SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(1), 647.
https://doi.org/10.62617/mcb647

Article

The role of motion analysis in enhancing personalized marketing experiences in e-commerce platforms: A biomechanics and biology-integrated perspective

Liming Liu[1], Mi Zhang[1,*], Xingchang Fan[2], Hui Cui[2], Chengnan Li[3]

[1] Qinhuangdao Vocational and Technical College, Qinhuangdao 066100, China
[2] Department of Commerce, Qinhuangdao Vocational and Technical College, Qinhuangdao 066100, China
[3] Department of Information Engineering, Qinhuangdao Vocational and Technical College, Qinhuangdao 066100, China
*** Corresponding author:** Mi Zhang, MiZhang100@outlook.com

CITATION

Liu L, Zhang M, Fan X, et al. The role of motion analysis in enhancing personalized marketing experiences in e-commerce platforms: A biomechanics and biology-integrated perspective. Molecular & Cellular Biomechanics. 2025; 22(1): 647. https://doi.org/10.62617/mcb647

ARTICLE INFO

Received: 28 October 2024
Accepted: 4 November 2024
Available online: 10 January 2025

Abstract: This paper explores the role of motion analysis in enhancing personalized marketing experiences within e-commerce platforms. Personalized marketing has become a vital strategy in e-commerce, allowing businesses to tailor content and recommendations to individual users based on data such as browsing history, purchase patterns, and customer preferences. Motion analysis, which tracks and interprets physical interactions such as mouse movements, scroll patterns, and gestures, offers an additional layer of real-time behavioral insights. This paper examines how motion data can lead to more accurate product recommendations, adaptive user interfaces, and dynamic marketing strategies. Furthermore, it highlights the key benefits, including improved customer engagement, conversion rates, and satisfaction. This study also explores the biological mechanisms underlying motion analysis. It investigates how motion analysis reflects users' physiological responses and psychological states, integrating these insights with personalized marketing strategies. Additionally, the paper examines how motion analysis data can enhance the understanding of users' biological characteristics, such as fatigue and attention, and how these insights can be applied to create more effective personalized marketing approaches. Moreover, the paper identifies the challenges associated with implementing motion analysis, such as the complexity of integrating real-time tracking tools, data processing limitations, and privacy concerns. The integration of motion analysis with AI and machine learning is explored as a promising avenue for the future, offering predictive and adaptive personalization techniques that can revolutionize the user experience in e-commerce.

Keywords: motion analysis; user behavior; physical interactions; real-time personalization; personalized marketing; e-commerce platforms; AI and machine learning; biological mechanisms

1. Introduction

Personalized Marketing (PM) has become a cornerstone of e-commerce, where businesses tailor their offerings and communications to individual customers based on data-driven insights [1,2]. By leveraging data such as purchase history, browsing behavior, and customer preferences, e-commerce platforms can provide users with product recommendations, targeted promotions, and a more relevant shopping experience [3,4]. Personalization enhances the user's journey and improves conversion rates and customer retention, making it a vital strategy for businesses aiming to compete in the crowded online marketplace [5,6].

Understanding customer behavior is critical for a successful PM. With the vast amounts of data generated through user interactions, businesses can develop a comprehensive view of individual shopping habits, preferences, and intentions [7,8]. The ability to predict what a customer may be interested in purchasing next or what content might engage them depends mainly on analyzing their behaviors in real time [9,10]. As the complexity of consumer behavior grows with the advent of multiple devices and platforms, businesses must continuously seek new ways to gain deeper insights into customer actions and preferences.

Motion analysis refers to studying and interpreting a user's physical movements and interactions within a digital environment, such as an e-commerce website or mobile application [11,12]. This includes tracking mouse movements, scroll patterns, gestures on touchscreens, and other physical inputs users make while navigating a platform [13]. Motion Analysis (MA) provides additional layers of information beyond basic metrics like clicks and time spent on a page, revealing insights into user intent, engagement levels, and navigation behaviors [14,15].

In e-commerce, MA is highly relevant as it allows platforms to refine their understanding of how customers interact with product listings, recommendation engines, and the overall interface. By analyzing these movements, businesses can adjust their marketing strategies in real-time, personalize user interfaces dynamically, and deliver a more seamless, intuitive shopping experience. It provides a more granular understanding of customer behavior, enabling marketers to create deeply personalized experiences beyond traditional data points.

This paper aims to explore how motion analysis can significantly enhance PM experiences on e-commerce platforms. Businesses can gain deeper insights into customer engagement and intent by tracking and interpreting user movements, such as mouse navigation, scrolling patterns, and gestures. This paper will investigate how these insights can lead to more accurate and timely product recommendations, dynamic content adjustments, and improved customer satisfaction, creating more effective PM strategies.

Additionally, the paper will identify the key benefits of integrating MA into existing marketing frameworks, such as providing a more granular understanding of customer behavior, improving real-time personalization, and optimizing user interfaces. However, this paper will also address the challenges of implementing MA, including technical hurdles, data privacy concerns, and the complexity of interpreting motion data effectively. Understanding the advantages and obstacles will provide a comprehensive view of how MA can reshape PM in e-commerce.

The rest of the paper is organized as follows: Section 2 reviews existing personalization techniques in e-commerce and highlights their limitations; Section 3 introduces MA, its key techniques, and the tools for collecting and analyzing motion data; Section 4 discusses the impact of MA on PM, focusing on enhancing user insights, improving recommendations, and tailoring interfaces; Section 5 presents a case study demonstrating the practical application of MA in e-commerce; Section 6 addresses the technical and ethical challenges of MA, Section 7 explores future advancements and the integration of AI for enhanced personalization; and Section 8 concludes the paper.

2. Existing solutions and limitations

2.1. Current personalization techniques in e-commerce

E-commerce platforms employ several personalization techniques to enhance user experience and drive sales. One common approach is user segmentation, which involves grouping customers based on shared characteristics such as demographics, purchase behavior, or browsing history. This allows businesses to target different segments with tailored offers, advertisements, and product suggestions. Although segmentation improves the relevance of marketing efforts, it often lacks the granularity required to target individual customer preferences accurately [16].

Another widely used method is purchase history-based recommendations, where businesses analyze a user's previous purchases to suggest products they may be interested in buying next. This technique effectively increases repeat purchases but primarily relies on past behavior, which may not always reflect current or evolving customer interests. Furthermore, it lacks real-time adaptability, limiting responsiveness to changing user behavior during browsing [17].

Collaborative filtering and content-based recommendations are also key techniques in e-commerce personalization [18]. Collaborative filtering uses the behavior of similar users to recommend products, while content-based recommendations suggest items based on a user's specific preferences and previous interactions. While these methods improve personalization by leveraging data patterns, they still depend heavily on static or historical data and do not fully capture the real-time context in which users make decisions [19].

2.2. Limitations of current approaches

Despite the effectiveness of these personalization techniques, they have notable limitations, particularly in their ability to capture real-time interactions. One of the primary issues is the lack of Machine Learning interaction analysis. Current methods often rely on static data or actions like clicks and previous purchases, but they do not provide insight into a user's active behavior while navigating the platform. This means that marketers miss out on understanding how users interact with content, products, and interfaces in real time, limiting the ability to adjust the shopping experience dynamically [20].

Additionally, an inadequate understanding of physical user engagement, such as motion and gestures, can provide crucial insights into user intent and decision-making. For instance, mobile device mouse movements, scrolling patterns, and touch gestures can reveal much about a user's engagement level, confusion, or interest in specific products. Traditional personalization techniques do not consider these physical interactions, which means platforms often fail to deliver experiences that respond to the nuances of user behavior. This gap highlights the need for more advanced solutions, such as motion analysis, to enhance personalization strategies and improve user experience in e-commerce [21,22].

3. Motion Analysis in e-commerce

3.1. Definition and types of MA

MA in e-commerce refers to systematically collecting and interpreting a user's physical interactions with a website or mobile application. Unlike traditional metrics such as clicks and page views, motion analysis tracks more granular behaviors like how users move their mouse, scroll through pages, or interact with touchscreen devices. This additional layer of behavioral data allows e-commerce platforms to understand better user intent, engagement levels, and navigational patterns [23–25].

Mouse tracking is one of the most commonly used motion analysis techniques, where the cursor's movement is monitored to gauge user interest in specific areas of a page. For example, hovering over an item for an extended period may indicate curiosity or consideration, even if the user does not click on it. Similarly, scroll patterns provide valuable insights into how deeply a user engages with content. Users who scroll quickly through a page may search for something specific, while those who pause and scroll slowly are likely reading or considering content more carefully. Another key type of motion data is click paths, which track the sequence of clicks users make during their session, revealing the order in which they explore a site's content.

For mobile and touchscreen devices, gesture recognition plays a vital role in understanding user behavior. Gestures such as swiping, pinching, or tapping can reveal how users interact with product images, catalogs, or menus. These gestures allow platforms to analyze user intent and adjust the interface or content presentation accordingly, making the user experience more intuitive and responsive.

3.2. Data collection techniques for MA

To capture and analyze motion data, e-commerce platforms rely on various tools and software, including heatmaps, session replays, and AI-based algorithms. Heatmaps visually represent areas of high interaction, such as where users click or hover most frequently, enabling businesses to identify popular sections of a webpage. These tools provide an overview of user engagement patterns and can help optimize layouts and content placement [26–30].

In addition to heatmaps, session replay software allows platforms to observe entire user sessions, replaying how individual users navigate through the site in real-time. This can be particularly useful for identifying usability issues or points of friction in the shopping experience. For more advanced motion analysis, AI-based algorithms often process large volumes of data and identify patterns that may not be immediately obvious. Machine Learning (ML) can be trained to recognize and predict user intent based on complex interaction data, providing businesses with actionable insights to optimize their marketing efforts in real-time.

However, with the growing use of MA, ethical considerations and data privacy concerns have become critical. Tracking user behavior at such a granular level raises questions about user consent and data protection. E-commerce platforms must comply with data privacy regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Transparency is essential, as users must be informed about what data is being collected, how it will be used, and how their privacy will be protected. Ethical practices must be in place to avoid overstepping privacy boundaries and maintain user trust while utilizing MA for personalization.

4. Impact of MA on PM

4.1. Enhancing user behavior insights

MA significantly enhances understanding of user behavior, providing deeper insights into customer intent that goes beyond traditional metrics. By tracking subtle interactions such as mouse movement, scrolling, and gestures, platforms can discern what users click on and how they interact with the content before making decisions. This allows for a deeper understanding of user intent, capturing moments when users may be considering a product without taking immediate action. For example, hovering over a product image or slowly scrolling through a product description can indicate interest, even if the user does not immediately make a purchase [31–33].

Another critical insight gained through motion analysis is identifying passive interest versus active engagement. Users who move quickly through a site, with minimal interaction, are likely browsing passively, while those who engage in actions like detailed scrolling, zooming in on images, or interacting with various page elements are more likely to be actively engaged and considering a purchase. This distinction helps marketers focus their efforts on users most likely to convert, allowing for more targeted and effective marketing strategies.

4.2. Improving product recommendations

MAs also improve the quality and relevance of product recommendations by incorporating real-time interaction data. Traditional recommendation systems often rely on static data such as past purchases or browsing history, which may not accurately reflect a user's current interests. By analyzing motion data—such as how long a user hovers over a product, the path they take through related products, or how they interact with product images—e-commerce platforms can make more relevant suggestions that align with the user's immediate behavior and preferences.

Furthermore, MA enables real-time adjustments in marketing strategies. For example, if a user consistently hovers over high-end products but does not purchase, the platform could offer personalized promotions or highlight related premium products, encouraging conversion. These dynamic adjustments, made possible by continuous tracking of user interactions, ensure that recommendations remain timely and relevant, improving the overall effectiveness of PM efforts.

4.3. Tailoring user interfaces

One of the most significant impacts of MA on e-commerce is its ability to tailor user interfaces based on real-time user interaction data. By analyzing patterns in user movements—such as common click paths, frequent scrolling areas, and gesture patterns—platforms can dynamically adjust the interface to suit individual user preferences. For instance, if users frequently scroll through product categories or hover

over specific filters, the platform could automatically prioritize those sections or features in subsequent visits, creating a more personalized navigation experience.

In addition, MA supports dynamic interface changes for better engagement, allowing the platform to respond to user behavior on the fly. For example, if motion data indicates that users struggle to find a particular product feature, the interface can adjust by making the feature more prominent or offering guided suggestions. This level of personalization improves usability, reduces friction, and leads to higher levels of user satisfaction. Ultimately, tailoring the user interface based on movement patterns helps create a seamless and intuitive shopping experience, significantly boosting user engagement and conversion rates.

5. Case study: Implementation of MA in e-commerce

To illustrate the practical application and impact of MA on PM in e-commerce, we will explore a case study of a well-known e-commerce platform (here referred to as "ShopEase") that integrated MA into its marketing strategy. This case study will outline the steps in implementing MA, the challenges faced, and the measurable outcomes observed.

5.1. Background

ShopEase is a mid-sized e-commerce platform specializing in consumer electronics and household products. The company has already employed traditional personalization methods, including user segmentation, purchase history-based recommendations, and collaborative filtering. However, despite these efforts, ShopEase struggled with user engagement, as many visitors abandoned their carts or spent limited time on the site before exiting. ShopEase identified the need for more advanced tools to better understand customer behavior in real-time, specifically to address these pain points.

5.2. Implementation of MA

Implementing MA was driven by gaining deeper insights into user behavior and improving product recommendations and customer engagement. ShopEase implemented a suite of tools for its mobile platform, including mouse-tracking software, scroll pattern analysis, and gesture recognition. Additionally, the company employed session replay tools to review customer interactions in real-time, combined with AI-based algorithms to analyze the large datasets generated.

The implementation process occurred in three phases:

1) Data collection and infrastructure setup: ShopEase integrated motion tracking software on its website and mobile app, ensuring that all user interactions—mouse movements, scrolling, and gestures—were captured in real-time. This data was linked to the platform's existing analytics systems, providing an enriched dataset that combined motion data with traditional customer metrics like purchase history and click behavior.
2) Pattern analysis and insight generation: AI-based algorithms were employed to analyze the motion data, identifying patterns in how users navigated the platform. For example, it was discovered that users who spent more time hovering over

product images and slowly scrolling through reviews were more likely to purchase high-ticket items. Additionally, users who frequently scrolled back to previous product pages showed signs of uncertainty or indecision, signaling an opportunity for targeted marketing interventions.

3) Real-time personalization and interface adjustments: Based on these insights, ShopEase implemented dynamic changes to its user interface. For instance, users who exhibited indecisive behavior were automatically presented with a pop-up offering additional product details, customer reviews, or a personalized discount. On the mobile app, gesture-based insights were used to streamline the interface, making it easier for users to swipe through product classes and compare items side by side.

5.3. Key challenges faced

During the implementation of MA, ShopEase encountered several challenges:

- Data overload: The vast amount of data generated from motion tracking required significant processing power and storage capacity. The company had to invest in cloud infrastructure to efficiently handle the volume of real-time data.
- Interpreting complex user behavior: While mouse movements and scroll patterns provided valuable insights, interpreting these actions was not always straightforward. For example, rapid scrolling could indicate disinterest or simply an attempt to skim through content quickly. Distinguishing between these behaviors required fine-tuning the algorithms to account for contextual factors, such as the time spent on other page areas.
- Balancing privacy and personalization: ShopEase had to ensure that its MA practices complied with data privacy regulations, including GDPR. This required transparency with users about the collected data and ensuring that users could opt out of motion tracking. Implementing these privacy features without compromising the effectiveness of MA was a balancing act.

5.4. Comparative analysis

Figure 1 shows that user engagement improved significantly with MA compared to the previous year without it. With MA, engagement steadily increased, peaking with noticeable fluctuations as the system adjusted to user behavior in real-time. In contrast, the progression without MA was slower and less pronounced, indicating that traditional methods had limited effectiveness in driving continuous engagement. The fluctuations in both lines reflect typical user behavior influenced by external factors, such as marketing campaigns or seasonal variations, but the overall difference shows that MA substantially boosts user involvement.

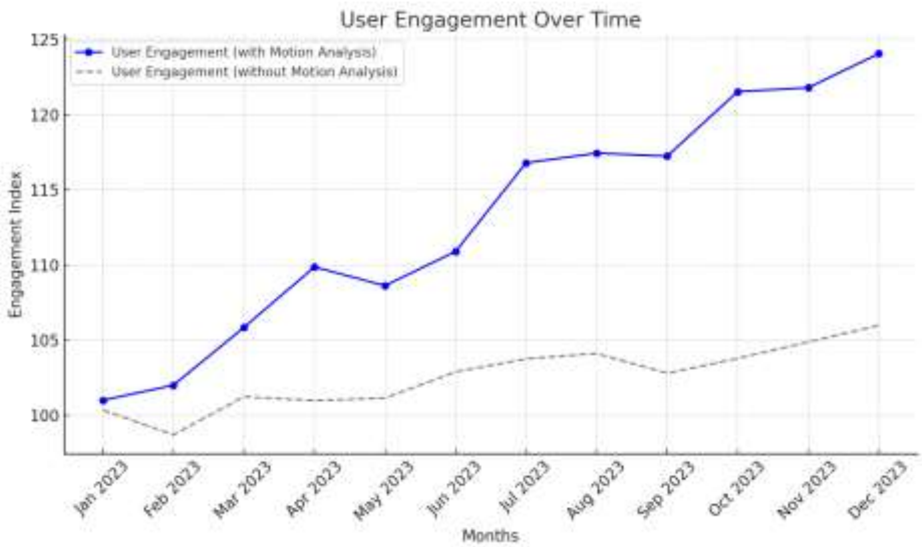

Figure 1. Comparison of user engagement.

The conversion rate chart (**Figure 2**) illustrates a similar trend, with MA driving more substantial development than the previous year's flatter progression. Conversion rates rose by 15% with MA, while the improvement without it was a modest 3%. The real-time insights gained from motion data allowed ShopEase to intervene at crucial points in the user journey, such as when indecision was detected, leading to more completed transactions. Without MA, the slow and minor improvements suggest that traditional methods struggled to adapt quickly to user needs.

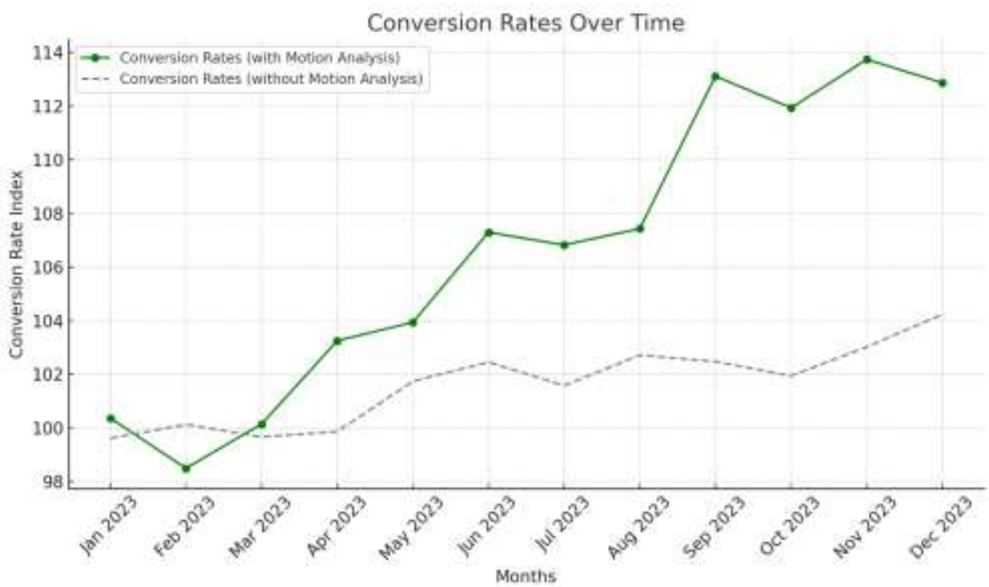

Figure 2. Comparison of conversion rate.

In the product recommendation chart (**Figure 3**), the impact of MA becomes even more evident. Recommendations became far more accurate and effective for the year, improving by 20%, while without MA, there was only a slight 2% improvement. Motion data allowed the platform to fine-tune recommendations based on real-time engagement, such as which products users hovered over or interacted with for extended periods. In contrast, the static methods employed without MA were less adaptive, resulting in less effective recommendations.

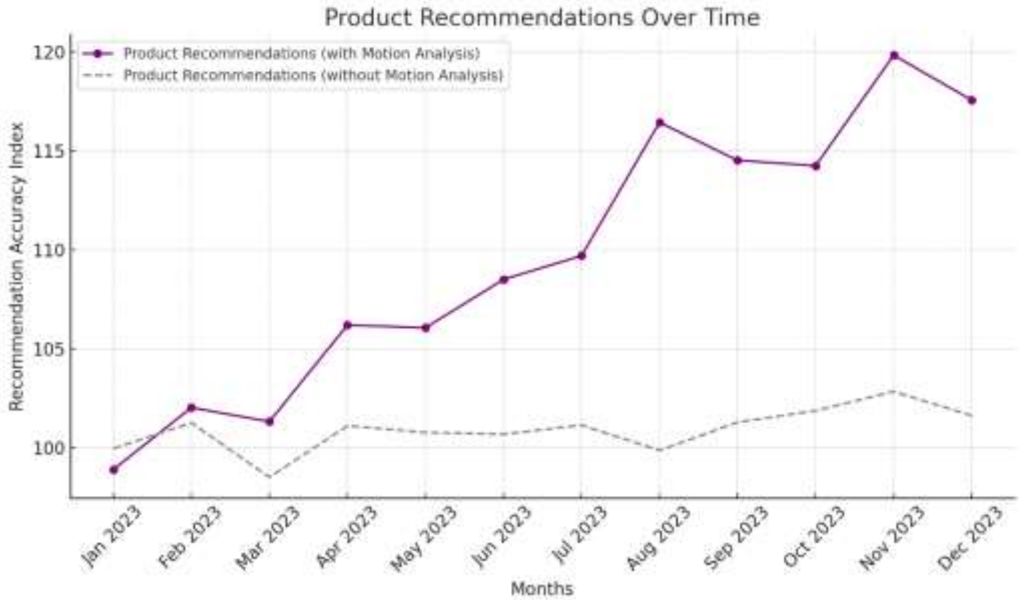

Figure 3. Comparison of product recommendation.

The customer satisfaction chart (**Figure 4**) demonstrates that users responded positively to the enhanced personalization enabled by MA, with a 10% rise in satisfaction over the year. Without motion analysis, satisfaction grew by only 4%, showing the limitations of traditional methods. The dynamic interface adjustments and personalized recommendations made possible by motion tracking led to a smoother and more intuitive user experience, driving higher satisfaction. The slight fluctuations in both lines reflect external factors, but the clear difference in the overall trend underscores the value of MA in improving user experience.

Figure 4. Comparison of customer satisfaction.

6. Challenges and limitations of MA

6.1. Technical challenges

i) Complexity in integrating real-time MA tools

One of the primary technical challenges of implementing MA in e-commerce is the complexity involved in integrating real-time motion tracking tools with existing systems. MA requires collecting vast amounts of interaction data, including mouse movements, scroll patterns, and gestures, which must be processed in real time to provide actionable insights. This requires a robust infrastructure capable of continuously handling and analyzing data streams without causing delays or performance issues on the platform. Integrating these tools with e-commerce websites often involves significant customization, as each platform's user interface and underlying systems may differ. Additionally, ensuring compatibility across devices—such as desktop, mobile, and tablets—adds another layer of complexity, as motion behaviors vary significantly across different platforms.

ii) Data processing and analysis limitations

Another major challenge lies in processing and analyzing the big motion data generated by users. While tools like heatmaps and session replays provide visual insights, making sense of this data meaningfully, especially at scale, can be difficult. Platforms must employ advanced ML to sift through the data and identify patterns in user behavior, but training these models requires significant resources. There is also the challenge of distinguishing between meaningful and trivial movements. For example, not all mouse movements or scrolls indicate interest or intent—some could be incidental or unintentional. Determining the context and relevance of these actions in real-time can be complex, and misinterpreting them can lead to ineffective or poorly targeted personalization efforts.

6.2. Privacy and ethical concerns

i) User consent and privacy issues

As with any user data collection, motion analysis raises significant privacy concerns. Tracking users' physical interactions, such as how they move their cursor or interact with elements on a page, can feel intrusive if not handled transparently. The collection of such granular data requires platforms to seek explicit user consent and adhere to regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Platforms must ensure that users are fully aware of the collected data, how it will be used, and the security measures to protect their information. However, obtaining meaningful consent can be a challenge. Users often disregard or quickly dismiss consent prompts without fully understanding the implications, leading to ethical concerns about whether they are genuinely informed about the extent of the data collection.

ii) Balancing personalization with user comfort and trust

One of the central ethical dilemmas in motion analysis is balancing the benefits of personalization with maintaining user comfort and trust. While personalized experiences can significantly enhance user satisfaction and engagement, they can also create discomfort if users feel they are being overly monitored or tracked in methods they did not expect. MA, in particular, can feel more invasive than traditional data collection methods, as it captures more nuanced and detailed interactions. If users perceive the tracking as excessive or unnecessary, it can erode their trust in the platform, leading to negative experiences and reduced loyalty. Striking the right balance requires transparency, giving users control over their data, and ensuring that personalization efforts are not overly intrusive or manipulative. Platforms must also be cautious about over-personalization, where the marketing efforts become too tailored and potentially alienate users by making them feel like they are being constantly monitored.

7. Future directions

7.1. Advancements in MA technology

i) Emerging tools and techniques for motion data analysis

As MA continues to evolve, new tools and techniques promise to enhance motion tracking and behavior analysis capabilities. Advanced AI-powered analytics platforms can now process larger datasets more accurately and efficiently, enabling e-commerce businesses to gain deeper insights into user behavior. For instance, integrating more sophisticated Computer Vision (CV) is expected to allow platforms to interpret better complex user interactions, such as multi-touch gestures on mobile devices or more nuanced cursor movements on desktops. Real-time motion detection tools are also becoming more efficient, offering faster data processing speeds and reducing the lag between data collection and actionable insights. As motion-tracking technology advances, we may also see more detailed heatmaps that can highlight user attention at a micro-level, offering granular insights into where users focus their attention, even within specific page elements or images.

Additionally, there is growing interest in gesture-based interaction tracking, especially with the proliferation of mobile commerce. These tools aim to understand how users interact with touchscreen devices more dynamically and intuitively, potentially predicting intent through gestures such as swiping, pinching, or tapping. As MAs evolve, they will become more adept at recognizing these patterns and translating them into actionable business insights.

7.2. Potential impact on e-commerce

i) Predictions for how MA will shape PM in the future

MA is poised to play a transformative role in the future of PM within e-commerce. As businesses refine their ability to track and interpret user motions, we can expect PM to become increasingly contextual and adaptive. Rather than relying solely on historical data, future platforms can adjust real-time marketing strategies based on immediate user behavior. For example, a customer's interaction method with a product page—such as hesitating over a particular item or scrolling past certain content—could trigger instant recommendations or adjustments to the user interface. This dynamic personalization will create shopping experiences more tailored to individual preferences and behaviors, leading to higher engagement and conversion rates.

Moreover, as consumers become accustomed to seamless and intuitive user experiences, MA could become a cornerstone of building user-centric e-commerce environments. The more precise the understanding of how users interact with content and products, the more likely platforms provide precisely what the user needs at each journey stage. In the long term, motion analysis could drive more predictive marketing, where platforms anticipate user needs before they fully manifest based on interaction patterns, creating a more proactive and satisfying shopping experience.

7.3. Integration with AI and ML

i) Combining motion analysis with AI to enhance predictive analytics

One of motion analysis's most promising future directions is its integration with AI and ML. When combined with AI, MA can go beyond descriptive analytics (understanding what happened) to predictive and even prescriptive analytics (predicting what will happen and advising what to do next). ML can analyze large datasets of user movements to identify patterns and predict future behaviors, such as likelihood to purchase, product preferences, or even potential dissatisfaction based on subtle interactions like cursor movements or scroll hesitations.

Platforms can continuously improve their predictive accuracy by applying ML to motion data. For instance, as more data is collected, AI can be trained to recognize increasingly subtle patterns, allowing businesses to fine-tune their marketing approaches in previously impossible ways. These predictive insights could adjust pricing dynamically, offer personalized promotions at the right moment, or rearrange product displays based on a user's inferred interest level.

Furthermore, Reinforcement Learning (RL) could be implemented to optimize the user experience continually. These models would learn from every user interaction, adjusting the interface and marketing tactics in real-time to maximize engagement and conversions. For example, if the model identifies that a user is likely to abandon a cart based on their interaction patterns, it could trigger an immediate discount or product suggestion to retain the user. In this method, the integration of motion analysis with AI and ML could lead to hyper-personalization, where every user receives a customized experience tailored to their specific needs and behaviors.

8. Conclusion and future work

MA has emerged as a powerful tool for enhancing personalized marketing experiences in e-commerce by providing deeper insights into user behavior. By tracking physical interactions such as mouse movements, scrolling, and gestures, e-commerce platforms can gain a more comprehensive understanding of customer intent and engagement, offering more relevant recommendations and creating dynamic, real-time personalization. However, implementing motion analysis presents challenges, including technical hurdles related to real-time data processing and ethical concerns regarding user privacy.

Despite these challenges, the integration of MA with AI and ML holds immense potential for the future of e-commerce. The ability to predict user needs and adapt marketing strategies based on real-time behavioral insights could lead to hyper-personalized experiences, driving higher engagement, conversion rates, and overall customer satisfaction. As technology evolves, MA is likely to become a critical component of personalized marketing strategies, transforming how businesses interact with customers online.

Author contributions: Conceptualization, LL, MZ, XF, HC and CL; methodology, LL, MZ, XF, HC and CL; software, LL, MZ, XF, HC and CL; validation, LL, MZ, XF, HC and CL; formal analysis, LL, MZ, XF, HC and CL; investigation, LL, MZ, XF, HC and CL; resources, LL, MZ, XF, HC and CL; data curation, LL, MZ, XF, HC and CL; writing—original draft preparation, LL, MZ, XF, HC and CL; writing—review and editing, LL, MZ, XF, HC and CL; visualization, LL, MZ, XF, HC and CL; supervision, LL, MZ, XF, HC and CL; project administration, LL, MZ, XF, HC and CL; funding acquisition, LL, MZ, XF, HC and CL. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

References

1. Tran MT. Unlocking the AI-Powered Customer Experience: Personalized Service, Enhanced Engagement, and Data-Driven Strategies for E-Commerce Applications. In Enhancing and Predicting Digital Consumer Behavior with AI (pp. 375-382). IGI Global. 2024.
2. Okorie GN, Egieya ZE, Ikwue U, et al. Leveraging big data for personalized marketing campaigns: a review. International Journal of Management & Entrepreneurship Research. 2024; 6(1); 216-242.
3. Wu K, Chi K. Enhanced e-commerce customer engagement: A comprehensive three-tiered recommendation system. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online). 2023; 2(3), 348-359.
4. Sakalauskas V, Kriksciuniene D. Personalized Advertising in E-Commerce: Using Clickstream Data to Target High-Value Customers. Algorithms. 2024; 17(1), 27.
5. Susiang MIN, Suryaningrum DA, Masliardi A, et al. Enhancing customer experience through effective marketing strategies: The context of online shopping. SEIKO: Journal of Management & Business. 2023; 6(2), 437-447.
6. Agarwal N. 26. Conceptual Framework for E-commerce Success: Consumer Behaviour and AI-Enhanced Digital Marketing. MOSAIC OF IDEAS: MULTIDISCIPLINARY REFLECTIONS. 2024; 241.
7. Bag S, Srivastava G, Bashir MMA, et al. Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. Benchmarking: An International Journal. 2022; 29(7), 2074-2098.
8. Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. From user-generated data to data-driven innovation: A research agenda to understand user privacy in digital markets. International Journal of Information Management. 2021 60, 102331.
9. Chaudhuri, N., Gupta, G., Vamsi, V., & Bose, I. On the platform but will they buy? Predicting customers' purchase behavior using deep learning. Decision Support Systems. 2021; 149, 113622.
10. Gal, D., & Simonson, I. Predicting consumers' choices in the age of the internet, AI, and almost perfect tracking: Some things change, the key challenges do not. Consumer Psychology Review. 2021; 4(1), 135-152.
11. Indumathi N et al., Impact of Fireworks Industry Safety Measures and Prevention Management System on Human Error Mitigation Using a Machine Learning Approach, Sensors, 2023, 23 (9), 4365; DOI:10.3390/s23094365.
12. Parkavi K et al., Effective Scheduling of Multi-Load Automated Guided Vehicle in Spinning Mill: A Case Study, IEEE Access, 2023, DOI:10.1109/ACCESS.2023.3236843.
13. Ran Q et al., English language teaching based on big data analytics in augmentative and alternative communication system, Springer-International Journal of Speech Technology, 2022, DOI:10.1007/s10772-022-09960-1.

14. Ngangbam PS et al., Investigation on characteristics of Monte Carlo model of single electron transistor using Orthodox Theory, Elsevier, Sustainable Energy Technologies and Assessments, Vol. 48, 2021, 101601, DOI:10.1016/j.seta.2021.101601.
15. Huidan Huang et al., Emotional intelligence for board capital on technological innovation performance of high-tech enterprises, Elsevier, Aggression and Violent Behavior, 2021, 101633, DOI:10.1016/j.avb.2021.101633.
16. Sudhakar S, et al., Cost-effective and efficient 3D human model creation and re-identification application for human digital twins, Multimedia Tools and Applications, 2021. DOI:10.1007/s11042-021-10842-y.
17. Prabhakaran N et al., Novel Collision Detection and Avoidance System for Mid-vehicle Using Offset-Based Curvilinear Motion. Wireless Personal Communication, 2021. DOI:10.1007/s11277-021-08333-2.
18. Balajee A et al., Modeling and multi-class classification of vibroarthographic signals via time domain curvilinear divergence random forest, J Ambient Intell Human Comput, 2021, DOI:10.1007/s12652-020-02869-0.
19. Omnia SN et al., An educational tool for enhanced mobile e-Learning for technical higher education using mobile devices for augmented reality, Microprocessors and Microsystems, 83, 2021, 104030, DOI:10.1016/j.micpro.2021.104030 .
20. Firas TA et al., Strategizing Low-Carbon Urban Planning through Environmental Impact Assessment by Artificial Intelligence-Driven Carbon Foot Print Forecasting, Journal of Machine and Computing, 4(4), 2024, doi: 10.53759/7669/jmc202404105.
21. Shaymaa HN, et al., Genetic Algorithms for Optimized Selection of Biodegradable Polymers in Sustainable Manufacturing Processes, Journal of Machine and Computing, 4(3), 563-574, https://doi.org/10.53759/7669/jmc202404054.
22. Hayder MAG et al., An open-source MP + CNN + BiLSTM model-based hybrid model for recognizing sign language on smartphones. Int J Syst Assur Eng Manag (2024). https://doi.org/10.1007/s13198-024-02376-x
23. Bhavana Raj K et al., Equipment Planning for an Automated Production Line Using a Cloud System, Innovations in Computer Science and Engineering. ICICSE 2022. Lecture Notes in Networks and Systems, 565, 707–717, Springer, Singapore. DOI:10.1007/978-981-19-7455-7_57.
24. Modi, N., & Singh, J. (2023). Understanding online consumer behavior at e-commerce portals using eye-gaze tracking. International Journal of Human-Computer Interaction, 39(4), 721-742.
25. Billewar, S. R., Jadhav, K., Sriram, V. P., Arun, D. A., Mohd Abdul, S., Gulati, K., & Bhasin, D. N. K. K. The rise of 3D E-Commerce: the online shopping gets real with virtual reality and augmented reality during COVID-19. World Journal of Engineering. 2022; 19(2): 244-253.
26. Jang, Y. T., & Hsieh, P. S. (2021). Understanding consumer behavior in the multimedia context: incorporating gamification in VR-enhanced web system for tourism e-commerce. Multimedia Tools and Applications, 80(19), 29339-29365.
27. Necula SC. Exploring the impact of time spent reading product information on e-commerce websites: A machine learning approach to analyze consumer behavior. Behavioral Sciences. 2023; 13(6): 439.
28. Giannakopoulos, N. T., Sakas, D. P., & Migkos, S. P. Neuromarketing and Big Data Analysis of Banking Firms' Website Interfaces and Performance. Electronics. 2024; 13(16): 3256.
29. Alves Gomes, M., & Meisen, T. A review on customer segmentation methods for personalized customer targeting in e-commerce use cases. Information Systems and e-Business Management. 2023; 21(3), 527-570.
30. Chatzidimitris, T., Gavalas, D., Kasapakis, V., Konstantopoulos, C., Kypriadis, D., Pantziou, G., & Zaroliagis, C. A location history-aware recommender system for smart retail environments. Personal and Ubiquitous Computing. 2020; 24, 683-694.
31. Fu L, Ma X. An improved recommendation method based on content filtering and collaborative filtering. Complexity, 2021(1), 5589285.
32. Asaithambi SPR, Venkatraman, S., & Venkatraman, R. Big data and personalisation for non-intrusive smart home automation. Big Data and Cognitive Computing. 2021; 5(1): 6.
33. Zhou X, Krishnan A, Dincelli, E. Examining user engagement and use of fitness tracking technology through the lens of technology affordances. Behaviour & Information Technology. 2022; 41(9):2018-2033.