Optimising the User Experience in E-Commerce Platforms Using Ergonomic Interface Design and Motion Analysis

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Abstract – This study investigates how Motion Analysis (MA) and Ergonomic Interface Design (EID) can enhance the User Experience (UX) in e-commerce (E-comm) platforms. MA, including Eye-Tracking (ET) and Gesture Recognition (GR), was used to examine User Interfaces (UI) patterns, while EID principles were applied to optimize UI elements such as button size, layout spacing, and navigation. A total of 45 participants, considered by device preference and shopping habits, were observed across PC, mobile, and tablet platforms. Key findings indicate that mobile users engage in more frequent hand and wrist movements and UX higher discomfort levels due to smaller screens and touch-based UI, while PC users reported the highest comfort levels. Scroll depth analysis revealed that mobile users scrolled the deepest, especially during product discovery, while PC users engaged less with deeper content. GA showed heavy UI with more complex gestures, such as pinch-to-zoom and drag-and-drop, while light users relied on more straightforward gestures like tapping and scrolling. EID improvements significantly reduced movement frequency and increased comfort, particularly for mobile and tablet users. The study concludes that optimizing E-comm platforms through MA and EID leads to enhanced usability, reduced physical strain, and greater user satisfaction across devices.

Keywords – Eye-Tracking, Gesture Recognition, E-Commerce Platforms, Machine Learning, Ergonomic Interface Design, Smart Device Users.

I. INTRODUCTION

In recent years, e-Commerce (E-comm) platforms have become increasingly integral to consumer shopping habits, offering convenience and a typical product development [1-2]. However, the effectiveness and User Experience (UX) of these platforms can vary greatly depending on the design and functionality of their UI [3-4]. As the digital marketplace continues to evolve, E-comm platforms must prioritize optimizing User Interfaces (UI) to enhance usability, engagement, and satisfaction [5]. Two key areas that significantly impact UX are Motion Analysis (MA) and Ergonomic Interface Design (EID) [6-7]. By understanding how UI works with E-comm platforms and addressing potential physical and cognitive strain, platform designers can create more seamless, efficient, and enjoyable UX [8].

MA is critical in understanding user behaviors during their UI with E-comm platforms [9]. This involves tracking users' micro-interactions, such as scrolling, clicking, hovering, and hand gestures, contributing to their overall UX [10]. This UI can reveal key visions into friction, confusion, or hesitation areas. For example, tools like Eye-Tracking (ET) and Gesture Recognition (GR) technologies can provide data on where users are focusing their attention and how they navigate through the platform [11]. By analyzing these patterns, designers can adjust UI to reduce user effort and create smoother UI. Such insights allow platforms to address user needs more effectively, improving functionality and satisfaction [12].

In parallel, EID focuses on reducing users' physical and cognitive strain by ensuring that E-comm platforms are comfortable and intuitive to UI [13-15]. The design of E-comm platforms must account for a range of factors, such as the size and spacing of UI elements (*e.g.,* buttons and menus), ease of navigation, and visual hierarchy [16-18]. Ensuring these EID elements helps prevent user prevention and fatigue, particularly during long browsing or purchasing sessions [19]. This is especially relevant in mobile environments, where smaller screens and touch-based inputs require extra attention to detail in UI layout and EID. By adhering to EDI, platforms can enhance user comfort, boost productivity, and promote more prolonged engagement, ultimately leading to higher satisfaction rates and increased sales [20,21].

This paper explores the application of MA and EID in optimizing UX on E-comm platforms. Through detailed experimentation and data collection, this work assesses how UI interacts with various elements of E-comm-UI, focusing on their physical and cognitive responses to different EID. By examining factors such as gaze duration, GR, UI speed, scroll depth, and comfort levels, this study aims to provide actionable insights into how E-comm platforms can be improved to meet the needs of a diverse user base. The research highlights current challenges in digital platform design and proposes a framework for creating more effective and user-centered E-comm UX.

This study aims to optimize the UX in E-comm platforms by analyzing UI and applying EID to UI. By leveraging MAs such as ET and GR, we aim to identify friction points and enhance user engagement through improved design. Additionally, the research investigates how EID-UI adjustments, such as better layout spacing, button size optimization, and navigation streamlining, can reduce physical and cognitive strain, promoting a more comfortable and satisfying UX. Ultimately, the goal is to provide actionable design insights that can be applied across different devices, particularly mobile, PC, and tablet platforms, where UI patterns differ significantly.

The paper is organized as follows: Section 2: Literature Review overviews previous studies on MA and EID in E-comm platforms. Section 2: Theory and Framework discusses key concepts related to MA and EID, including Fitts' Law and Hick-Hyman Law. Section 3: Methodology details the participant selection, MA setup, and the variables measured in the study across different devices. Section 4: Results present the findings on UI patterns, GR frequencies, UI speed, scroll depth, and comfort levels. Section 5: Conclusion summarizes key visions and proposals recommendations for future research and practical applications.

II. THEORY AND FRAMEWORK

MA and UI E-comm Platforms

Understanding UI in E-comm platforms requires a detailed examination of how users navigate, search, and UI with various UI elements. In a digital shopping environment, users engage with the platform through scrolling, clicking, hovering, and other micro-interactions that impact their overall UX. MA focuses on these behavioral patterns by capturing data related to user movements, such as ET, hand gestures, and mouse movements. This data is essential in identifying friction points, areas of confusion, or moments of hesitation during the user journey. For instance, ET data can reveal where users focus most of their attention, while GR can show how users interact physically with touchscreens or other input devices. By studying these motion patterns, designers can optimize the UI for smoother interactions, improving usability and user satisfaction.

Theoretical models that link MA to UX are based on principles of Human-Computer Interaction (HCI) and cognitive psychology. The Fitts' Law, for example, predicts the time it takes for users to move to and select an item based on the size and distance of the target, which is particularly relevant in designing E-comm UI with interactive elements. Similarly, the Hick-Hyman Law suggests that users take longer to make decisions when presented with multiple options, a challenge frequently faced in E-comm due to numerous product choices. These models help understand the cognitive load associated with user motions, allowing for the development of intuitive designs that minimize effort and maximize engagement. Applying such models to MA enables E-comm platforms to create more efficient and enjoyable UX.

Ergonomics in UI Layout

Ergonomics in UI design involves applying principles of human ergonomics to create comfortable and efficient UI for users. In the context of E-comm platforms, this means designing layouts that reduce strain on the user, whether physical or cognitive. EID principles translate to UI design through thoughtful consideration of factors such as element spacing, button size, and the overall visual hierarchy. For example, ensuring that buttons are large enough to be easily clicked or tapped without excessive precision minimizes user frustration, especially on mobile devices. Similarly, maintaining sufficient spacing between UI elements helps prevent accidental clicks, which can lead to user dissatisfaction.

Defining EID benchmarks for E-comm UI involves establishing criteria that ensure ease of use and comfort. These benchmarks include minimizing excessive scrolling, designing layouts that facilitate quick access to essential functions, and ensuring that visual and textual content is easily comprehended at a glance. Accessibility features, such as adjustable font sizes and voice-enabled search functions, further contribute to EID by catering to diverse user needs. By adhering to these ergonomic standards, E-comm platforms can enhance usability, reduce user fatigue, and promote longer engagement sessions, ultimately leading to a more positive shopping UX.

Fig 1. Visual Representation of Key Concepts Related to Ergonomics.

As **Fig 1** portrays, ergonomics is critical in optimizing UX by addressing human physiology, posture, and comfort. Translating these principles into UI design means ensuring that E-comm platforms reduce cognitive and physical strain for users. For instance, the layout of buttons, menus, and other UI elements should promote ease of use and prevent user fatigue. As ergonomic chairs are designed to support the back, EID-UI supports seamless UI, minimizing user effort while maintaining functionality and aesthetic appeal. As seen in the image, ergonomic benchmarks for E-comm platforms include elements like enhancing human performance, improving productivity, and ensuring user safety and comfort. When designing E-comm UI, these factors must be carefully considered to create environments that facilitate efficiency and prioritize user well-being. For instance, applying these principles to the UI ensures that users do not UX excessive strain from poor UI layouts, much like how ergonomic office equipment minimizes physical strain.

III. METHODOLOGY

Participant Selection

The selection of participants for this study was guided by the need to collect diverse UI data across different emographics to effectively assess the usability of E-comm platforms. A total of 45 participants were recruited, ensuring a balance between age, gender, and familiarity with E-comm platforms. Participants ranged from 18 to 55 years old, with 12 participants in the 18-25 age range, 16 participants in the 26-35 age range, 9 participants in the 36-45 age range, and 8 participants in the 46-55 age range. This demographic variation allowed the study to investigate how different user groups respond to various ergonomic and motion-related features of the platforms. Participants were further divided into three categories based on their E-comm usage habits: light users (occasional shoppers, 13 participants), moderate users (those who shop online regularly but infrequently, 18 participants), and heavy users (frequent shoppers who engage in online transactions multiple times per week, 14 participants). This classification helped analyze how user proficiency with E-comm UI affected their motion patterns and EID-UI.

Recruitment was conducted through online channels, including social media platforms and email invitations, targeting individuals who regularly use computers and mobile devices for online shopping. Participants indicated their device preferences, with 10 participants primarily using PCs, 14 using laptops, 7 using tablets, and 14 preferring smartphones. Before participation, each individual completed a pre-study survey to gather initial data on their e E-comm habits, device preferences, and physical or cognitive limitations. Among the participants, 4 reported physical limitations (*e.g.,* hand dexterity, vision), and 2 reported cognitive limitations *(e.g.,* memory, attention). This pre-screening process ensured that the study included a representative sample, providing insights into the broader UX in E-comm environments.

MA Setup

Several tools and technologies were employed to capture UI and MA accurately during their engagement with E-comm platforms. The primary instruments used for MA were ET devices and GR sensors, which allowed for detailed observation of user behavior and movement patterns. ET devices were integrated to monitor where users focused their attention on the screen, providing data on gaze duration, fixation points, and areas of interest. This information helped identify UI elements that users found confusing or particularly engaging. The Tobii Pro Nano ET was chosen for its high precision and non-intrusive design, ensuring that participants' natural behavior was not affected by the data collection process. In addition to ET, GR sensors were utilized to analyze hand and body movements, especially for UI with touchscreen devices and virtual shopping environments. Leap motion controllers were employed for their ability to capture hand gestures in 3D space, allowing the study to track swipe motions, pinch-to-zoom gestures, and other UI behaviors that are common in mobile and tablet-based E-comm UX. Combining these tools enabled a comprehensive understanding of how users physically UI with the platform across different devices.

The experimental environment was judiciously designed to simulate real-world E-comm usage scenarios while maintaining control over external variables. Participants were seated in a quiet, distraction-free room with adjustable lighting to reduce any impact on the ET results. The study was conducted across three different device setups: PCs, laptops, and mobile devices, with each participant engaging in typical E-comm tasks, such as browsing products, adding items to the cart, and completing checkout processes. Each device was calibrated to the participant's preferences to ensure comfort and a standardized set of E-comm tasks was used to ensure consistency in the data collected. Participants UI with the platforms naturally during the sessions while the motion tracking tools recorded their movements. Multiple cameras ensured comprehensive coverage of the user's body positioning, including hand movements, facial expressions, and posture, further enriching the data on UI with the digital interface. This setup provided a controlled yet flexible environment to capture a wide range of motion behaviors, ensuring robust and reliable data for subsequent analysis.

Variables and Measurements

In this study, various key variables were measured to evaluate the effects of MA and EID on UX in E-comm platforms. These variables were broadly considered into MA and EID, each offering insights into specific UI features.

Motion-related variables included gaze duration, which tracked participants' time focusing on particular UI elements. Prolonged gaze durations frequently indicated either confusion or substantial interest, helping to identify areas of the interface that required further attention. Fixation points were recorded to pinpoint the specific areas on the screen where users concentrated their attention the most, highlighting whether critical elements, such as product descriptions or buttons, were easily noticed or required more effort to find. Gesture patterns were another significant variable, capturing everyday hand movements like swipes, taps, and pinches. These patterns provided valuable insights into how users navigate the platform, especially on mobile and tablet devices.

Additionally, UI speed measured participants' time to complete specific tasks, such as adding items to their cart or finishing the checkout process. Faster completion times indicated a more intuitive and user-friendly design, while slower times pointed to difficulties in navigation. Scroll depth was also analyzed, measuring how far down participants scrolled on a page, which revealed whether important information was easily accessible or required additional searching.

Ergonomic-related variables focused on user comfort and physical UI with the interface. Comfort levels were self-reported by participants at different points during the UI, allowing the study to assess their physical ease when engaging with the platform. This was particularly important for repetitive motions like scrolling and typing, which could cause discomfort over extended use. Posture and body movement were observed using cameras, with particular attention paid to participants' posture while UI with PC and laptop devices. Poor posture or excessive leaning indicated that the interface might require undue concentration or physical effort. Hand and wrist movements were also closely monitored, primarily for UI with mobile and tablet devices. Excessive movements or difficult wrist positions indicated ergonomic shortcomings in the design. Finally, the cognitive load was inferred from the decision-making process during tasks, particularly when participants were required to select between multiple options, such as product variations. Higher cognitive load was identified when participants took longer to make decisions or engaged in repetitive back-and-forth actions.

IV. RESULT AND DISCUSSION

The analysis **Table 1** and **Fig 2** of gaze duration across various UI elements reveals key insights into user behavior on different devices (PC, Mobile, and Tablet). For product images, users on mobile devices spent the longest time (5.19 *Sec.*), followed by tablet users (4.95 *Sec.*) and PC users (4.72 *Sec.*). This suggests that mobile users focus more on visual content, possibly due to smaller screen sizes requiring greater attention to details. Regarding product descriptions, PC users exhibited the most prolonged gaze duration (5.33 *Sec.*), indicating that they may rely more on textual information to make decisions, whereas tablet and mobile users had slightly shorter durations at 5.01 and 4.68 *Sec*. This could reflect differences in how users engage with content based on the device type, with PC users preferring to read through information more thoroughly.

For checkout buttons, mobile users once again had the most extended gaze duration (3.12 *Sec.*), followed closely by tablet users (2.98 *Sec.*) and PC users (2.87 *Sec.*). This longer focus on mobile devices could be attributed to smaller touch targets, requiring users to spend more time making the correct selection. The navigation menu saw the most extended gaze durations on mobile devices (3.81 *Sec.*), suggesting that users difficulty navigating complex menus on smaller screens. Tab may be UXlet users followed with 3.43 *Sec.* PC users had the shortest gaze duration at 3.16 *Sec.*, indicating more efficient navigation on larger screens. Finally, for the search bar, mobile users also took the longest time (2.46 *Sec.*), compared to 2.08 *Sec.* on tablets and 1.94 *Sec.* on PC. This may indicate that mobile users find it slightly more challenging to locate and use the search function, potentially due to the UI layout or smaller input areas on mobile screens.

Table 1. Gaze Duration Analysis

UI Element	PC (s)	Mobile (s)	Tablet (s)
Product Images	4.72	5.19	4.95
Product Descriptions	5.33	4.68	5.01
Checkout Buttons	2.87	3.12	2.98
Navigation Menu	3.16	3.81	3.43

Search Bar	1.94	2.46	2.08

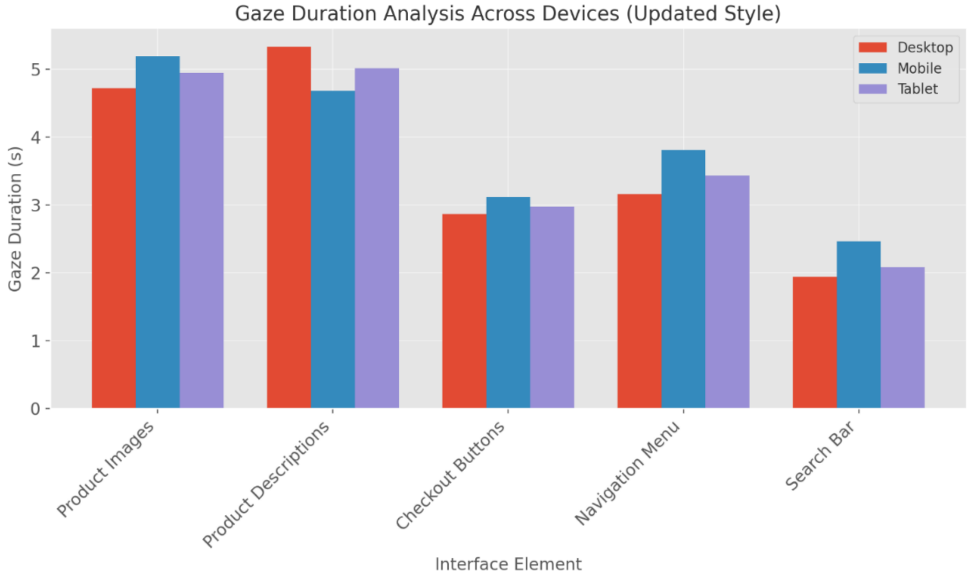

Fig2. Gaze Duration Analysis.

Table 2. Gesture Pattern Frequency Analysis

Gesture Type	**Light Users (Freq)**	**Moderate Users (Freq)**	**Heavy Users (Freq)**
Swipe Left/Right	21	28	36
Tap	34	43	58
Pinch to Zoom	9	11	16
Scroll	18	27	34
Drag & Drop	4	6	9

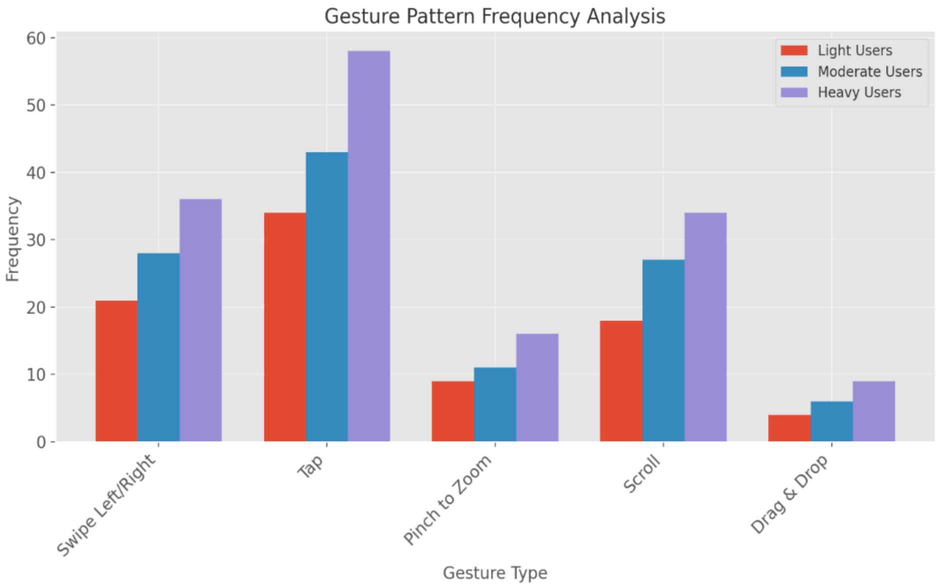

Fig 3. Gesture Pattern Frequency Analysis.

The analysis of gesture pattern frequency across different user groups (light, moderate, and heavy users) provides insights into how UI with E-comm platforms **Table 2** and **Fig 3**. For the swipe left/right gesture, heavy users performed this action the most frequently, with 36 occurrences, followed by moderate users at 28 and light users at 21. This suggests that heavier users tend to engage more with gesture-based navigation due to their higher familiarity with the platform and more frequent usage.

Regarding tapping, the most common gesture across all groups, heavy users again performed this gesture most frequently, with 58 occurrences, while moderate users performed it 43 times and light users 34 times. Heavy users' higher frequency of taps could be attributed to their more extensive UI with products and interface elements, such as selecting items or navigating through menus. For pinch to zoom, a gesture primarily used for viewing product details, heavy users demonstrated a higher frequency (16 times) compared to moderate (11 times) and light users (9 times). This suggests that heavy users may be more inclined to zoom in on images or product details, possibly due to their more significant engagement with the platform or desire for more detailed information during product exploration. The scrolling gesture was also more frequently used by heavy users, with 34 occurrences, compared to 27 by moderate users and 18 by light users. This reflects that heavy users tend to explore more content on E-comm platforms, likely scrolling through product listings or pages more extensively than light or moderate users. Lastly, the drag & drop gesture, though less common overall, followed a similar pattern, with heavy users performing it 9 times, moderate users 6 times, and light users 4 times. This gesture is typically associated with more complex UI, such as organizing or customizing product views, and its higher frequency among heavy users indicates their more profound UI with the platform.

Table 3. Ui Speed Analysis

Task	Light Users (s)	Moderate Users (s)	Heavy Users (s)
Add to Cart	7.24	6.71	5.89
Checkout	12.89	11.55	10.16
Search for Product	5.67	5.33	4.72
Navigate Categories	8.44	7.82	6.68
Apply Discount Code	6.21	5.94	5.47

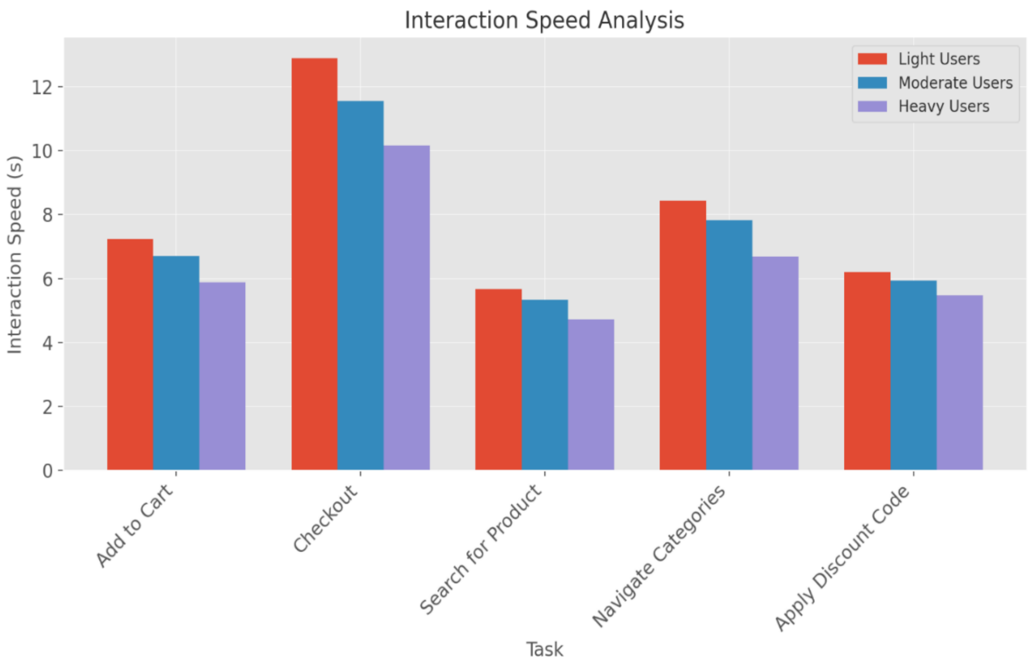

Fig 4. UI Speed Analysis.

The UI Speed Analysis **Table 3** and **Fig 4** highlights notable differences in the time taken to complete various tasks across light, moderate, and heavy users. Light users took the longest time for the Add to Cart task, averaging 7.24 *Sec.*, while moderate users completed the task in 6.71 *Sec.* and heavy users in just 5.89 *Sec.* This pattern suggests that heavier users, being more familiar with the interface, can complete basic tasks like adding items to the cart more efficiently than lighter users. The Checkout process, being more complex, took considerably longer for all user groups. Light users required 12.89 *Sec.* on average, with moderate users taking 11.55 *Sec.* and heavy users 10.16 *Sec.* The significant time difference between light and heavy users may be due to heavy users' greater familiarity with the checkout steps, including entering payment details or navigating multi-step forms more quickly.

For the Search for Product task, heavy users completed the action fastest at 4.72 *Sec.*, followed by moderate users at 5.33 *Sec.*, and light users at 5.67 seconds. This relatively small difference in search times across user groups suggests that the search function may be well-optimized for all users, but more UX users still perform slightly better due to their familiarity with keyword searches or filtering options. When Navigating Categories, light users took the longest time at 8.44 *Sec.*, moderate users at 7.82 *Sec.*, and heavy users at 6.68 *Sec*. This difference may indicate that light users need more time to explore and locate relevant product categories, whereas heavy users are likely more adept at navigating through category structures. Finally, for Applying Discount Codes, light users took 6.21 *Sec.* on average, moderate users took 5.94 *Sec.*, and heavy users took 5.47 *Sec.* The minor differences here suggest that while familiarity with the platform does lead to faster completion of this task, the variation between groups is less pronounced, possibly due to the relatively straightforward nature of this task.

Table 4. Scroll Depth Insights Across Devices

Device	Average Scroll Depth (%)	Product Discovery Scroll Depth (%)
Mobile	68.74	82.65
PC	52.49	61.28
Tablet	64.38	78.54

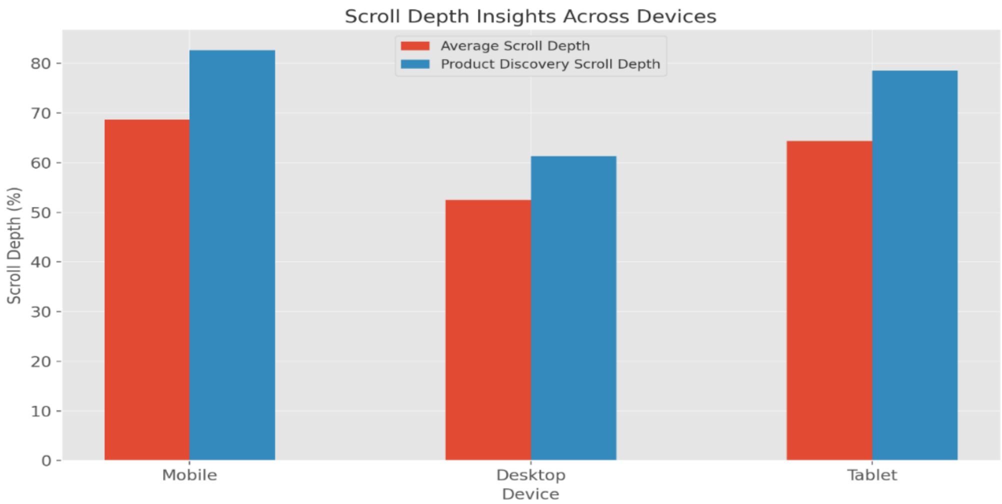

Fig 5. Scroll Depth Insights.

The Scroll Depth Insights Analysis **Table 4** and **Fig 5** reveals distinct differences in scrolling behavior across devices (Mobile, PC, and Tablet), highlighting how UI interacts with content when exploring products. Mobile users scrolled the deepest for average scroll depth, with an average of 68.74%, indicating that they are more likely to explore content further down a page than users on other devices. Tablet users followed with an average scroll depth of 64.38%, while PC users scrolled the least, with an average depth of 52.49%. This suggests that mobile users may be more accustomed to continuous scrolling, possibly due to the nature of mobile interfaces that rely heavily on vertical navigation. On the other hand, PC users may rely more on visual cues from above-the-fold content, engaging less with content further down the page.

Regarding product discovery scrolls depth, mobile users again led with 82.65%, showing that they tend to scroll significantly more when actively searching for products. Tablet users followed closely with a scroll depth of 78.54%, while PC users remained lower at 61.28%. This indicates that mobile and tablet users are more likely to explore deeply when browsing product listings, likely driven by the smaller screen sizes that encourage more scrolling. With their more significant screen real estate, PC users may find it easier to view multiple products at once without needing to scroll as much.

Table 5. Comfort Level Analysis

Device	Average Comfort Level (1-5)	Comfort Increase After EID (%)
Mobile	3.92	7.48
PC	4.31	9.36
Tablet	4.05	8.21

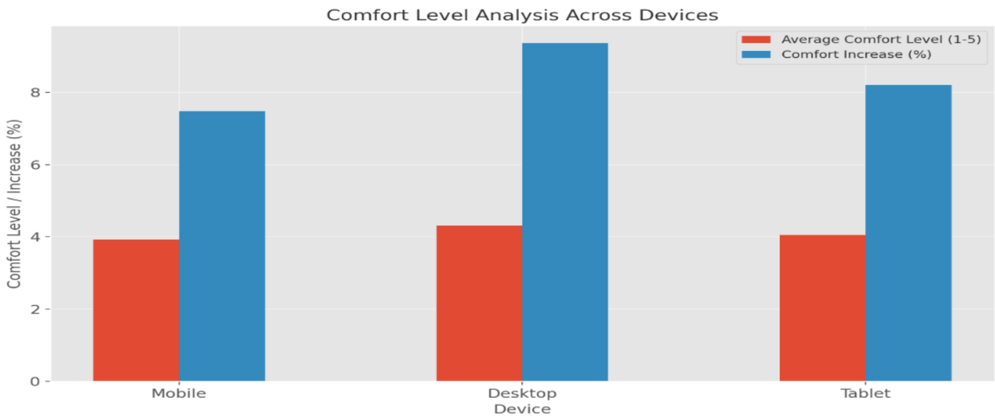

Fig 6. Comfort Level Analysis.

The Comfort Level Analysis **Table 5** and **Fig 6** across different devices (Mobile, PC, and Tablet) provides key insights into user comfort during UI with E-comm platforms and the impact of EID. PC users reported the highest comfort score for average comfort levels, averaging 4.31 out of 5. This suggests that PC interfaces, typically designed for extended use with features like larger screens and physical keyboards, offer a more comfortable UX. Tablet users followed with an average comfort level of 4.05, while mobile users reported the lowest comfort level, with an average score of 3.92. The lower comfort level on mobile devices may be due to smaller screens and more complex navigation requirements, which can lead to fatigue or frustration over time.

In terms of comfort increase after EID, PC users again saw the most significant improvement, with a 9.36% increase in reported comfort. This suggests that EID, such as optimized layout spacing, larger click targets, and simplified navigation, had the most significant impact on PC users, possibly due to the extended UI periods associated with PC usage. Tablet users UX an 8.21% increase in comfort after EID, while mobile users saw a 7.48% increase. While mobile users reported the smallest comfort increase, this indicates that even minor ergonomic adjustments, such as improving touch target sizes and simplifying navigation, can make a noticeable difference in user comfort. **Table 6** shows Posture and Body Movement Pattern Analysis.

Table 6. Posture And Body Movement Pattern Analysis

Device	Postural Change Frequency (per hour)	Reported Discomfort After Prolonged Use (%)
Mobile	12	63.21
PC	5	45.78
Tablet	8	58.36

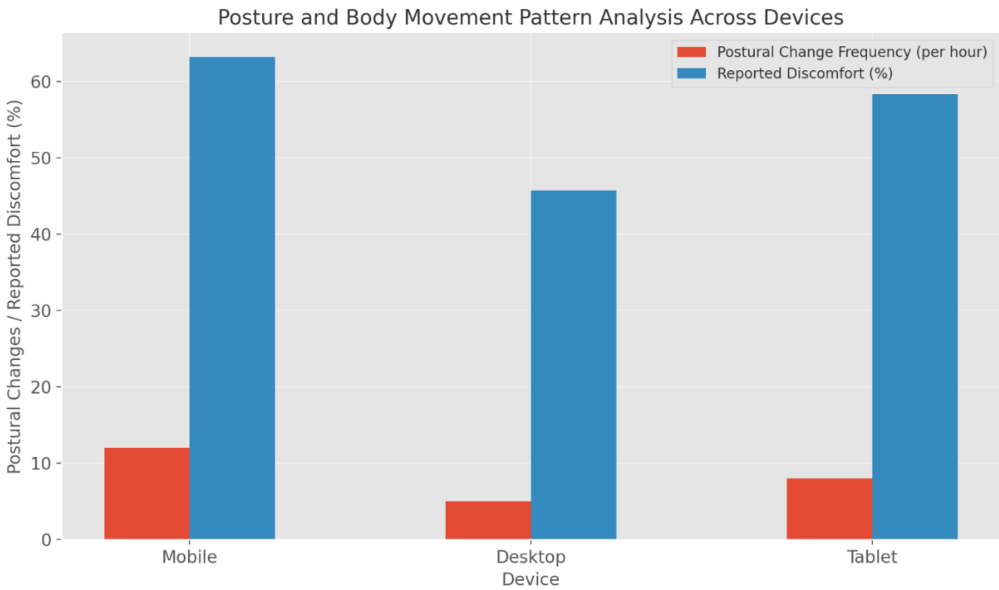

Fig 7. Posture And Body Movement Pattern Analysis.

The Posture and Body Movement Pattern Analysis highlights key differences in user postural changes and reported discomfort after prolonged use across mobile, PC, and tablet devices. For postural change frequency, mobile users exhibited the highest rate of changes, averaging 12 movements per hour. This suggests that mobile devices, with their smaller screens and reliance on touch UI, lead to more frequent adjustments in posture, likely due to the need to switch between different hand positions or to maintain comfort while holding the device. Tablet users followed with 8 postural changes per hour, reflecting a slightly more stable UI pattern, likely due to larger screens and more flexible use positions, such as resting the device on a surface. PC users had the lowest postural change frequency, averaging 5 movements per hour, consistent with the more stationary and ergonomic setup typically associated with PC environments, such as using a mouse, keyboard, and monitor at a fixed distance. **Fig 7** shows Posture and Body Movement Pattern Analysis.

Regarding reported discomfort after prolonged use, mobile UX had the highest level of discomfort, with 63.21% reporting discomfort after extended sessions. This can be attributed to the physical strain of holding a device for long periods, frequent posture adjustments, and the need to focus on smaller screens. Tablet users reported a slightly lower level of discomfort at 58.36%, possibly due to the ability to position the device more ergonomically, such as resting it on a table or using a stand. PC users reported the lowest level of discomfort, with 45.78% experiencing discomfort after prolonged use. The lower discomfort on PC can be explained by the generally better ergonomic setup, which reduces physical strain over extended periods. **Table 7 s**hows Hand and Wrist Movement Frequency Across Different Sessions.

Table 7. Hand And Wrist Movement Frequency Across Different Sessions

	Mobile (Movements)	**PC (Movements)**	**Tablet (Movements)**	**Ergonomic Layout Impact (%)**
Browsing Products	45	28	39	8.67
Adding to Cart	61	35	46	11.12
Checkout Process	53	34	42	9.88

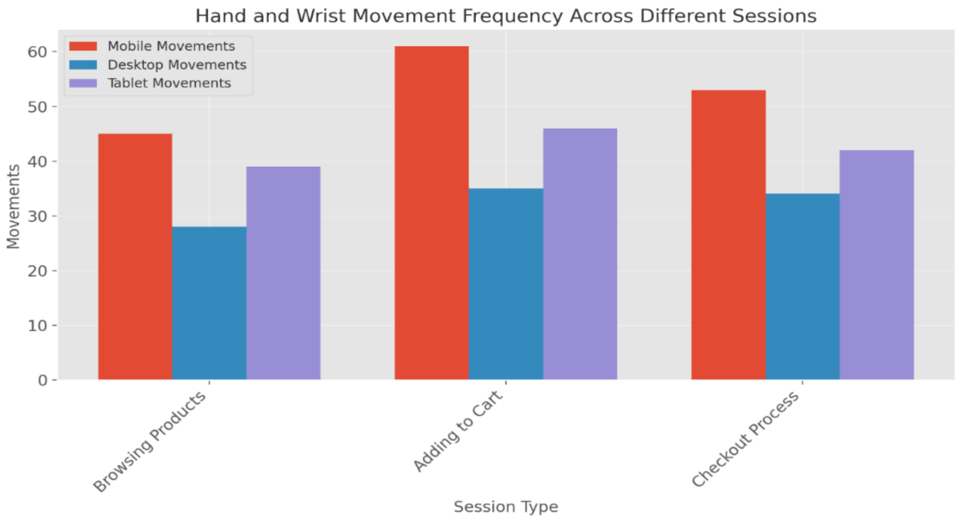

Fig 8. Hand And Wrist Movement Analysis.

Table 8. Comparison Between Different UI Layouts and Their Ergonomic Impact

Interface Layout	**Mobile (Movements)**	**PC (Movements)**	**Tablet (Movements)**	**Reduction in Movements After EID (%)**
Standard	58	36	47	9.14
Minimalist	43	28	34	12.33
Complex	67	42	53	7.68

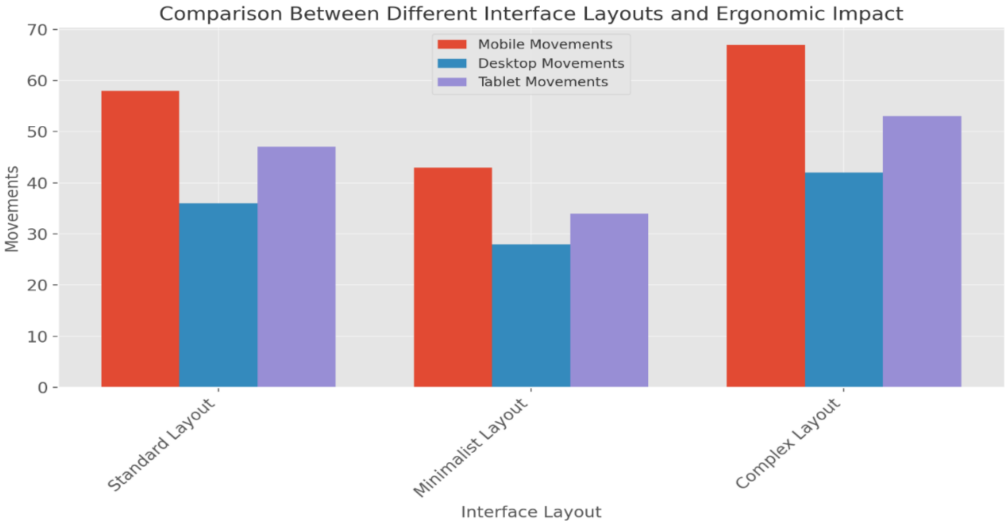

Fig 9. Comparison Between Different UI Layouts and Their Ergonomic Impact

The Hand and Wrist Movement Frequency Analysis **Table 8** and **Fig 9** across different session types (browsing products, adding to cart, and checkout process) provides insights into how users engage with E-comm platforms on mobile, PC, and tablet devices, as well as the impact of ergonomic layout improvements. Mobile users performed the most hand and wrist movements for browsing products, with 45 movements recorded on average, followed by tablet users with 39 movements and PC users with 28 movements. This higher movement frequency on mobile devices can be attributed to the smaller screen size, which frequently requires more scrolling, swiping, and tapping to view product details. Ergonomic layout improvements reduced movements by 8.67%, suggesting that optimizing the interface, such as improving navigation or product display, can help reduce the physical effort required during browsing, particularly on mobile and tablet devices. During the adding to cart session, mobile users again exhibited the highest number of movements, with 61 movements on average, compared to 46 on tablets and 35 on PCs. The higher frequency of movements on mobile and tablet devices can be linked to smaller touch targets and more steps involved, such as selecting product options or confirming details before adding items to the cart. EID improvements had the most significant impact in this session, reducing movements by 11.12%. This shows that optimizing elements like button size, placement, and overall process flow can significantly reduce physical strain, especially on mobile devices where movement is most frequent. In the checkout process, mobile users performed 53 on average, while tablet users averaged 42 movements and PC users 34 movements. The higher movement frequency on mobile devices during checkout can be attributed to the complexity of entering payment information, verifying shipping details, and navigating through multiple steps. Ergonomic layout improvements reduced movements by 9.88%, suggesting that simplifying the checkout process through better form design, auto-fill options, and fewer steps can reduce the effort required, particularly for mobile users.

V. CONCLUSION AND FUTURE WORK

This study demonstrates the critical role that MA and EID play in improving the UX on E-comm platforms. By analyzing UI patterns, this study identified key areas where mobile, tablet, and PC-UX friction, such as increased hand and wrist movements on mobile devices and deeper scroll depths during product discovery. Applying EID principles, including optimizing layout spacing, button sizes, and navigation elements, significantly improved user comfort and reduced physical strain, particularly on mobile, PC, and tablet devices. Heavy users who exhibited more frequent and complex gestures benefited from EID improvements that minimized movement and cognitive load. The findings suggest that tailored ergonomic adjustments can enhance usability and engagement, leading to longer UI sessions and higher user satisfaction.

Future work should focus on refining EID standards for mobile UI and UX adaptive design solutions that respond dynamically to real-time user behaviors.

CRediT Author Statement

The authors confirm contribution to the paper as follows:

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