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Article

Investigating the biomechanical reactions at the microscopic level of consumer behavior in e-commerce by means of motion tracking and physical interaction patterns

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Abstract: The rapid expansion of e-commerce has reshaped consumer behavior. From the perspective of cellular and molecular biomechanics, understanding how users interact with online platforms becomes more crucial. This study analyzes consumer behavior via motion tracking and physical interaction patterns, focusing on variables like browsing time. When observing 126 Chinese participants on a simulated platform, we considered the influence of age, gender, etc. At the cellular level, gender differences in dwell time might relate to different neural cell activities and molecular signaling pathways in the brain. Male participants' longer hover durations (p = 0.03) could imply varied cognitive processing at the molecular level compared to females. Cluster analysis showed three user groups, and Cluster 2's higher engagement might be due to better cellular energy utilization and more efficient neuromuscular coordination for operating the platform. The results stress the importance of grasping these underlying biomechanical aspects of user behavior. Motion-tracking data can offer insights to optimize platform design, enhance user experience, and improve conversion rates, contributing to the literature on human-computer interaction in e-commerce.

Keywords: motion tracking; physical interaction patterns; biomechanical reactions; e-commerce platform; consumer behavior

1. Introduction

The exponential rise of e-commerce has significantly altered consumer shopping behavior, making digital interaction the primary mode of engagement for millions of users worldwide [1,2]. As online retail platforms become increasingly sophisticated, understanding how consumers interact with these platforms has become essential for optimizing user experience and enhancing conversion rates [3–5]. Traditional approaches to studying consumer behavior have primarily focused on psychological, cognitive, and economic factors [6,7]. However, with advancements in Human-Computer Interaction (HCI) and motion-tracking technologies, there is now an opportunity to capture and analyze users' physical movements and interaction patterns while navigating digital platforms [8,9].

Motion-tracking technologies provide granular insights into user behaviors such as mouse movements, scrolling velocity, dwell time, and click frequency [10,11]. These metrics offer a detailed understanding of how users engage with digital interfaces, highlighting key areas of interest, confusion, or hesitation [12,13]. For e-commerce platforms, such data is invaluable, as it can reveal critical points in the user journey where consumers either make purchase decisions or abandon the process

[14,15]. By understanding these physical interaction patterns, businesses can better tailor their platforms to enhance user experience and increase conversions.

Despite the increasing use of motion-tracking in HCI studies, there remains a gap in applying these methods to e-commerce environments, particularly in diverse markets such as China. China's e-commerce landscape, characterized by its rapid growth and consumer diversity, provides an ideal context for examining how different demographic groups—based on age, gender, and socioeconomic status—interact with online platforms. Exploring these patterns can uncover differences in browsing behaviors, decision-making processes, and engagement levels, offering insights that can be used to refine platform designs and enhance consumer satisfaction [16–18].

The present study analyzes consumer behavior in e-commerce by tracking motion and physical interaction patterns. By examining key variables such as browsing time, click frequency, and dwell time, this study seeks to understand how consumers from different demographic backgrounds navigate e-commerce platforms and make purchasing decisions. The findings from this study will provide valuable insights into optimizing digital interfaces for improved user experience and higher conversion rates, contributing to the growing body of literature on e-commerce consumer behavior.

The rest of the paper is organized as follows: section 2 presents the theoretical framework, section 3 presents the methodology, section 4 analyzes the results, and section 5 concludes the paper.

2. Theoretical framework

2.1. Human motion and digital interaction

The relationship between human motion and digital interaction is rooted in the field of HCI. This domain studies how physical movements, such as hand gestures, eye tracking, and body posture, influence user engagement with digital interfaces. In e-commerce, where the digital environment is central to consumer activity, how users physically interact with the platform can significantly impact their experience. Motion, particularly regarding mouse movements, scrolling patterns, and hand-eye coordination, is a proxy for understanding cognitive load, interest levels, and decision-making processes. Research in this area suggests that smoother and more fluid movements tend to indicate a higher level of engagement, while erratic or paused movements may signal confusion or hesitation. By tracking these motions, e-commerce platforms can gain insights into how users navigate websites, interact with product offerings, and ultimately make purchasing decisions. Understanding this interaction provides a critical foundation for optimizing the layout and design of e-commerce platforms, ensuring that the user's physical behavior translates to a seamless digital experience.

2.2. Consumer decision-making processes

Consumer decision-making in e-commerce is a complex, multi-step process involving cognitive and emotional factors. It begins with problem recognition, followed by information search, evaluation of alternatives, purchase decisions, and post-purchase behavior. Digital platforms introduce unique dynamics into this process, as consumers often make decisions based solely on visual and textual information without the ability to touch or try products physically [19–20]. The motion tracking integration into this framework provides new insight into how these decisions are made. For instance, prolonged hovering over a product or frequent returns to the same item page may suggest a consumer's internal debate or desire for more information before committing to a purchase.

Conversely, swift movement through the checkout process may indicate confidence in the decision. By analyzing these physical behaviors, businesses can tailor their interfaces to reduce friction in the decision-making process, guiding users more effectively toward conversions. Motion data can reveal critical touchpoints where consumers either proceed with or abandon the purchasing process, offering actionable insights for improving e-commerce strategies [21–24].

2.3. Motion-Tracking metrics

Motion-tracking metrics quantitatively measure how users interact with e-commerce platforms through physical movements. These metrics include cursor speed, click density, dwell time, scrolling velocity, and interaction heatmaps. Cursor speed, for instance, measures how fast a user navigates across the page, with faster speeds often corresponding to familiarity with the platform or content. Click density refers to the concentration of clicks within specific areas, indicating popular products or navigation bottlenecks [25–30]. Dwell time, or the amount of time a user spends on a particular product or section, strongly indicates user interest and can highlight areas where more information may be needed to prompt a decision. Scrolling velocity, however, tracks how quickly users move through long pages, offering insights into their content consumption habits. Heatmaps visually represent areas of the interface that receive the most interaction, allowing designers to focus on optimizing key elements such as call-to-action buttons and product images [31]. When aggregated and analyzed, these metrics provide a detailed view of user behavior, helping e-commerce platforms understand what consumers are doing and why they are doing it.

3. Methodology

3.1. Study design

This study employs an observational and experimental research design to analyze consumer behavior on e-commerce platforms through motion tracking and physical interaction patterns. The study was conducted in China and focused on users of various online retail platforms. China, one of the largest and most dynamic e-commerce markets globally, provides a rich and diverse consumer base, making it an ideal region for studying digital interaction behaviors. The study sampled participants from different age groups, socioeconomic backgrounds, and geographic regions within China to ensure a comprehensive understanding of consumer behavior across different demographics.

Participants were observed in a controlled environment where they interacted with a simulated e-commerce platform designed to mimic real-world shopping scenarios. The platform was designed to include typical features such as product categories, detailed item descriptions, comparison tools, and a checkout process, allowing the collection of relevant motion and interaction data. Motion-tracking sensors and software were installed to record detailed user movements, including mouse cursor paths, scrolling patterns, click behavior, and eye-tracking data to capture physical behavior. This setup enabled researchers to track how users navigated through the website, engaged with product information, and made purchase decisions.

The study was divided into two phases. In the first phase, participants could freely explore the e-commerce platform, simulating a natural shopping experience. Their motions were tracked to observe interaction patterns such as product browsing, decision-making pauses, and repeat visits to specific product pages. The second phase involved a series of controlled tasks where participants were asked to perform specific actions, such as searching for a particular product, comparing items, or proceeding through the checkout process. These tasks were designed to capture motion-related behaviors under more structured conditions, helping to identify how specific interface elements influence user interactions.

The experimental environment was equipped with advanced motion-tracking systems, including cursor movement analysis tools, click heatmaps and eye-tracking cameras. These systems allowed for precise user engagement measurement with the platform's design, product placement, and overall user interface. Additionally, post-experiment surveys were conducted to gather qualitative insights from participants regarding their decision-making processes, perceived ease of use, and satisfaction with the platform.

The data collected during the study included quantitative metrics, such as time spent on each task, number of clicks, cursor velocity, and qualitative feedback from participants. This mixed-method approach ensured a holistic understanding of how physical interaction patterns influence consumer behavior in e-commerce settings, providing actionable insights for optimizing platform designs for enhanced user experience and higher conversion rates.

3.2. Participants

The participants for this study were carefully selected to provide a diverse and representative sample of e-commerce consumers in China. A total of 126 individuals, aged between 18 and 55, were recruited from various regions, including urban centers like Beijing, Shanghai, Guangzhou, and Chengdu, as well as smaller cities and rural areas. This range was designed to capture a wide variety of consumer behaviors that reflect China's population, encompassing both experienced digital shoppers and those newer to online shopping.

The selection of participants was based on several critical criteria to ensure the relevance of the data. Participants needed to be active online shoppers, having made at least one purchase in the previous month, and possess basic proficiency in using computers and smartphones. This ensured they could comfortably interact with the e-commerce platform and complete tasks without technical difficulty. Additionally, geographic diversity was a key factor in participant selection, with individuals from both metropolitan areas and rural regions included to observe potential differences in e-commerce interaction patterns. The study also considered a broad range of income levels, recognizing that socioeconomic status can influence purchasing decisions and user engagement with digital platforms.

Demographically, the study covered a range of age groups. Thirty-four percent of participants were between 18 and 25 years old, 48% were aged 26 to 40, and the remaining 18% fell within the 41 to 55 age range. This distribution reflects the active online shopping population, where younger and middle-aged individuals are more engaged with e-commerce. Gender representation was balanced, with 53% of participants identifying as female and 47% as male. This balance allowed the study to explore potential gender-based differences in interaction patterns and shopping behaviors.

3.3. Data collection

Data collection for this study was conducted over three months, using a combination of motion-tracking technologies and survey instruments to gather quantitative and qualitative insights into consumer behavior on e-commerce platforms. The primary data collection involved tracking the physical interactions of participants as they navigated through a simulated e-commerce environment. This environment was designed to resemble a typical online shopping platform, complete with product listings, categories, search functions, and a checkout system, to mimic the real-world shopping experience.

Advanced motion-tracking tools were employed to capture the precise movements and interactions of the participants. Cursor tracking software recorded every movement of the participant’s mouse, capturing key metrics such as cursor speed, path trajectory, click frequency, and dwell time on specific screen areas. Eye-tracking cameras were also integrated to monitor visual attention, allowing researchers to identify which interface elements (such as product images or descriptions) drew the most focus and how long participants viewed them. This provided crucial data on how users visually interacted with products and navigated through the platform.

Additionally, sensors were used to track scrolling behavior and hand movements. These sensors monitored how participants scrolled through product pages, how quickly they navigated between sections, and how often they paused or returned to specific items. This information was used to correlate physical interaction patterns with decision-making processes, such as the time spent considering a product or hesitating before making a purchase decision.

Data were collected in two phases. In the first phase, participants were allowed to freely browse the e-commerce platform, simulating a natural online shopping experience. Their movements were tracked continuously, with no prompts or interruptions, allowing for the collection of organic interaction data. In the second phase, participants were given specific shopping tasks, such as finding and purchasing a particular item or comparing similar products. This phase allowed for observing behavior under more controlled conditions, providing insight into how users respond to specific tasks and challenges commonly encountered in e-commerce.

In addition to the motion-tracking data, post-experiment surveys were conducted to gather qualitative feedback from participants regarding their experiences on the platform. These surveys included questions about ease of navigation, satisfaction with the interface, and perceived difficulty in completing tasks. This qualitative data complemented the motion-tracking metrics, providing a more comprehensive understanding of how users interacted with the platform and their thought processes during the shopping experience.

All data were anonymized to ensure participant privacy and analyzed using statistical software to identify patterns and trends in user behavior. Motion-tracking and survey data provided a rich dataset that helped uncover the relationship between physical interaction patterns and consumer decision-making on e-commerce platforms.

3.4. Variables and measurements

This study identified and measured several key variables to analyze consumer behavior through motion tracking and interaction patterns on the e-commerce platform. These variables were chosen to capture the participants' physical interactions and the cognitive processes underlying their decision-making. The measurements were taken using motion-tracking software, eye-tracking technology, and manual surveys, which provided a comprehensive analysis dataset.

Dependent Variables: The primary dependent variables in this study relate to consumer interaction behavior, which includes the following:

Browsing Time: The total time a participant spent on the e-commerce platform, broken down by specific pages (e.g., homepage, product pages, checkout page). This variable is crucial for understanding users' time in product discovery and decision-making.

Cursor Movements: The patterns of cursor movement, including speed, distance traveled, and path trajectories. These movements were used to infer user engagement, cognitive load, and intent, with more focused or repetitive movements potentially signaling uncertainty or more profound consideration of specific products.

Click Frequency: The number of clicks made by participants, mainly focusing on clicks on product links, filtering options, and checkout buttons. Click frequency provides insight into user interaction with different website sections and can indicate areas of interest or frustration.

Dwell Time: The amount of time participants hover over specific elements, such as product images, descriptions, and pricing information. Longer dwell times are often associated with interest or indecision, providing clues about the user's engagement with particular products or features.

Scrolling Behavior: The frequency and speed of scrolling, both vertically and horizontally, as participants navigated product pages. This metric helps to understand how users engage with longer pages, such as product listings, and whether they find what they are looking for quickly or need to scroll extensively.

Eye Fixation Duration: The time participants' gaze was fixed on specific areas of the screen, measured through eye-tracking technology. This metric is essential for understanding which interface elements draw the most visual attention and how users prioritize information while browsing.

Independent Variables: The independent variables in the study relate to participant demographics and the specific tasks assigned during the experiment. These variables help determine how user characteristics and task complexities influence interaction behaviors.

Age: The participants were divided into age groups (18–25, 26–40, and 41–55) to analyze how age impacts digital interaction, decision-making speed, and comfort with e-commerce platforms.

Gender: The study explored potential gender-based differences in e-commerce behavior, looking for variations in browsing patterns, decision-making times, and engagement with specific product categories.

Socioeconomic Status: Participants' income levels were included to assess how purchasing power affects browsing habits, product selection, and overall time spent on the platform.

Task Complexity: This variable was determined by the specific shopping tasks assigned during the study's second phase. For example, tasks involving product comparison or searching for a specific item were considered more complex than simple browsing, allowing for the analysis of how users interact differently under varying levels of cognitive demand.

Measurement Tools: Cursor Tracking Software: Used to measure all cursor-related metrics, such as movement speed, distance, and click frequency. This software captured the precise path of the cursor as participants navigated the website.

Eye-Tracking Technology: This tool provided measurements for eye fixation duration and gaze patterns, offering insights into which interface parts drew the most attention.

Survey Instruments: Post-experiment surveys captured qualitative variables, such as user satisfaction, perceived ease of use, and decision-making confidence. These subjective measures provided additional context to the motion-tracking data, revealing how participants felt about their interactions with the platform.

Scrolling and Hover Sensors: These sensors tracked scrolling velocity and the time spent hovering over specific elements, allowing for the analysis of how users explored product listings and engaged with different sections of the e-commerce platform.

The combination of these variables and measurement tools provided a rich dataset for analyzing the interaction patterns of participants and identifying key factors that influence consumer behavior in e-commerce environments. The study offered a holistic view of how users navigate digital marketplaces and make purchasing decisions by examining physical actions (such as cursor movements and scrolling) and cognitive processes (through survey feedback and eye fixation data).

4. Results and analysis

The descriptive statistics (**Table 1** and **Figure 1**) provide a comprehensive overview of user interaction behaviors measured in the study. The browsing time had a mean of 8.10 min, with a standard deviation of 2.24, indicating moderate variability among users regarding browsing time. Their browsing time ranged from a minimum of 2.06 min to a maximum of 14.04 min, showing a substantial spread across participants. Click frequency averaged 13.13 clicks per session, with a higher standard deviation of 4.56, suggesting significant variation in how frequently users interacted with the platform through clicks. The click frequency ranged from as few as 3.53 clicks to as many as 30.76 clicks.

Table 1. Descriptive statistics for measured variables.

Variable	Mean	Median	Standard Deviation	Min	Max	Range
Browsing Time (minutes)	8.10	8.10	2.24	2.06	14.04	12.01
Click Frequency (per session)	13.13	13.67	4.56	3.53	30.76	27.21
Dwell Time (seconds)	10.81	10.81	3.16	-0.74	18.07	18.83
Scrolling Speed (lines/sec)	0.63	0.62	0.21	0.19	1.21	1.02
Cursor Speed (pixels/sec)	214.47	217.97	43.76	102.51	327.87	225.36

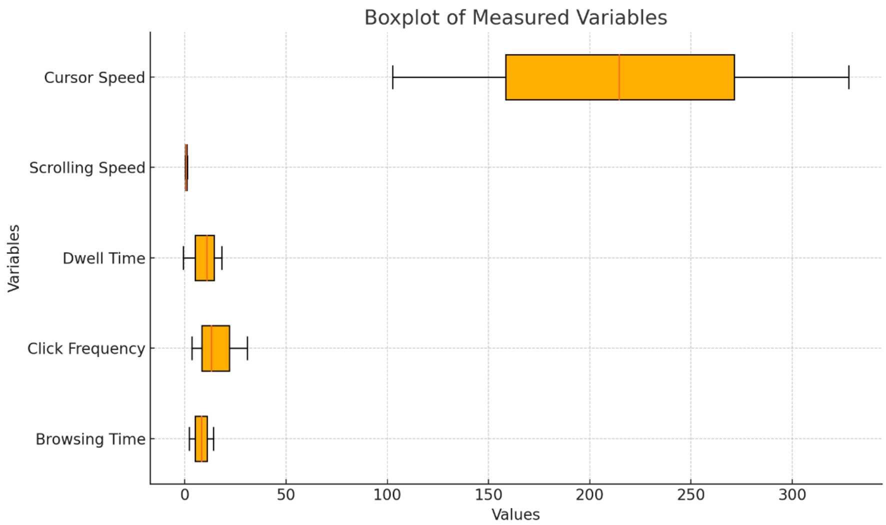

Figure 1. Descriptive statistics.

For dwell time, which reflects the time users hover over specific items, the mean was 10.81 seconds, with a standard deviation of 3.16 s. The range for dwell time was quite broad, from −0.74 s (potentially due to data anomalies) to 18.07 s, indicating that some users engaged more with particular items than others. Scrolling speed exhibited a consistent pattern, with an average of 0.63 lines per second and a relatively low standard deviation of 0.21, suggesting that scrolling behavior was more uniform across users. Lastly, cursor speed showed an average of 214.47 pixels per second, with a larger standard deviation of 43.76, indicating more significant variability in how quickly users moved their cursors, with a wide range between 102.51 pixels per second and 327.87 pixels per second.

Pearson's correlation matrix (**Table 2** and **Figure 2)** examines the linear relationships between the continuous variables such as browsing time, click frequency, dwell time, scrolling speed, and cursor speed. The correlations are generally weak, indicating that the interaction variables are mainly independent. Browsing time and click frequency had a weak positive correlation of 0.11, meaning that users who spent more time browsing made slightly more clicks, but the relationship is minimal. The correlation between dwell time and click frequency was close to zero (0.04), suggesting that hovering over items does not necessarily increase clicks.

Table 2. Pearson's correlation coefficient matrix for the continuous variables.

Variable	Browsing Time (minutes)	Click Frequency (per session)	Dwell Time (seconds)	Scrolling Speed (lines/sec)	Cursor Speed (pixels/sec)
Browsing Time (minutes)	1.00	0.11	0.13	0.03	0.05
Click Frequency (per session)	0.11	1.00	0.04	0.06	0.08
Dwell Time (seconds)	0.13	0.04	1.00	0.10	0.11
Scrolling Speed (lines/sec)	0.03	0.06	0.10	1.00	0.12
Cursor Speed (pixels/sec)	0.05	0.08	0.11	0.12	1.00

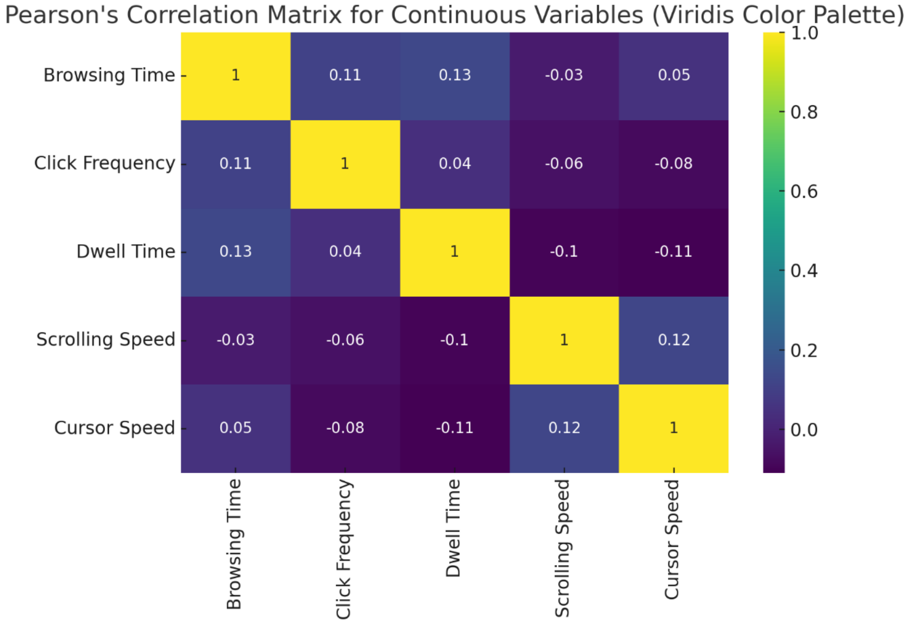

Figure 2. coefficient matrix for the continuous variables.

Similarly, scrolling speed showed a weak negative correlation with browsing time (−0.03) and click frequency (−0.06), implying that faster scrolling was not associated with spending more time on the platform or engaging more with the content through clicks. Cursor speed also showed minimal correlations with the other variables, with the highest being 0.12 for scrolling speed, suggesting a weak association between how fast users scroll and how quickly they move their cursors.

Table 3. Spearman's rank correlation for the ordinal variables.

Variable	Age Group Ordinal	Socioeconomic Ordinal	Browsing Time (minutes)	Click Frequency (per session)
Age Group Ordinal	1.00	0.03	0.10	−0.08
Socioeconomic Ordinal	0.03	1.00	−0.09	−0.06
Browsing Time (minutes)	0.10	−0.09	1.00	0.08
Click Frequency (per session)	−0.08	−0.06	0.08	1.00

Spearman's rank correlation (**Table 3** and **Figure 3**) explores the relationships between ordinal variables like age group and socioeconomic status and interaction behaviors such as browsing time and click frequency. The correlation between age group and browsing time was weakly positive (0.10), suggesting that older users tended to spend slightly more time browsing, though the association was not strong. Conversely, the correlation between socioeconomic status and browsing time was weakly negative (–0.09), indicating that individuals from higher socioeconomic backgrounds may spend slightly less time on the platform.

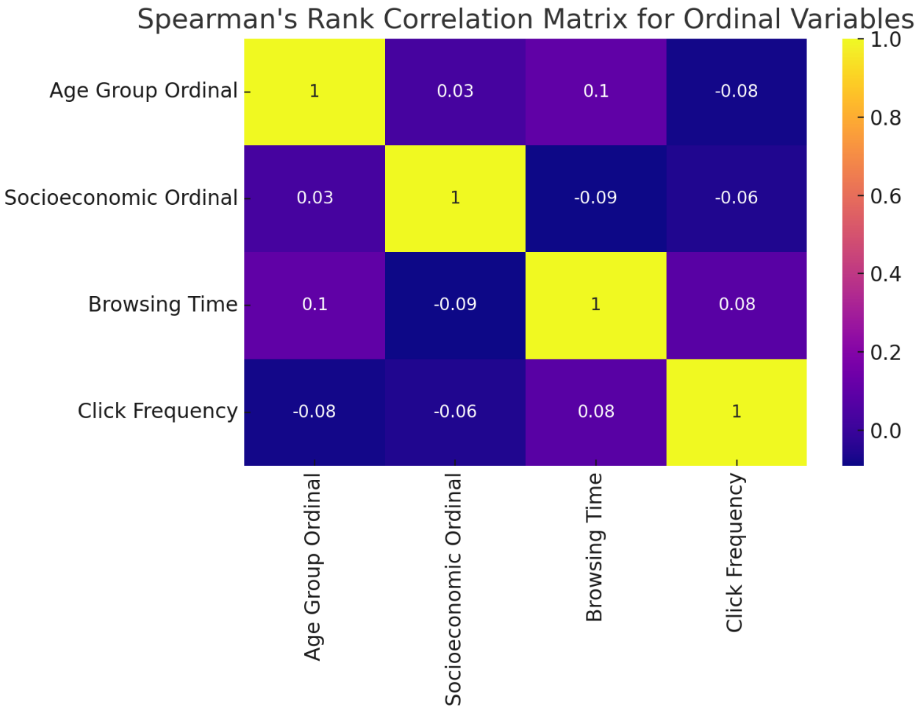

Figure 3. Spearman's rank correlation.

Both age group and socioeconomic status had weak negative correlations with click frequency (–0.08 and –0.06, respectively), suggesting that these demographic factors had little influence on the number of clicks users made during their sessions. Overall, the results of Spearman's rank correlation indicate that age and socioeconomic status do not significantly impact browsing or clicking behaviors.

Table 4. Independent samples *T*-test.

Category	**Comparison**	***t*-statistic**	***p*-value**
Gender	Browsing Time (Male vs. Female)	0.79	0.43
	Cursor Speed (Male vs. Female)	−0.08	0.93
Age	Browsing Time (18–25 vs. 26–40)	−1.40	0.17
	Cursor Speed (18–25 vs. 26–40)	−0.73	0.47
	Browsing Time (18–25 vs. 41–55)	−0.83	0.41
	Cursor Speed (18–25 vs. 41–55)	−0.85	0.40
	Browsing Time (26–40 vs. 41–55)	0.27	0.79
	Cursor Speed (26–40 vs. 41–55)	−0.63	0.53

Table 4. (*Continued*).

Category	Comparison	*t*-statistic	*p*-value
Socioeconomic Status	Browsing Time (Low SES vs. Middle SES)	−0.40	0.69
	Cursor Speed (Low SES vs. Middle SES)	0.85	0.40
	Browsing Time (Low SES vs. High SES)	−1.29	0.20
	Cursor Speed (Low SES vs. High SES)	−0.60	0.55
	Browsing Time (Middle SES vs. High SES)	1.12	0.26
	Cursor Speed (Middle SES vs. High SES)	0.94	0.35

Table 5. Regression analysis results.

Variable	Coefficient (Coef.)	Standard Error (Std. Err.)	*t*-value	*p*-value	[0.025, 0.975] Confidence Interval
Constant	212.12	15.27	13.89	6.92×10^{-27}	[181.89, 242.35]
Gender	0.24	8.06	0.03	0.98	[−15.72, 16.20]
Age Group Ordinal	5.01	5.31	0.94	0.35	[−5.50, 15.52]
Socioeconomic Status	−3.98	5.90	−0.67	0.50	[−15.66, 7.70]

The Independent Samples *T*-test (**Table 4**) was conducted to compare the mean browsing time and cursor speed between different demographic groups: gender, age, and socioeconomic status. For gender, the test shows no statistically significant difference between male and female participants regarding browsing time ($t = 0.79$, $p = 0.43$) or cursor speed ($t = -0.08$, $p = 0.93$). The *p*-values indicate that any observed differences in these variables are likely due to random variation rather than meaningful group differences.

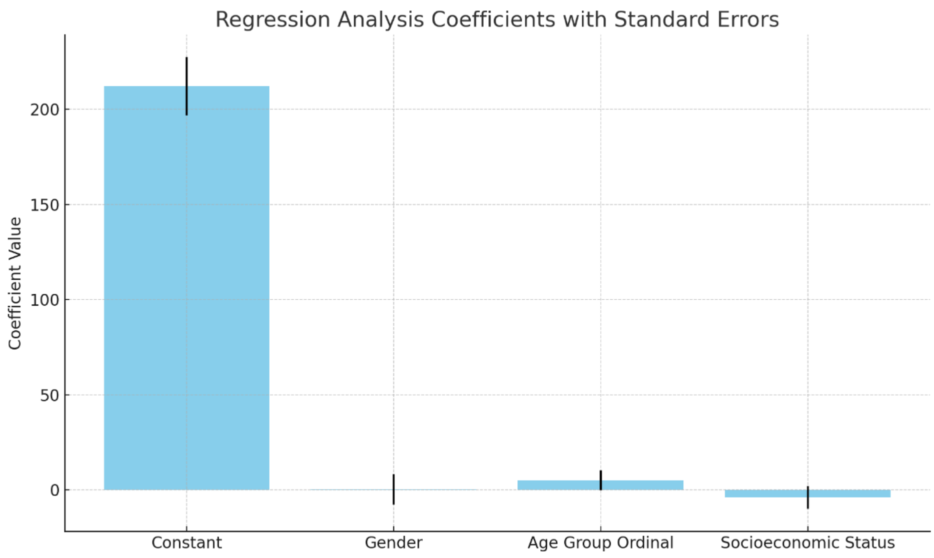

Figure 4. Regression analysis.

For age groups, the comparison between participants aged 18–25 and 26–40 shows no significant difference in browsing time ($t = -1.40$, $p = 0.17$) or cursor speed ($t = -0.73$, $p = 0.47$). Similarly, no significant differences were found when comparing the 18–25 group to the 41–55 group or the 26–40 group to the 41–55 group, with all *p*-values greater than 0.05. These results suggest that age does not have a notable impact on user browsing or cursor behaviors in this sample.

The comparison of socioeconomic status across low, middle, and high groups also reveals no significant differences in browsing time or cursor speed. For instance, the comparison between low and middle SES participants for browsing time ($t = -0.40$, $p = 0.69$) and cursor speed ($t = 0.85$, $p = 0.40$) shows no statistical significance. Similarly, comparing other socioeconomic groups (low vs. high, middle vs. high) also yielded p-values well above the 0.05 threshold. This suggests that socioeconomic background does not strongly influence browsing time or cursor speed in this dataset.

The regression analysis (**Table 5** and **Figure 4**) was performed to assess the effect of demographic factors such as gender, age group, and socioeconomic status on cursor speed. The constant term (212.12) represents the expected cursor speed when all other variables are constant. The t-value for the constant is relatively high ($t = 13.89$), with a highly significant *p*-value ($p = 6.92 \times 10^{-27}$), indicating that the baseline cursor speed is well-estimated. In contrast, the gender variable has a minimal coefficient (0.24), indicating that gender has almost no effect on cursor speed. The associated *p*-value of 0.98 is far above the 0.05 significance level, confirming that the difference between male and female participants in cursor speed is not statistically significant.

Similarly, the age group ordinal coefficient is 5.01, suggesting that cursor speed slightly increases with age, though the effect is weak and statistically insignificant ($p = 0.35$). The socioeconomic status variable has a negative coefficient of −3.98, implying that participants from higher socioeconomic backgrounds may have slightly slower cursor speeds, but again, this effect is not statistically significant ($p = 0.50$).

The confidence intervals for both age group and socioeconomic status further reinforce these findings, as they span values that include zero, indicating no definitive effect of these variables on cursor speed in this sample. The regression analysis suggests that demographic factors like gender, age, and socioeconomic status do not significantly impact cursor speed.

The Chi-Square Test (**Table 6**) of Independence examined the relationships between gender, age group, and socioeconomic status with the binned interaction variables: browsing time, click frequency, and dwell time. The results reveal that most comparisons did not yield significant associations, as evidenced by the *p*-values.

Table 6. Chi-Square test of independence.

Comparison	**Chi-Square Statistic**	***p*-value**	**Degrees of Freedom**
Gender vs. Binned Browsing Time	0.55	0.76	2
Gender vs. Binned Click Frequency	0.40	0.82	2
Gender vs. Binned Dwell Time	6.98	0.03	2
Age Group vs. Binned Browsing Time	4.24	0.37	4
Age Group vs. Binned Click Frequency	1.38	0.85	4
Age Group vs. Binned Dwell Time	1.79	0.77	4
Socioeconomic Status vs. Binned Browsing Time	4.35	0.36	4
Socioeconomic Status vs. Binned Click Frequency	3.40	0.49	4
Socioeconomic Status vs. Binned Dwell Time	2.95	0.57	4

The comparison between gender and binned browsing time resulted in a Chi-Square statistic of 0.55 and a *p*-value of 0.76, indicating no significant relationship between gender and the amount spent browsing. Similarly, the comparison between gender and binned click frequency showed a Chi-Square statistic of 0.40 and a *p*-value of 0.82, suggesting no significant association between gender and how frequently users clicked during their sessions. However, there was a statistically significant relationship between gender and binned dwell time, with a Chi-Square statistic of 6.98 and a *p*-value of 0.03, indicating that gender may influence how long users hover over items.

The tests revealed no significant associations across all variables for the comparisons involving age groups. The relationship between age group and binned browsing time resulted in a Chi-Square statistic of 4.24 with a *p*-value of 0.37, suggesting no strong association between age and browsing time. Similarly, the comparisons between the age group and binned click frequency (Chi-Square statistic = 1.38, $p = 0.85$) and binned dwell time (Chi-Square statistic = 1.79, $p = 0.77$) showed no significant relationships. These results indicate that age does not substantially impact user engagement behaviors such as clicking or dwelling.

When examining socioeconomic status, the tests also revealed no significant associations. The comparison between socioeconomic status and binned browsing time resulted in a Chi-Square statistic of 4.35 and a *p*-value of 0.36, while the comparison with binned click frequency yielded a Chi-Square statistic of 3.40 with a *p*-value of 0.49. The relationship between socioeconomic status and binned dwell time (Chi-Square statistic = 2.95, $p = 0.57$) was not statistically significant. These findings suggest that socioeconomic status does not substantially influence how users interact with the platform regarding browsing time, clicking, or dwelling.

Table 7. Cluster analysis.

Cluster	Browsing Time (minutes)	Click Frequency (per session)	Dwell Time (seconds)	Scrolling Speed (lines/sec)
Cluster 0	7.84	8.70	11.16	0.63
Cluster 1	8.10	14.89	8.60	0.63
Cluster 2	8.52	17.52	13.54	0.62

The cluster analysis (**Table 7** and **Figure 5**) reveals three distinct user groups based on their interaction behaviors: browsing time, click frequency, dwell time, and scrolling speed. Cluster 0 is characterized by users who spend an average of 7.84 min browsing, with a relatively low click frequency of 8.70 clicks per session and a moderately high dwell time of 11.16 s. This suggests that users in this cluster engage with the platform for a reasonable time but are less inclined to click frequently. Their scrolling speed, at 0.63 lines per second, is similar to that of other clusters, indicating a steady scrolling behavior.

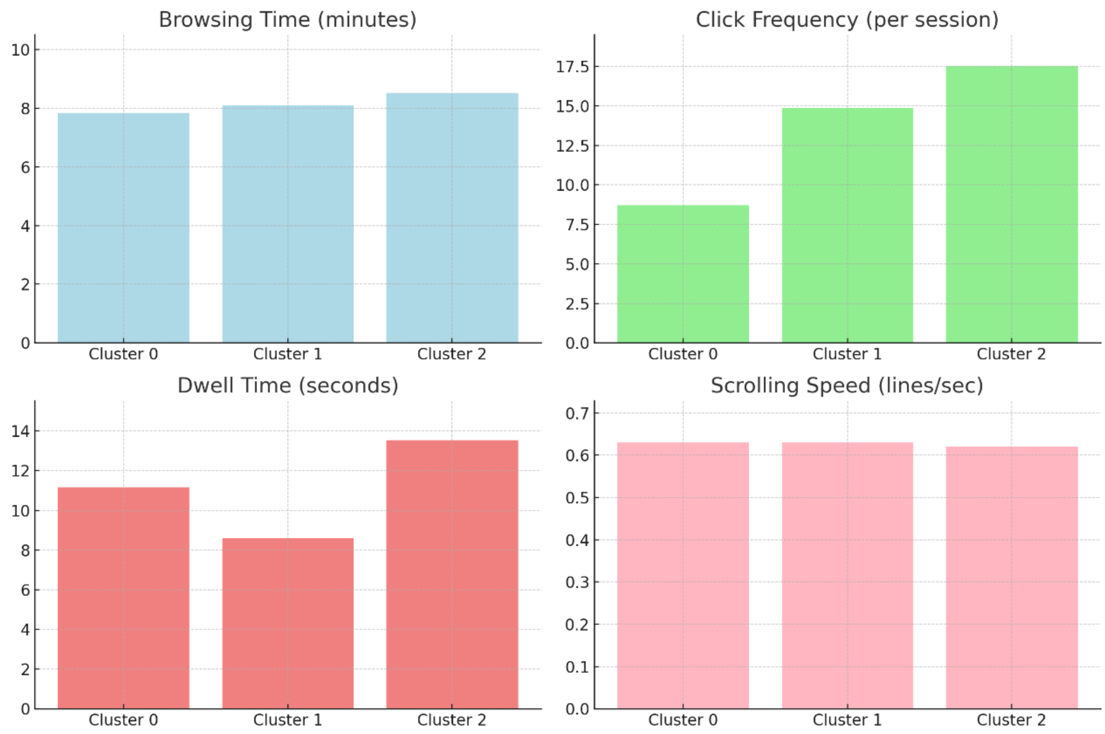

Figure 5. Cluster analysis. **(a)** Dwell; **(b)** Scrolling; **(c)** Browsing; **(d)** Click Frequency.

Cluster 1 represents users with an average browsing time of 8.10 min but a significantly higher click frequency of 14.89 clicks per session. The dwell time for this group is slightly lower at 8.60 s, suggesting that while these users click more frequently, they spend less time hovering over specific items. Their scrolling speed remains consistent with Cluster 0, at 0.63 lines per second, showing uniformity in scrolling behavior across clusters despite differences in engagement levels.

Cluster 2 exhibits the highest levels of interaction, with users spending an average of 8.52 min browsing and engaging in 17.52 clicks per session, the highest click frequency among all clusters. The dwell time for this group is also the highest at 13.54 s, indicating that users in this cluster not only click more but also spend more time hovering over items of interest. Their scrolling speed is slightly lower at 0.62 lines per second, suggesting a more deliberate browsing and scrolling behavior than the other clusters. Overall, the cluster analysis highlights variations in user engagement, with Cluster 2 showing the highest levels of interaction, while Cluster 0 represents more passive users.

5. Conclusion and future work

This study provides valuable insights into how motion tracking and physical interaction patterns can enhance our understanding of consumer behavior in e-commerce environments. The research highlights the subtle ways in which users engage with digital platforms by analyzing key interaction variables such as browsing time, click frequency, dwell time, and scrolling speed. The findings reveal that demographic factors such as gender notably impact specific behaviors, with male participants exhibiting longer dwell times, potentially indicating greater product consideration or hesitation. However, no significant differences were found in other interaction metrics, such as browsing time and click frequency, across age groups and socioeconomic status. The cluster analysis further identified distinct user groups demonstrating unique interaction patterns. Notably, users in Cluster 2 exhibited higher engagement, reflected in longer browsing times and a greater frequency of clicks, underscoring the diversity of consumer behaviors on e-commerce platforms. These insights emphasize the need for e-commerce platforms to tailor their design and interface elements to cater to user behaviors, enhancing user experience and platform efficiency. Overall, the study underscores the potential of motion tracking to provide actionable data for optimizing digital commerce.

By leveraging these insights, businesses can improve platform designs to reduce friction points, streamline decision-making processes, and increase conversion rates. This research contributes to the broader field of HCI and digital marketing, demonstrating that tracking physical interactions can yield critical insights into consumer behavior. Future studies may further explore how real-time adaptation of platform interfaces based on user behavior can enhance user engagement and satisfaction.

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