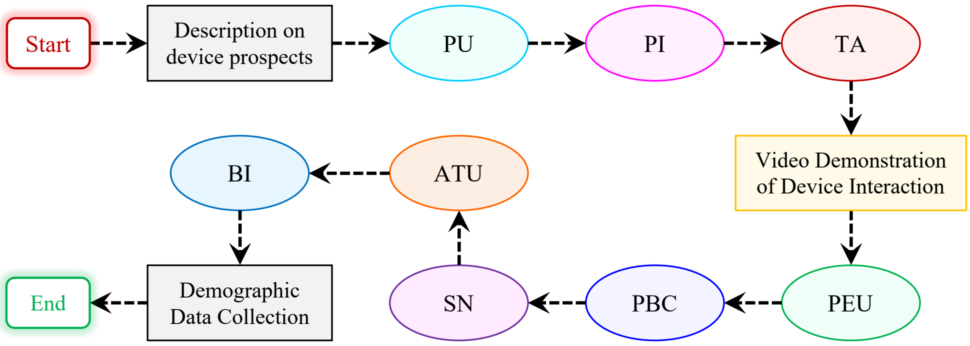


Figure 4.25: Organization of the Technology Acceptance Model (TAM) questionnaire session of the proposed Assistive Mouse Controller (AMC). **PU**: Perceived Usefulness, **PEU**: Perceived Ease of Use, **SN**: Subjective Norm, **PI**: Personal Innovativeness, **TA**: Technology Anxiety, **PBC**: Perceived Behavioral Control, **ATU**: Attitude Towards Usage, and **BI**: Behavioral Intention.

It is to be noted from this organization that the response to the items of the factors PU, PI, and TA are recorded, before the video demonstration of device interaction and after the device description, and that of the factors PEU, PBC, SN, ATU, and BI, after the video demonstration. Such organization of the questionnaire was made with the following objectives in mind –

(a) To record their PI that might affect their ATU later on and to capture their initial thoughts on the factors, PU and TA, from the device description.

(b) Since, first-hand interaction with the proposed AMC could not be accommodated, it was necessary that they had a clear understanding of the working mechanism of the AMC for analyzing their acceptance of the technology using the TAM. In connection to this, the video demonstration of device interaction will assist them with the factors, PEU, PBC, and SN, which in the end, would be reflected on their ATU and BI of accepting the proposed AMC that facilitates human-computer interaction for the people with upper limb disability.

In the context of this study, a total of 28 items were considered from prior studies for developing the construct measures, where few items were adopted directly, some were adapted to suit the context of this study, while some were newly developed specifically for this study. As pointed out by Jonald L. Pimentel [149], Likert scales essentially quantifies bipolar opinions (*positive* or *negative*) about a particular statement. However, the responses may be biased due to several reasons, e.g., respondents' tendency to avoid extreme opinions (*central tendency bias*) [149]. To remove this type of bias, Likert scale items with even number of options (4-point or 6-point), or in other words, items with no choice of *neutrality* are generally suggested for greater reliability of the responses [149,181–183]. In connection to this, a 4-point Likert scale was used to quantify the responses to the psychological constructs of the proposed research model, where the Likert scale representations were as follows – 1 – *Strongly Disagree*, 2 – *Disagree*, 3 – *Agree*, and 4 – *Strongly Agree*. The items corresponding to different psychological constructs considered for this study, with references to prior studies, from which they were either *adopted*, *adapted*, or *newly developed*, are summarized in **Table 4.23**.

Before the questionnaire could be deployed for online data collection, it was evaluated by a panel of 10 reviewers, having experience with wearable technologies and no upper limb disability. They were first briefed online about the purpose of this study and the survey, followed by scrutinization of the understandability and ambiguity of the measurement items. They agreed with the organization of the sections in the questionnaire and pointed out some minor formatting issues about some items, which were then rephrased, and the questionnaire was deemed suitable for data collection.

Table 4.23: Measures of the constructs of Technology Acceptance Model (TAM).

Psychological Construct	Items	Descriptions
Perceived Usefulness (PU) [54, 69, 73, 135, 141, 144, 146–148, 150, 151, 164]	PU1	The ability to interact with a computer will improve work efficiency.[b]
	PU2	The ability to interact with a computer will improve productivity.[b]
	PU3	The ability to interact with a computer will make life more convenient.[b]
Technology Anxiety (TA) [73]	TA1	I initially thought that the device would be uncomfortable as a wearable technology.[c]
	TA2	I initially thought that the device would be difficult to wear.[c]
	TA3	I initially thought that the device would not be adjustable to fit my head size.[c]
	TA4	I initially thought that the device would pose ergonomic issues.[c]
	TA5	I initially thought that the device would be costly.[b]
Subjective Norm (SN) [69, 137, 144, 146–148]	SN1	People who are important to me think that I should use the device.[a]
	SN2	People who influence my behavior think that I should use the device.[a]
Perceived Behavioral Control (PBC) [144, 146, 148]	PBC1	I am confident that I can easily interact with a computer using this device.[a]
	PBC2	I am confident that I can control my interaction with a computer using this device.[a]
Perceived Ease of Use (PEU) [54, 69, 73, 141, 144, 146–148, 150, 151]	PEU1	The device is easy to put on and off.[c]
	PEU2	The interaction mechanism of the device is adequate and easy.[b]
	PEU3	The device requires very less physical and mental effort to use.[b]
	PEU4	Overall, the device is easy-to-use.[a]
Personal Innovativeness (PI) [137, 138, 140, 145–147]	PI1	If I heard about a new interaction device, I would look for ways to experiment with it.[b]
	PI2	I like to experiment with the interaction devices that make my life easier.[b]
	PI3	I like to experiment with the devices that make my computer interaction interesting.[b]
Attitude Towards Usage (ATU) [73, 135, 141, 144, 146, 150]	ATU1	I think positively about the device when it comes to the possibility of improving Health Related Quality of Life (HRQoL).[c]
	ATU2	I think positively about the device when it comes to the possibility of facilitating employment opportunities.[c]
	ATU3	I think positively about the device when it comes to the possibility of facilitating economically independence.[c]
	ATU4	I think positively about the device when it comes to the possibility of facilitating innovation process.[c]
	ATU5	I think that the ability to interact with a computer, like a healthy person, will have a positive effect on mental wellbeing.[c]
	ATU6	Overall, I have a positive attitude towards the usage of this device.[a]
Behavioral Intention (BI) [73, 135, 137, 141, 144–146, 148, 150, 159]	BI1	I intend to use this device in the future.[a]
	BI2	I intend to use this device for performing basic computational tasks.[c]
	BI3	I intend to use this device for being self-reliant.[c]

[a] Items that were ***adopted*** from prior studies.

[a] Items that were ***adapted*** from prior studies.

[c] Items that were ***newly developed***, specifically for this study.

4.5.4.3 Data Processing

In this study, data analysis was done in *python*, leveraging the python library "*semopy*" for SEM [184]. Prior to conducting Confirmatory Factor Analysis (CFA) for assessing the reliability and the validity of the corresponding measurement model, an adequacy test was performed to verify whether the sample size ($n = 150$) is suitable for CFA. Both Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy [152,153] were used for this purpose. Structural Equation Modeling (SEM) was then performed using the General Least Square (GLS) method [162,184] for testing and validating the hypotheses (**H1-H18**) and generating the final path model. The "*semopy*" library, that was used for SEM, utilizes Z-test to calculate p-values [184]. Therefore, a hypothesis was *accepted*, if the z-value was either < -1.96 or > 1.96 and the p-value was less than 0.05, otherwise, it was *rejected*. The R^2-values were used to quantify the percentage of variance explained by the predictor variables in the proposed research model. In connection to these analyses, a path model was generated, summarizing the results of SEM. Finally, the relative fit of the data to the model was analyzed using the different fit indices (e.g., χ^2/df, GFI, AGFI, CFI, TLI, NFI, RMSEA) [72, 150, 152, 166, 167], mentioned earlier.

4.5.5 Results

4.5.5.1 Sample Adequacy Test and Assessment of the Measurement Model

The adequacy test of the sample considered for this study, was conducted using both Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy [152, 153]. The sphericity test ($\chi^2 = 2016.17, p < 0.001$) indicated that the inter-construct correlation matrix was not an identity matrix, which is also evident from **Table 4.26**. The KMO value for the sample ($KMO = 0.8057$) indicated that the sample size was "*Adequate*" for Confirmatory Factor Analysis (CFA). A summary of the sample adequacy test results is given in **Table 4.24**.

Table 4.24: Summary of the sample adequacy testing for Confirmatory Factor Analysis (CFA).

Test	Recommended Value	Sample Adequacy Test Value	Remark
Bartlett's test of sphericity [152, 153]	Large χ^2value at p <0.05	χ^2 =2016.17, p <0.001	Inter-construct correlation matrix is not an identity matrix.
Kaiser-Meyer-Olkin (KMO) measure of sample size adequacy [152, 153]	Adequate ($0.80 \leq$ KMO < 1.00) Middling ($0.70 \leq$ KMO < 0.79) Mediocre ($0.60 \leq$ KMO < 0.69) Inadequate (KMO < 0.60)	0.8057	Adequate

The results of the measurement model, obtained using CFA, as shown in **Table 4.25**, indicated that the measurement items demonstrated strong psychometric properties. The internal reliability of the items in each of the psychological constructs, measured using Cronbach's Alpha (CA) [73, 135], ranged between 0.7248 and 0.8969 and the overall reliability of the questionnaire was found to be 0.8801, which indicates "*Good*" reliability. In simple terms, the items could quantify the constructs accurately. The internal consistency of all the psychological constructs except for Perceived Behavioral Control (PBC), measured using Composite Reliability (CR) [73, 135, 137, 151, 154, 155], ranged between 0.7293 and 0.8224, which is indicative of "*Good*" internal consistency. The value of CR for the construct PBC was found to be 0.6821, which is also acceptable [135, 155]. The factor loadings (λ), as a measure of individual item reliability, were obtained using Principal Component Analysis (PCA) method with "*varimax*" rotation [151, 153]. The values of λ for 50% of the items ranged between 0.5 and 0.7, while the rest were above 0.7, both of which are permissible [72, 73, 137, 151, 152, 155]. In connection with these results, the reliability of the constructs can be ascertained.

The validity of the measurement model was tested using Convergent Validity (CV) and Discriminant Validity (DV). For ensuring CV of the measurement model, both CR and Average Variance Extracted (AVE) were considered [73, 153, 155–158]. *Five* out of the *eight* constructs (PU, TA, PBC, PEU, and ATU), considered in this study exhibited "*Acceptable*" CV with AVE ranging between 0.4384 and 0.5181, and CR ranging between 0.6821 and 0.8224. The remaining three constructs (SN, PI, and BI) had AVE ranging between 0.5110 and 0.6690, and CR ranging between 0.7575 and 0.8109, suggesting "*Good*" CV. Overall, the model had satisfactory convergent validity.

Table 4.25: Reliability and Convergent Validity (CV) of the measurement model of users' acceptance of the proposed Assistive Mouse Controller (AMC) ($n = 150$).

Psychological Construct	**Items**	**Reliability**		**Individual Item Reliability**	**Internal Consistency and Convergent Validity (CV)**		
		Cronbach's Alpha (CA)	*Remark on Reliability*	*Factor Loading (λ)*	*Composite Reliability (CR)*	*Average Variance Extracted (AVE)*	*Remark on CV*
Perceived Usefulness (PU)	PU1 PU2 PU3	0.7248	Acceptable	0.7924 0.7170 0.5428	0.7293	0.4789	Acceptable
Technology Anxiety (TA)	TA1 TA2 TA3 TA4 TA5	0.7423	Acceptable	0.6373 0.6792 0.7141 0.7202 0.8073	0.8192	0.4759	Acceptable
Subjective Norm (SN)	SN1 SN2	0.8969	Good	0.8284 0.8073	0.8016	0.6690	Good
Perceived Behavioral Control (PBC)	PBC1 PBC2	0.7379	Acceptable	0.7532 0.6848	0.6821	0.5181	Acceptable
Perceived Ease of Use (PEU)	PEU1 PEU2 PEU3 PEU4	0.7903	Acceptable	0.7876 0.6269 0.6654 0.6980	0.7896	0.4858	Acceptable
Personal Innovativeness (PI)	PI1 PI2 PI3	0.7602	Acceptable	0.7859 0.7992 0.7145	0.8109	0.5890	Good
Attitude Towards Usage (ATU)	ATU1 ATU2 ATU3 ATU4 ATU5 ATU6	0.8375	Good	0.5126 0.7233 0.7110 0.6519 0.6883 0.6636	0.8224	0.4384	Acceptable
Behavioral Intention (BI)	BI1 BI2 BI3	0.8396	Good	0.6776 0.6861 0.7767	0.7575	0.5110	Good
	Overall Reliability	0.8801	Good		Overall Convergent Validity		Satisfactory

The Discriminant Validity (DV) of the constructs were evaluated using the Fornell and Larcker criterion [159], where DV is ensured if the squared root of AVE of each of the constructs, usually placed on the diagonal of the correlation matrix, is greater than the corresponding inter-construct correlations. The DV of the constructs of this study along with the Mean and the Standard Deviation (SD) are summarized in **Table 4.26**. It can be seen from this table that for each of the constructs, the corresponding squared root of AVE is greater than all the corresponding inter-construct correlations, fulfilling the Fornell and Larcker criterion in the process. Therefore, it can be stated that the model demonstrates discriminant validity.

Table 4.26: The Mean, Standard Deviation (SD) and Discriminant Validity (DV) of the measurement model on users' acceptance of the proposed Assistive Mouse Controller (AMC) ($n = 150$).

	Mean	SD	PU	TA	SN	PBC	PEU	PI	ATU	BI	Remark on DV
PU	3.63	0.55	**0.6920** [a]	-	-	-	-	-	-	-	Good
TA	2.85	0.88	0.1680	**0.6899** [a]	-	-	-	-	-	-	Good
SN	3.22	0.87	0.3990	0.1550	**0.8179** [a]	-	-	-	-	-	Good
PBC	3.57	0.59	0.3515	0.0246	0.2396	**0.7198** [a]	-	-	-	-	Good
PEU	3.27	0.70	0.4282	-0.0700	0.3005	0.4965	**0.6970** [a]	-	-	-	Good
PI	3.63	0.60	0.3455	0.0649	0.2655	0.2886	0.1045	**0.7675** [a]	-	-	Good
ATU	3.60	0.56	0.5614	0.1398	0.4418	0.4981	0.4944	0.3504	**0.6621** [a]	-	Good
BI	3.50	0.72	0.4560	0.1652	0.6435	0.4233	0.3255	0.3013	0.5581	**0.7148** [a]	Good

[a] Squared root of the Average Variance Extracted (AVE); values below the diagonal are inter-construct correlations.

4.5.5.2 Structural Equation Modeling (SEM) and Hypothesis Testing

In this study, Structural Equation Modelling (SEM) was used for hypothesis testing, following the General Least Square (GLS) method [162,184]. As mentioned earlier, hypothesis testing was conducted using Z-test to calculate p-values at a significance level of 0.05. From the results of the analysis, it was observed that 13 (72.22%) of the 18 hypotheses were supported. The strength of significance of a factor on another was determined from the corresponding standardized β coefficient. Considering the case of BI, the factor SN ($\beta = 0.4847, p =< 0.0001$) had the strongest positive influence, followed by ATU ($\beta = 0.2026, p = 0.0075$) and PBC ($\beta = 0.1705, p = 0.0083$), and therefore, the hypotheses **H7**, **H18**, and **H9** were supported, respectively. These findings are consistent with prior studies related to technology adoption [73, 135, 138, 142, 144, 145]. Therefore, it can be inferred that among all the factors influencing BI, a change of 1 unit of social influence on a disabled person will dictate their intention to adopt the proposed AMC by 0.4847 units. Although prior studies have reported PU to have a direct significant effect on BI, the same was not observed for PU ($\beta = 0.0658, p = 0.3423$) in the context of this study, and therefore **H2** was not supported. However, this is consistent as well, since prior studies have reported similar occurrences [73]. Among the antecedents of ATU, it was observed that PU had the strongest, significant positive influence ($\beta = 0.2554, p = 0.0004$), followed by PBC ($\beta = 0.2188, p = 0.0020$), PEU ($\beta = 0.2111, p = 0.0046$), and SN ($\beta = 0.1949, p = 0.0031$), supporting **H1**, **H8**, **H12**, and **H6** in the process, respectively. As expected, all the constructs, PEU ($\beta = 0.3434, p =< 0.0001$), PI ($\beta = 0.2562, p = 0.0002$), and SN ($\beta = 0.2320, p = 0.0013$), were found to have significant positive influence on PU, which supported the hypotheses, **H10**, **H4**, and **H13**. In the context of this study. Although insignificant, Technology Anxiety (TA) was found to affect PEU ($\beta = -0.1217, p = 0.1193$) negatively, which is consistent with the results of prior studies [70, 73] and the influence of PI ($\beta = 0.0295, p = 0.7126$) on PEU was positive but insignificant, and therefore, **H3** and **H14** were not supported, respectively. Only the psychological construct SN ($\beta = 0.3129, p = 0.0001$) had significant positive impact on PEU, and therefore, **H5** was supported. Interestingly, both PEU ($\beta = 0.4766, p =< 0.0001$) and PI ($\beta = 0.2405, p = 0.0004$) had significant influence on PBC, which indicates that the confidence of interacting with the AMC will be significantly driven by its ease-of-use and the level of innovativeness of the corresponding user. Prior studies also have reported PEU as a significant predictor of PBC [142], when technology acceptance is of concern. A summary of the hypothesis test results is provided in **Table 4.27** and the TAM path model of the proposed research model using SEM analysis is given in **Fig. 4.26**.

Table 4.27: Summary of hypothesis test results using Structural Equation Modeling (SEM) ($n = 150$).

Influencing Construct	Hypothesis	Path[a]	Standardized β co-efficient	Standard Error	z-value[a]	p-value[a]	Support[a]
PU	H1	PU→ATU	0.2554	0.0725	3.5382	0.004	Yes
	H2	PU→BI	-0.0658	0.0697	0.9497	0.3423	No
TA	H3	TA→PEU	-0.1217	0.0780	-1.5577	0.1193	No
SN	H4	SN→PU	0.2320	0.0704	3.2200	0.0013	Yes
	H5	SN→PEU	0.3129	0.0807	3.8678	0.0001	Yes
	H6	SN→ATU	0.1949	0.0646	2.9600	0.0031	Yes
	H7	SN→BI	0.4847	0.0632	7.5402	<0.0001	Yes
PBC	H8	PBC→ATU	0.2188	0.0699	3.0913	0.0020	Yes
	H9	PBC→BI	0.1705	0.0638	2.6417	0.0083	Yes
PEU	H10	PEU→PU	0.3434	0.0684	4.9161	<0.0001	Yes
	H11	PEU→PBC	0.4766	0.0679	6.9835	<0.0001	Yes
	H12	PEU→ATU	0.2111	0.0733	2.8306	0.0046	Yes
PI	H13	PI→PU	0.2562	0.0675	3.7101	0.0002	Yes
	H14	PI→PEU	0.0295	0.0799	0.3683	0.7126	No
	H15	PI→PBC	0.2405	0.0678	3.5241	0.0004	Yes
	H16	PI→ATU	0.1293	0.0648	1.9578	0.0502	No
	H17	PI→BI	0.0326	0.0611	0.5249	0.5997	No
ATU	H18	ATU→BI	0.2026	0.0759	2.6737	0.0075	Yes
						Total hypotheses	18
						Number of hypotheses supported	13 (72.22%)
						Number of hypotheses not supported	5 (27.78%)

[a]A path was considered significant if z-value was either $<$ -1.96 or $>$ 1.96 and p-value was less than 0.05.

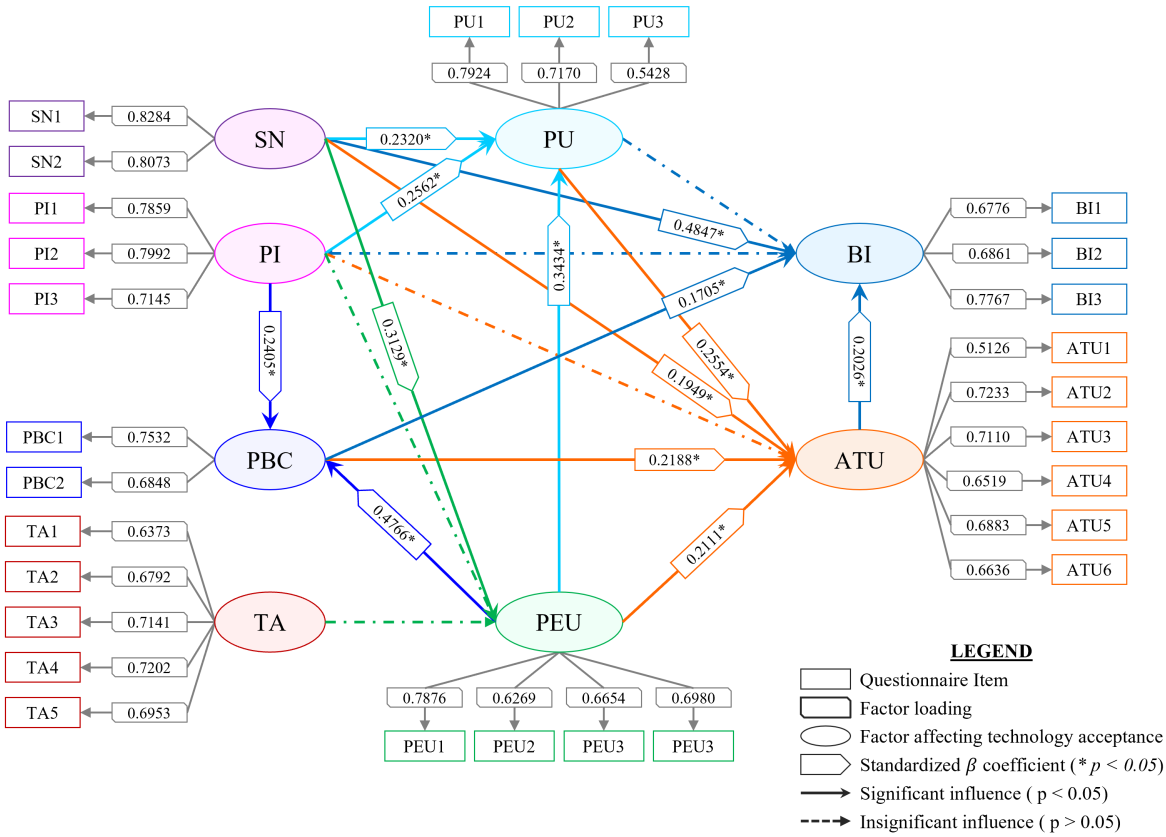


Figure 4.26: Final Technology Acceptance Model (TAM) of the proposed Assistive Mouse Controller (AMC) using Structural Equation Modelling (SEM), showing standardized β-coefficients of the significant influences only.

After the hypotheses were tested, the explanatory power of the research model was assessed using the R^2-values of regression analysis. Prior studies have stated that R^2-values greater than $0.67, 0.33$, and 0.19 can be termed, "*substantial*", "*moderate*", and "*weak*", respectively [135]. It was found that the proposed model explained about 49.02% of the variation in users' Attitude Towards Usage (ATU) and 53.71% of the variation in their Behavioral Intention (BI) to accept the proposed Assistive Mouse Controller (AMC) for human-computer interaction. The corresponding R^2-values, along with the F-statistics and the corresponding p-value of the other constructs, ATU, PU, PEU, and PBC are reported in **Table 4.28** as well. It can be observed from this table that all the predictions were significant at $p \leq 0.001$. Furthermore, the constructs TA, SN, and PI altogether, explained about 10.50% of the variation in PEU, with SN being a significant predictor. Although the R^2-value of PEU was very low compared to the other constructs, it was statistically significant at $p = 0.001$ and exceeded the recommended benchmark, which requires R^2 being greater than 0.10 [140, 159]. Moreover, it can be observed from **Table 4.28** that the R^2 values exhibited an increasing trend as the model proceeds towards determining BI of accepting the proposed AMC, which indicated that the predictors of the research model were adequate in the context of this study. In connection to this, it can be established that the model explained an acceptable variation in the predicted constructs, such as – BI, ATU, PU, PEU, and PBC. Furthermore, the relative fit of the structural model was analyzed using various fit indices (e.g., χ^2/df, GFI, AGFI, CFI, TLI, NFI, RMSEA), as shown in **Table 4.29**. It is evident from this table that the values of all the indices were consistent with their recommended threshold values, suggesting a good model fit.

Table 4.28: Summary of R^2 statistic of the psychological constructs.

Predicted Construct	Predictor Constructs	R^2-Value	F-stat	p-value
BI	**ATU** [a], PU, **PBC** [a], **SN** [a], PI	0.5371	33.4171	<0.0001
ATU	**PU** [a], **PEU** [a], **PBC** [a], **SN** [a], PI	0.4902	27.6876	<0.0001
PU	**PEU** [a], **SN** [a], **PI** [a]	0.3212	23.0332	<0.0001
PBC	**PEU** [a], **PI** [a]	0.3031	31.9698	<0.0001
PEU	TA, **SN** [a], PI	0.1050	5.7121	0.0010

[a] Significant predictors at $p < 0.05$.

Table 4.29: Structural model fit analysis ($n = 150$).

Fit Indices	Recommended Value	Research Model	Remark
χ^2/df	$\leq$3.00	1.1987	Good Fit
Goodness-of-Fit Index (GFI)	$\geq$0.90	0.9610	Good Fit
Adjusted GFI (AGFI)	$\geq$0.80	0.9070	Good Fit
Comparative Fit Index (CFI)	$\geq$0.90	0.9930	Good Fit
Tucker-Lewis Index (TLI)	$\geq$0.90	0.9833	Good Fit
Normed Fit Index (NFI)	$\geq$0.90	0.9610	Good Fit
Root-Mean-Square Error of Approximation (RMSEA)	$\leq$0.08	0.0365	Good Fit

4.5.6 Discussion

The main motivation behind this study was to investigate the key factors and their relationship, significant or otherwise, that might influence the acceptance of the proposed wireless head-mounted Assistive Mouse Controller (AMC) by people with upper limb disability for interaction with a computer. In connection to this, different psychological constructs were considered, some of which (e.g., *perceived usefulness*, *perceived ease-of-use*, *attitude towards usage*, and *behavioral intention*) were consistent with the original framework of TAM [53, 54, 69], while the rest (e.g., *technology anxiety*, *perceived behavioral control*, *subjective norm*, and *personal innovativeness*), were adapted from prior studies [70, 72–74, 136–147]. However, few of the studies were related to the acceptance of wearable technologies in general and not specific to the context of this study. Thus, considering eight psychological constructs, we have analyzed the acceptance of the proposed AMC using the Technology Acceptance Model (TAM) and developed a path model that describes the significance of influence of one or more constructs, directly or indirectly, on another.

From the results of this investigation, it was found that the constructs PU and PEU had significant positive influence on the construct ATU. However, few prior studies [74, 141, 159] have reported only the significant influence of PU on ATU, some have reported the significant influences of both PU and SN [146], or only SN [143], while others [70,73,135,142,144,150] have found both PU and PEU to have significant influences on ATU. Again, evidence of insignificant influence of the constructs PBC and PI on ATU can also be found in the literature [146]. However, in the context of this investigation, the constructs PU, PEU, PBC and SN were found to have significantly influenced users' ATU, as evident from the path model of this research in **Figure 28**.

Again, some studies have analyzed the effects of both PU and PEU on BI and found them to be significant [72, 160], while some have considered the effect of only PEU [147] or only PU [135,144] and found it to be significant. Meanwhile, insignificant influence of PU on BI has also been reported in some cases [73,141,150]. Furthermore, for the effect of the constructs PBC, SN, and PI on BI, some studies have considered only PBC [142], or only SN [72, 74, 138, 144], or all three [145] and reported significant influence. In this investigation, however, the effects of ATU, PU, PI, SN, and PBC on BI were considered, where PU and PI had insignificant influences, ATU, SN, and PBC had significant influences, and the effect of PEU on BI was not even considered in the proposed research model, as shown in **Figure 28**.

In line with previous studies [142, 144], the path model of this study suggests a significant influence of PEU on PU and considering the constructs PI and SN, both were found to be significant predictors of PEU and PU, as previously reported by Lu. et al. [147]. Although the construct TA should logically have a significant negative influence on PEU, controversies exist in the literature. For example, Lin et al. [70] found the effect of TA on PEU to be significant, while Tsai et al. [73] found it to be significant in some cases and insignificant in the other.

In some cases, researchers have alternatively termed the construct Perceived Behavioral Control (PBC) as Performance Expectancy [45]. Prior studies [142,145] have reported PEU and PI to have significant effects on PBC, which also is the case for this investigation in particular.

To summarize, the findings of this study suggest that for the proposed AMC, in addition to perceived usefulness, ease-of-use, and positive social influence, a high level of confidence owing to easier working mechanism of the device and highly innovative personality significantly influences positive attitude towards using the device. Among the psychological constructs, attitude, usefulness, ease-of-use, confidence, and subjective norm, the most influential construct that determined users' intention to accept the proposed AMC, facilitating human-computer interaction, was found to be subjective norm. Therefore, the design of wearable AMCs should be based on a user-centric approach, considering different subjective norms.

4.5.6.1 Research Implications

One of the major contributions of this study is the proposal of a novel theoretical model based on TAM that analyzes the key factors and the inter-factor relationships that influence the adoption of the proposed AMC. Prior relevant studies were not specifically dedicated to wearable AMCs. In fact, the scope of TAM analysis in these studies spanned across the adoption of smartwatches, wearable technologies in general, etc. To the best of our knowledge, this investigation is the first of its kind that extensively analyzes the acceptance of a wearable Assistive Mouse Controller (AMC) using the Technology Acceptance Model.

Some psychological constructs, considered in these studies, had consistent effects compared to other studies, while some had controversial effects. Therefore, it can be inferred that the results of the TAM analysis that are specific to this study and the respondents of the survey, may not be consistent for a different wearable AMC technology in a different context; however, it may serve as a starting point for future research on the development of newer AMC technologies.

The proposed model can explain about, 49.02% and 53.71% of the variation in users' positive attitude and intention to adopt the proposed AMC, respectively. In connection to this, a good starting point for future research could be to improve the explanatory power (R^2-value) of the exact model or a different model with the same or a newer AMC technology, by considering a larger sample size, or by including more psychological constructs, such as – perceived enjoyment, perceived ubiquity, pricing, facilitating conditions, aesthetics, resistance to change, compatibility, etc., that were not considered in this study, thereby, increasing the chances of enhanced explanatory power of the model with different observations and path models, in the process.

Due to the methodological approach of this study, few limitations exist. For example, due to the onset of COVID-19 pandemic, the sample size considered for this study was a bare minimum. More importantly, the respondents of the survey could not be provided with first-hand interaction of the device, in the case of which the results may have been different. These limitations of the current study may lead to yet another avenue for a longitudinal study, where participants can be given away prototypes of the AMC for interacting with a computer for a given period, after which the TAM analysis can be conducted again to get an understanding of the change in their intention to adopt or reject the AMC.

Chapter 5

Discussion

5.1 Research Challenges

The development of a head-mounted assistive technology has its fair share of research challenges. One of the most crucial steps in the development process of a wearable assistive technology is to understand the requirements of its primary stakeholders. In connection to this, understanding the requirements of people with upper limb disability is very crucial to the development of a wearable Assistive Mouse Controller (AMC), facilitating human-computer interaction. To understand these requirements, input from the stakeholders need to be incorporated in the design and development process. In the context of this study, due to the onset of COVID-19, it was challenging for us to recruit individuals or focus groups to carry out primary user-based requirement analysis through face-to-face interview sessions. However, we were able to overcome this challenge by analyzing prior studies [19, 38] for specific design principles as part of user requirements in such contexts. Based on these requirements, once a working prototype of the AMC was developed, it was essential to determine the feasibility of the prototype in facilitating human-computer interaction for people with upper limb disability by evaluating its performance, usability, user satisfaction, and acceptability. To ensure reliability of the evaluation, it was necessary that such people interacted with the AMC first-hand, identifying potential design and/or performance issues in the process. Again, due to the COVID-19 pandemic, it was challenging to recruit many real-life users for this purpose. However, after communicating with several local rehabilitation centers, local NGOs, and acquaintances, we managed to recruit only 15 people with upper limb disability for interacting with the AMC first-hand and to provide their feedback on its performance, usability, and user satisfaction. An interesting observation from our experiment sessions with these people was that though we explained about the purpose of their recruitment, the features, functionalities and prospects of the AMC, majority of them thought that they were recruited to be provided with some sort of employment opportunities after testing the device first-hand. This gulf of expectation might hamper their responses to the survey, which was a challenging task as well. For analyzing acceptability of the AMC using the TAM model, however, only 15 responses were insufficient, and it was challenging to physically recruit more participants. Despite the challenges, apart from the 15 participants, we were able to recruit an additional 135 participants online, for analyzing user acceptance of the proposed AMC. To ensure that all the participants had a proper understanding of the prospects of the AMC, regardless of their first-hand interaction with it, and to minimize bias in the survey responses, we accommodated a comprehensive description along with a video illustration of device interaction in the survey questionnaire. To minimize the bias in the responses further, they were normalized prior to analysis.

Due to the differences in the form-factor of the human head, developing a generic design for a wearable AMC that will fit all possible head shapes and sizes is a challenging task. In connection to this, adjustability of such devices is a crucial factor, which we have facilitated using adjustable straps. On the other hand, the eye wink gesture was initially intended for actuating mouse clicks. However, it is not an ergonomic gesture for long term interaction with a computer, as it can cause eye strain leading to headache [58]. Considering the long-term health issues of the eye wink gesture, it was challenging for us to determine an alternative generic facial gesture that could facilitate the actuation of mouse clicks, while ensuring ergonomic human-computer interaction. After rigorous analysis and brainstorming sessions, and with motivation from prior studies [102], we adopted cheek muscle twitches as the click actuating gesture for the proposed AMC.

One of the main things to take into consideration while designing a microcontroller-based device is the selection of its hardware components and modules. The same task can be accomplished using different components or modules, achieving different levels of performance and accuracy. However, such performance and accuracy also come with associated extra cost. Considering the socio-economic condition of our country and the target users for the device, we had to establish a balance between the different hardware components used in the system. For instance, using more sensors would result in a smoother performance due to the averaging done in the filters and normal noises from different sensors cancelling each other. However, doing so would also significantly contribute to the overall costing of the final device. Hence, from a hardware perspective, the device is kept as minimal as possible without sacrificing adequate performance and accuracy, and rigorous processing is done in the software end to offer a better user experience.

Another challenge we faced while developing the driver for the AMC was the decision between a Plug and Play (PnP) driver or a custom-made one. Almost every modern operating system and computer hardware have support for generic mice with up to five buttons, such as -

left, *right*, *middle* and *two thumb* buttons. It is possible to make the AMC emulate the behavior of a generic mouse, eliminating the necessity of an external driver required to be installed. Albeit easy to connect, the approach has significant problems when it comes to a specially designed device for special users, which led to the development of a custom driver software. For the developed AMC, a handful of functionalities are required to perform properly under the desired condition, which are not available in a generic mouse driver. For instance, it is required to be able to control the sensitivity of the mouse cursor based on the extent of neck rotation, which cannot be efficiently and smoothly done via a generic mouse driver. Moreover, it is also necessary to have support for gestures, allowing the users to *enable* or *disable* the mouse on the fly and having the option to customize or extend this gesture could result in overall better user experience. In connection to this, a custom driver facilitates the scope required to implement such features and functionalities and keep the software open for future extension without hindering the development process.

As we decided to build a custom driver for the AMC, the next decision we had to take was the programming language and framework for driver implementation. Initially, we had chosen *python* 3 as the programming language due to its ease-of-use and widespread use cases with community support. However, *python*, being an interpreted language, is quite slow in terms of processing speed and in our case, it failed to keep up with the data produced by the AMC hardware. As a result, we had to shift from *python* 3 to C# and .NET framework. The rationale behind the choice was manifold, some of which include but are not limited to - C# being a fast, compiled, and cross-platform object-oriented language with native support for events, makes the development of the driver easier and extensible. After doing some proof of concept, C# and .NET proved to be fast and efficient enough to implement the driver.

5.2 Future Works and Conclusion

The purpose of this thesis work was to develop and evaluate a working prototype of an Assistive Mouse Controller (AMC) to facilitate human-computer interaction for the people with upper limb disability. As part of our research, we have tested out the performance of the developed prototype in different tasks, such as – pointing and typing. Then we have evaluated the *usability*, analyzed *user satisfaction* and *acceptability* of the device to the targeted user group.

However, the developed prototype is still far from our final envisioned device and requires a significant amount of modification and tests before it can be used by the general mass. Though the currently developed prototype supports a wide range of head sizes, it is still not adequate for supporting majority, if not all, possible head sizes. Despite having significantly less weight (365 grams) while compared with other head mounted devices, such as contemporary VR headsets (around $400 - 1000$ grams [185]), there is scope to reduce the form-factor of the proposed AMC even more. The current prototype ships with basic gesture support as of now, which we wish to extend to facilitate customizable gestures, enhancing the overall user experience. The efficiency and user-friendliness of the driver can be enhanced, and support for different operating systems and mobile devices can be incorporated as well. The device can be repurposed, and a programmable API can be exposed to integrate it directly with external applications without treating it like a mouse, which will open the possibility of various novel and innovative use cases, subject to further investigation. Beside the development activities, once the prototype reaches a state close to the final envisioned device, usability, user satisfaction and acceptability need to be reevaluated and analyzed to get a better understanding of the AMC as a human-computer interaction device.

Furthermore, how a user adapts to the device usage, needs to be analyzed as well. To facilitate this, we plan to carry out a longitudinal cohort study, involving users with upper limb disability, where the user has to repeat the same task several times using the proposed AMC, during which the time required to complete that task will be recorded. The power law of practice [186, 187] may be utilized in this case, to understand users' adaptability to the device interaction mechanism, while performing specific tasks with it. This analysis will also help us figure out whether the device will have any detrimental effects on a user's health, such as neck pain, due to its long term usage.

We are actively working on the proposed AMC as of the time of writing this report to incorporate the functionalities to ensure that we can offer a final device that is beneficial to both the disabled community and the academic research body as well.

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