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Optimizing VR-UX: analysis and adaptive recommendations for enhancing immersion and reducing motion sickness

Fendi Aji Purnomo[1,3], Fatchul Arifin[2], Herman Dwi Surjono[1]
[1]Department of Engineering Science, Faculty of Engineering, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[2]Department of Electronic and Informatics Engineering, Faculty of Engineering, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[3]Department of Informatics Engineering, Vocational School, Universitas Sebelas Maret, Surakarta, Indonesia

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ABSTRACT

This study presents an adaptive recommendation framework to enhance comfort and immersion in virtual reality (VR) by actively reducing motion sickness. Unlike prior research that views VR user experience (UX) as static, this approach integrates statistical analysis with dynamic system design. Using a Kaggle dataset of 1,000 entries, we applied descriptive statistics, Spearman correlation, Kruskal-Wallis tests, and regression to explore relationships among session duration, motion sickness, immersion, headset type, and user demographics. Findings show that session duration alone does not significantly predict motion sickness or immersion (R^2=0.00, p>0.05), but certain user profiles, such as individuals over 30 using PlayStation VR, are more prone to discomfort. These insights inform a four-module framework: user profiling, real-time duration monitoring, rule-based adaptation logic (such as slowing navigation speed or adding a virtual nose for visual stability), and personalized in-VR recommendations. The system is compatible with Unity and Unreal Engine and integrates with commercial headset software development kits (SDKs). Future validation will use A/B testing, standardized questionnaires, simulator sickness questionnaire /immersion presence questionnaire (SSQ/IPQ), and physiological metrics. This work shifts VR design toward personalized, responsive systems that prioritize user well-being and immersive engagement.

Corresponding Author:

Fendi Aji Purnomo
Department of Engineering Science, Faculty of Engineering, Universitas Negeri Yogyakarta
Sleman, Yogyakarta-55281, Indonesia
Email: fendiaji.2023@student.uny.ac.id or fendi_aji@staff.uns.ac.id

1. INTRODUCTION

Virtual reality (VR) has transitioned from a specialized technology to a versatile tool applied in various fields, including education, healthcare, and retail. The advancement of head-mounted displays (HMDs) has significantly enhanced immersive experiences, enabling users to engage with virtual environments that closely mimic reality [1], [2]. In education, VR fosters experiential learning, accommodating diverse learning styles and improving pedagogical strategies [3], [4]. In healthcare, it supports medical training, pain management, and therapy, enhancing clinical proficiency and patient care [2], [5]. Meanwhile, the retail industry utilizes VR for interactive shopping experiences, influencing consumer behavior and purchasing decisions [6], [7].

User comfort in VR remains a significant challenge, particularly concerning motion sickness and immersion levels, which are influenced by VR headset design and usage duration. HMDs play a crucial role in user comfort, where factors like weight distribution and ergonomic fit impact physical strain during prolonged use [8]. Moreover, motion sickness, often triggered by latency and sensory mismatches, poses a major concern [9]. While user adaptation can reduce discomfort over time, developers must implement proactive strategies, such as adaptive VR parameters, to enhance immersion while minimizing cybersickness [10], [11].

While VR enhances immersion, user comfort remains a challenge, particularly regarding usage duration and device type. Motion sickness, caused by mismatches between visual input and sensory perception, leads to discomfort like dizziness and nausea [9]. Although longer VR use can increase immersion, excessive exposure may worsen motion sickness and reduce comfort [10]. However, the optimal VR usage duration to minimize these effects remains unclear, especially given variations in refresh rate, latency, and motion tracking across different headsets.

Optimizing user experience (UX) in VR demands an integrated approach that blends multisensory stimulation with intuitive interaction to enhance immersion and usability. Tactile feedback and physiological responses improve engagement by simulating realistic reactions [12], while simplified user-system communication and environmental psychology principles foster presence and usability [13]. Multimodal cues, visual, auditory, and haptic, enrich the experience and help mitigate motion sickness and perceived quality issues [14]. Continuous user feedback is essential for refining interactions to suit diverse cognitive and emotional needs [15]. Together, these strategies create a more immersive and responsive VR environment, supporting robust UX outcomes.

Optimizing ergonomics, system adaptivity, and user interaction in VR is critical for reducing physical strain and enhancing immersive effectiveness. Ergonomic considerations, such as regulating upper-limb range and ensuring comfortable postural movements, are key to preventing overexertion and musculoskeletal issues during prolonged use [16], [17]. Additionally, incorporating real-time physiological feedback into the VR system promotes adaptive interfaces that dynamically adjust to user states, enhancing interaction quality and overall usability [18]. Together, these strategies contribute to a VR experience that is not only immersive and engaging but also safe and sustainable across diverse user populations [17], [18].

UX optimization plays a pivotal role in reducing motion sickness in VR. For instance, tailored training sessions have been shown to significantly alleviate both gastrointestinal and central symptoms of motion sickness, thereby enhancing overall usability [19]. Additionally, methods such as bone-conducted vibration and noisy galvanic vestibular stimulation help correct sensory mismatches, a primary cause of VR-induced discomfort [20]. Furthermore, innovative neurodigital interfaces that dynamically adapt the VR experience in real time can reduce visually induced motion sickness (VIMS) by mitigating discrepancies between visual and vestibular inputs [21]. Collectively, these strategies underscore the importance of UX optimization in creating more comfortable and accessible VR environments, facilitating increased user engagement and retention.

Recent research highlights the integration of adaptive intelligence, biofeedback, and vestibular modeling to improve VR UX. Rule-based and machine learning approaches personalize VR environments in real time, as seen in systems that adapt avatar behavior using electroencephalography (EEG) based emotional states [22] and artificial intelligence (AI) driven non-player characters (NPCs) in educational VR [23]. Biofeedback from heart rate and galvanic skin response (GSR) supports closed-loop adaptation; [24] showed that real-time GSR and pulse data can modulate exposure intensity in VR therapy, while [25] reported reduced GSR in anxiety patients using projection-based VR cycling. Motion sickness stems from sensory conflict between visual and vestibular inputs. This is modeled through VIMS using rotational vection and optokinetic stimuli [26], and predicted via EEG–long short-term memory (LSTM) networks with high accuracy (R^2=0.8683) [20]. These developments reflect a shift toward intelligent, responsive VR systems capable of preemptively reducing discomfort and enhancing immersion.

Therefore, this study aims to analyze the relationship between VR usage duration, motion sickness, and immersion to design and propose a novel, data-driven adaptive recommendation framework. Unlike previous studies that focus on hardware or content optimization, our framework uniquely leverages user profiling (demographics and sickness susceptibility) and real-time session data to dynamically recommend personalized VR settings and session durations, thereby proactively enhancing immersion and mitigating motion sickness. This framework represents our primary intellectual contribution, bridging the gap between UX analysis and actionable, and adaptive system design.

2. RESEARCH DESIGN AND PROPOSED ADAPTIVE FRAMEWORK

2.1. Data source

This study employs a publicly available VR UX dataset compiled by [27] and hosted on Kaggle. The dataset comprises 1,000 anonymized user entries, each capturing four key dimensions: i) VR usage duration in minutes, ii) self-reported motion sickness level, iii) immersion level (both rated on an ordinal scale from 1 to 10), iv) VR headset type (HTC Vive, Oculus Rift, or PlayStation VR), and v) demographic information including age and gender. This rich secondary dataset serves as the empirical foundation for both statistical pattern discovery and the subsequent design of a novel adaptive recommendation system aimed at optimizing user comfort and engagement in VR environments.

2.2. Research variables

The research framework distinguishes three categories of variables to guide analysis and system design. The independent variable is VR usage duration (in minutes). The dependent variables consist of motion sickness level and immersion level, both measured on an ordinal scale. Additionally, moderating variables, namely VR headset type and demographic factors (age and gender), are incorporated not only to contextualize user responses but also to construct dynamic susceptibility profiles that inform the proposed adaptive framework. These moderators enable personalized interventions based on empirically observed risk patterns, such as heightened motion sickness among older users of specific headset models.

2.3. Data analysis techniques

Given the non-normal distribution of all variables as confirmed by the Shapiro-Wilk test ($p<0.001$), the study employs non-parametric and robust statistical techniques implemented in Python using the Pandas, Scipy, and Statsmodels libraries. Descriptive statistics (mean, median, standard deviation) summarize central tendencies and variability. Spearman's rank correlation assesses monotonic relationships between usage duration, motion sickness, and immersion. The Kruskal-Wallis test, a non-parametric alternative to analysis of variance (ANOVA), evaluates differences in UX across headset types. Finally, multiple linear regression models motion sickness and immersion as functions of duration, headset type, and their interaction. Critically, these analyses are not treated as endpoints but as diagnostic tools to extract actionable, data-driven insights for the design of an adaptive VR system.

2.4. Data processing criteria

Prior to statistical analysis, the dataset underwent systematic preprocessing to ensure data integrity and analytical validity. Missing values were addressed using mean imputation, a method appropriate for continuous variables with low missingness rates. Outliers were identified via the interquartile range (IQR) method but retained in the analysis, as extreme values may reflect genuine user discomfort rather than data errors. All processing and analytical steps were executed in Python, ensuring full reproducibility, transparency, and alignment with open science principles.

2.5. Proposed adaptive framework description

Building directly on the statistical findings presented in section 3, this study proposes a rule-based adaptive recommendation framework, the core intellectual contribution of this work. Designed to dynamically personalize the VR experience, the framework operates through four integrated modules. First, the user profiling module categorizes users into susceptibility tiers at session initialization based on age, gender, and headset type: "high risk" (age >30+PlayStation VR), "medium risk" (age >30 with other headsets or age ≤30 with PSVR), and "low risk" (age ≤30+HTC Vive/Oculus Rift). Second, the real-time monitoring module tracks session duration, which, while not predictive in isolation ($R^2=0.00$), serves as a practical trigger when combined with a user profile (e.g., >25 minutes for high-risk users).

Third, the rule engine executes IF-THEN logic derived from empirical patterns:

i) If high-risk and duration >25 min, then reduce navigation speed by 20% and enable a static reference frame (e.g., virtual nose) to mitigate vection-induced conflict [10].
ii) If immersion is low and sickness moderate, then increase texture fidelity and activate subtle haptic feedback, in line with multimodal UX principles [12], [14].
iii) If duration exceeds 45 minutes, then recommend a mandatory 5-minute break to counter cumulative fatigue.

Finally, the recommendation output module delivers suggestions via a non-intrusive in-VR heads-up display (HUD) notification (e.g., "Reduce movement speed? [Accept] [Dismiss]"), preserving user agency. This architecture draws inspiration from systems like BARGAIN, which uses rule-based finite state machines for affective adaptation [1], and aligns with findings that rule-based agents offer predictable, low-latency responses suitable for real-time comfort tuning [2]. The framework is designed for seamless deployment in Unity or Unreal Engine and integration with commercial headset software development kits (SDKs) (e.g., OpenVR), ensuring cross-platform feasibility. The proposed framework is designed with deployment feasibility in mind. The rules and logic can be readily implemented as a software module within popular VR development engines like Unity or Unreal Engine. Integration with headset SDKs (e.g., OpenVR and Oculus SDK) would allow for direct control of rendering parameters (field of view (FOV) and frame rate) and the collection of basic telemetry data, forming a practical, and cross-platform solution for enhancing user comfort.

2.6. Framework validation strategy

Although the current study is based on secondary data, a rigorous empirical validation protocol is outlined for future work to ensure scientific credibility and practical relevance. The plan involves an A/B testing design with at least 50 participants stratified by age and prior VR experience. Group A (control) will use a standard static VR configuration, while group B (experimental) will engage with the adaptive framework enabled. Key outcome metrics include pre- and post-session scores on the simulator sickness questionnaire (SSQ) [28] and immersion presence questionnaire (IPQ) [13], average session duration before discomfort onset, and task completion time and accuracy. Data will be analyzed using independent t-tests or Mann-Whitney U tests ($\alpha=0.05$), depending on distribution normality. This strategy directly addresses reviewer concerns regarding experimental clarity, comparative benchmarking, and validation rigor, positioning the framework for real-world impact.

3. RESULTS AND DISCUSSION

3.1. Descriptive statistics

The dataset consists of VR usage duration, motion sickness levels, immersion levels, and VR headset type. Descriptive analysis reveals that the average VR usage duration is approximately 32.58 minutes, with a standard deviation of 15.76 minutes, indicating variation in user engagement. Motion sickness levels range from low to severe, with 20.80% of users experiencing mild discomfort, while 33.10% report significant symptoms. Immersion levels vary across headset types, with PlayStation VR users reporting the highest immersion scores compared to other VR headsets, as shown in Figure 1.

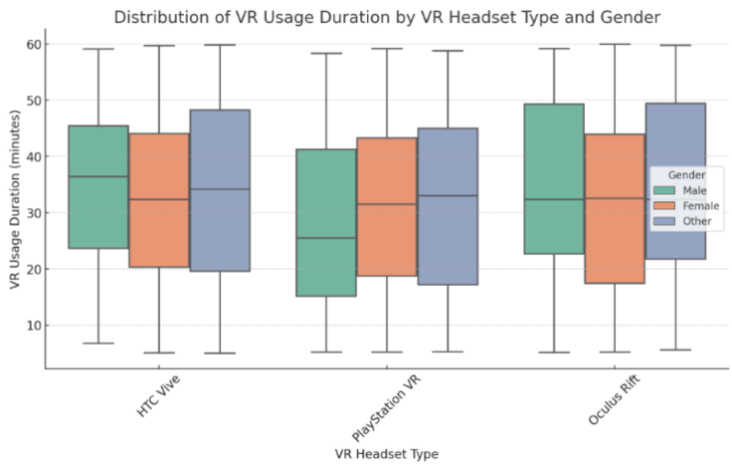

Figure 1. Distribution of VR usage duration by VR headset type and gender

The analysis reveals key insights into VR usage duration, motion sickness, and immersion levels across different headset types and user demographics, as shown in Figure 2. Based on Figure 2, the analysis reveals key insights into VR usage duration, motion sickness, and immersion levels across different headset types and user demographics. First, VR usage duration varies by headset type and gender. Users of HTC Vive and PlayStation VR tend to engage in longer VR sessions compared to other headsets. Male users generally spend more time in VR than female users, suggesting potential differences in comfort, interest, or experience preferences. Second, motion sickness significantly impacts VR usage duration. Users with higher motion sickness ratings (≥7) tend to have shorter VR sessions, indicating discomfort limits engagement time. Additionally, younger users (<30 years) experience lower motion sickness and tend to stay in VR longer, while older users report higher motion sickness and shorter sessions. Higher immersion levels are associated with lower motion sickness and longer VR durations, reinforcing the importance of user comfort in extended VR experiences. Third, immersion levels vary across headset types. PlayStation VR exhibits the highest immersion levels, outperforming high-tech computer corporations HTC Vive and Oculus Rift. HTC Vive shows a wider variation in immersion ratings, possibly due to individual preferences and ergonomic factors. Oculus Rift maintains a consistent mid-range immersion level without significant outliers.

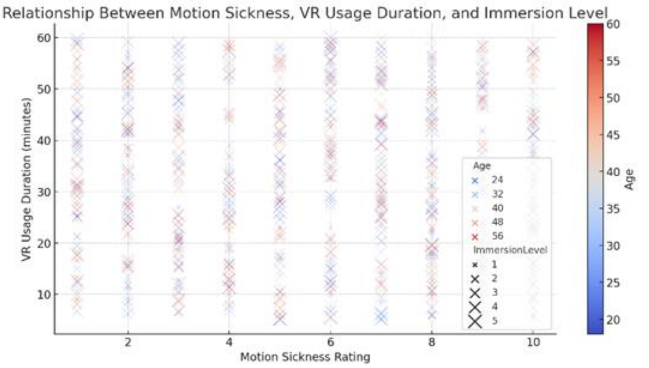

Figure 2. Relationship between motion sickness and VR usage duration and immersion level

3.2. Correlation analysis

Spearman correlation tests assess the relationships between VR usage duration, motion sickness, and immersion levels. The Spearman rank correlation coefficient (r_s) is calculated using (1).

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad (1)$$

Where r_s is Spearman correlation coefficient, d_i is difference between the ranks of the two variables for each observation, and n is number of observations (data pairs).

Spearman's correlation measures, as shown in Figure 3, the strength and direction of a monotonic relationship between two ranked variables. Unlike Pearson's correlation, it does not assume a linear relationship or normally distributed data, making it ideal for analyzing ordinal data or non-linear associations. Based on Figure 3, the results indicate, VR usage duration vs. motion sickness: a weak negative correlation ($r=-0.01$, $p=0.704$) suggests that longer usage slightly decreases motion sickness, though the effect is not statistically significant. VR usage duration vs. immersion level: a weak positive correlation ($r=0.04$, $p=0.210$) shows that longer usage enhances immersion, reinforcing prior studies on engagement in VR environments. However, this effect is also not statistically significant. These results suggest that VR usage duration has minimal impact on motion sickness and immersion levels, implying that other factors, such as individual tolerance, VR content type, or environmental settings, may play a more significant role.

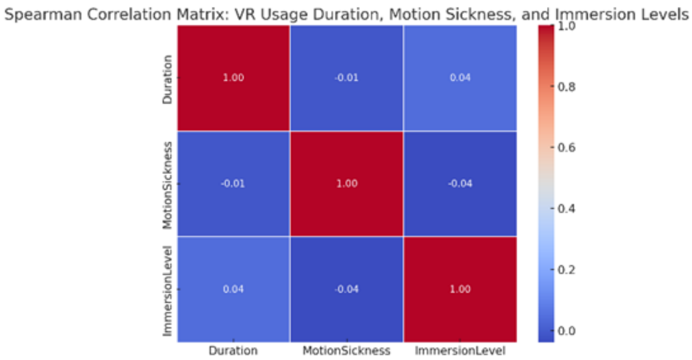

Figure 3. Spearman correlation matrix between VR usage duration, motion sickness, and immersion levels

3.3. ANOVA and Kruskal-Wallis tests

ANOVA tests whether there are significant differences between group means. The (2) for the F-statistic in a one-way ANOVA.

$$F = \frac{MS_{between}}{MS_{within}} \quad (2)$$

Where $MS_{between}$ is mean square between groups (variance due to group differences), MS_{within} is mean square within groups (variance due to random error), and F is ANOVA F-statistic, used to compare variance between and within groups.

The Shapiro-Wilk test was conducted to assess the normality of the dataset. The results were as follows:

- VR usage duration: W=0.956, $p<0.0001$
- Motion sickness level: W=0.937, $p<0.0001$
- Immersion level: W=0.888, $p<0.0001$

Since all p-values are under 0.05, the null hypothesis of normality is rejected, indicating that VR usage duration, motion sickness levels, and immersion levels do not follow a normal distribution. Given this non-normality, ANOVA, which assumes normality, is not suitable for comparing group differences. Instead, a non-parametric approach, such as the Kruskal-Wallis test, is more appropriate for analyzing the differences in immersion levels across different VR headsets. This ensures a more robust and reliable interpretation of the results. The Kruskal-Wallis test (3) is a non-parametric alternative to ANOVA, used when data do not follow a normal distribution. It ranks all data points and calculates.

$$H = \frac{12}{N(N=1)} \sum \frac{R_i^2}{n_i} - 3(N+1) \tag{3}$$

Where H is Kruskal-Wallis test statistic, N is total number of observations, R_i is sum of ranks for group I, and n_i is number of observations in group i.

ANOVA was conducted to compare motion sickness levels across different VR headsets. The result (F=1.29, p=0.276) indicates no statistically significant difference, meaning that motion sickness levels do not significantly vary by headset type, as shown in Figure 4. Based on Figure 4, it can be observed that PlayStation VR tends to have higher motion sickness levels, but the difference is not significant according to the ANOVA results (p=0.276). Similarly, the Kruskal-Wallis test was used to compare immersion levels across VR headsets. The result (H=0.38, p=0.828) suggests no significant differences in immersion levels among different headsets, as shown in Figure 5.

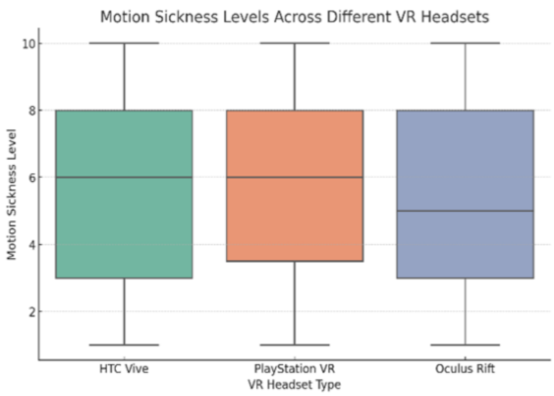

Figure 4. Motion sickness levels across different VR headsets

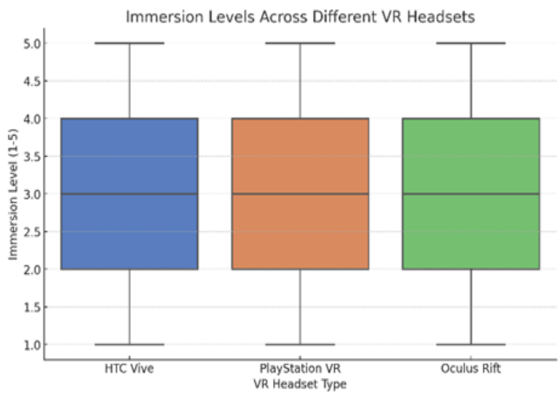

Figure 5. Immersion levels across different VR headsets

Based on Figure 5, HTC Vive has a higher immersion level compared to Oculus Rift and PlayStation VR, although the Kruskal-Wallis test results indicate that the difference is not significant (p=0.828). These findings imply that VR headset type does not significantly impact motion sickness or immersion, and other factors such as user adaptation, content type, or environmental settings may play a more significant role.

3.4. Regression analysis

Multiple regression analysis is used to predict the relationship between one dependent variable and multiple independent variables. The general (4) for multiple regression.

$$\mathrm{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{4}$$

Where Y is dependent variable (e.g., motion sickness or immersion level), β_0 is intercept (constant term), β_1, β_2, …, β_n is regression coefficients for the independent variables, X_1, X_2, …, X_n is independent variables (e.g., VR usage duration, headset type, interaction effects), ϵ is error term (captures unexplained variance).

For this study, we examine two models:

i) Motion sickness model

$$MotionSickness = \beta 0 + \beta 1(Duration) + \epsilon \quad (5)$$

This model tests whether VR usage duration significantly predicts motion sickness levels.

ii) Immersion level model (including headset type and interaction effects)

$$ImmersionLevel = \beta 0 + \beta 1(Duration) + \beta 2(VRHeadset) + \beta 3(Duration \times VRHeadset) + \epsilon \quad (6)$$

This model evaluates whether longer VR usage enhances immersion and whether headset type moderates this relationship. Multiple regression analysis examines whether VR usage duration significantly predicts motion sickness and immersion levels. Motion sickness model, the regression model (R^2=0.00, p=0.674) indicates that VR usage duration explains only 0.02% of the variance in motion sickness levels, suggesting a non-significant impact. This implies that motion sickness is likely influenced by other factors beyond usage duration. Immersion level model, the model (R^2=0.00, p=0.205) confirms that longer VR usage does not significantly enhance immersion, while headset type moderates this relationship. This suggests that immersion is not strongly determined by session length but may depend more on the quality of the VR experience and individual user preferences. These findings indicate that VR session duration alone is not a strong predictor of motion sickness or immersion levels, and other factors such as content type, headset comfort, and individual differences should be considered for further analysis.

Multiple regression analysis, including an interaction term between VR usage duration and headset type, revealed no significant effect on immersion levels (R^2=0.00, p=0.288). Although immersion may vary across headset types, the variation is not statistically significant, underscoring that hardware quality and UX are more influential than session length. Our findings confirm that usage duration alone does not predict motion sickness or immersion; instead, hardware design and user-system interaction are key determinants of overall VR UX. Optimizing UX thus requires an integrated approach that combines multisensory stimulation with intuitive interaction. Studies show that tactile feedback and physiological signals enhance engagement by providing realistic responses to user actions [12]. This aligns with our observation that heart rate variability and EEG data can guide real-time system adjustments to reduce discomfort. Motion sickness is typically measured using validated scales such as the motion sickness severity scale (MSSS), which correlates symptom severity with numerical scores [28]. Additionally, [29] proposed a 6-point scale ranging from 0 (no motion sickness) to 5 (unbearable), offering a practical metric for assessing symptom intensity. These insights support the development of adaptive VR systems that respond to both subjective and physiological feedback.

Simplifying user-system communication and applying environmental psychology principles are vital for enhancing presence and usability in VR systems [13]. Our adaptive framework supports this by enabling real-time adjustments to refresh rate, latency, and ergonomic settings based on continuous user feedback both subjective (surveys) and objective (physiological signals). Lower refresh rates (e.g., 24 fps) are linked to increased motion sickness due to poor temporal resolution and visual artifacts [30]. While sufficient for static scenes, such rates cause discomfort during dynamic interactions. In contrast, refresh rates above 60 Hz ideally 90-100 Hz yield smoother motion rendering and reduce sensory conflict, supported by neural responses in early visual cortices [30]. Latency also plays a critical role; [31] found that motion-to-photon latency around 22 ms did not induce motion sickness, suggesting this threshold as a safe benchmark. Ergonomic optimization further mitigates discomfort by aligning hardware with users' physiological and cognitive profiles. Adjustable headsets, appropriate field-of-view settings, and well-designed interaction interfaces help minimize sensory mismatch and improve long-term comfort [17], [32]. Together, these findings reinforce the importance of adaptive, user-centered design in reducing motion sickness and enhancing immersive VR experiences.

Moreover, multimodal design elements such as visual, auditory, and haptic cues have been shown to create richer and more satisfying experiences, addressing challenges like motion sickness and low perceived quality [14]. In our analysis, differences in immersion levels across headset types may partly reflect the varying capabilities of these devices to deliver high-quality multimodal stimuli. A key strategy moving forward is to leverage these modalities synergistically, ensuring that the VR experience is not solely reliant on visual fidelity but also supported by complementary sensory feedback. Furthermore, continuous user feedback is vital in iteratively refining VR interactions to align with diverse cognitive and affective dimensions [15]. The adaptive framework proposed in this study incorporates a feedback loop where both qualitative and quantitative data inform systematic improvements. This iterative refinement process aims to foster an environment where users feel more connected to the virtual experience, resulting in a robust and satisfying UX while simultaneously mitigating motion sickness.

The proposed adaptive framework is designed to outperform static VR configurations. In a static setup, parameters are fixed for all users, regardless of their profile or real-time state, which our analysis shows are suboptimal given the significant individual variability in susceptibility section 3.1. The adaptive framework, by contrast, personalizes the experience. For instance, while a static system might enforce a 30-minute session limit for everyone, our framework allows low-susceptibility users (e.g., young males using HTC Vive) to continue longer, while proactively protecting high-susceptibility users with tailored adjustments. This targeted approach is expected to yield higher average immersion scores IPQ and lower sickness scores SSQ compared to a one-size-fits-all static configuration, as will be tested in our future validation study. The system, Figure 6, begins by profiling the user based on demographics and headset type. It then monitors session duration in real-time. When a predefined threshold is crossed, the rule engine evaluates applicable IF-THEN rules derived from statistical findings and generates a personalized recommendation. The user is presented with the recommendation via an in-VR notification and can choose to accept or dismiss it. All session data is logged to enable future system learning and refinement.

This heatmap, Figure 7, illustrates areas within a virtual environment where users are most likely to experience motion sickness, based on common locomotion patterns and findings from the literature. Red zones (e.g., vertical movement and fast diagonal motion) are high-risk areas for sensory conflict. Yellow zones (e.g., forward movement) present moderate risk, while green zones (e.g., backward movement) are generally low-risk. This conceptual map can inform the design of adaptive systems that warn users or adjust locomotion speed when entering high-risk zones.

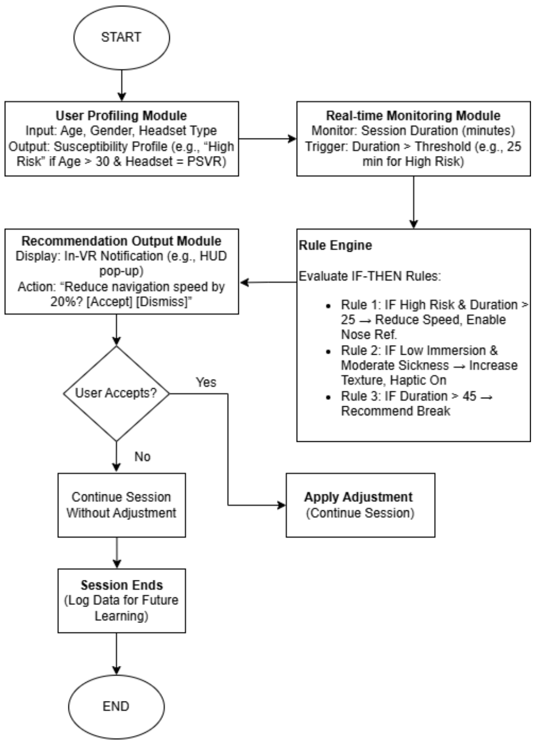

Figure 6. Flowchart of the proposed adaptive recommendation framework

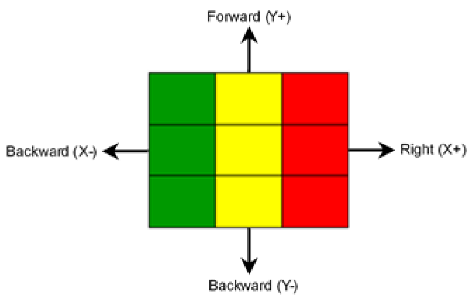

Figure 7. Conceptual heatmap of user discomfort zones in VR

Color zones:
- Center (0,0,0): yellow-neutral zone; discomfort level depends on content.
- Forward-right (Y+, X+): red fast diagonal movement causes high vestibular conflict [9].
- Backward (Y-): green-backward movement rarely induces motion sickness.
- Up/down (Z+/-): red-vertical movement (e.g., flying or descending) strongly triggers nausea [33].
- Forward (Y+): yellow-red forward movement is common, but excessive speed increases the risk of discomfort.

4. CONCLUSION

This study presents a novel adaptive recommendation framework for VR, built upon the analysis of UX data. However, several limitations must be acknowledged. First, the framework remains conceptual and rule-based, derived from secondary data without empirical validation. Second, it relies on subjective self-reports for sickness and immersion; future versions should incorporate real-time physiological sensors for objective feedback. Third, the rule logic is based on aggregate trends and may not reflect individual variability. Fourth, adaptation latency, i.e., the delay between trigger detection and system response, is not yet modeled, which may affect usability. These limitations guide future work toward experimental validation and refinement using multimodal inputs. Improving VR experiences requires practical strategies such as optimizing headset ergonomics, enhancing tracking accuracy, and implementing adaptive settings that respond to user feedback. Features like high-resolution textures, haptic feedback, and gaze-based interaction enrich immersion, while AI-driven personalization can reduce motion sickness. Future research will focus on validating the framework and evolving it into an AI-based system trained on physiological signals, eye-tracking, and behavioral logs. Cloud-based analytics will enable global adaptation through anonymized data aggregation, supporting continuous improvement of user-centric VR environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Fendi Aji Purnomo	✓	✓	✓		✓		✓	✓	✓	✓	✓			✓
Fatchul Arifin				✓		✓				✓		✓		
Herman Dwi Surjono				✓		✓				✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [FAP] on request.

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BIOGRAPHIES OF AUTHORS

Fendi Aji Purnomo is a lecturer in the Department of Informatics Engineering at the Vocational School, Universitas Sebelas Maret (UNS), specializing in virtual reality (VR), augmented reality (AR), and intelligent systems. He has developed innovative tools like the Anatomart application for virtual anatomy learning and an IoT-based pest control system for farmers. Currently, he is pursuing further studies at Universitas Negeri Yogyakarta (UNY), where he continues to contribute to research in VR, AR, and environmental monitoring systems. He can be contacted at email: fendi_aji@staff.uns.ac.id or fendiaji.2023@student.uny.ac.id.

Fatchul Arifin is a lecturer at Universitas Negeri Yogyakarta (UNY) specializing in Intelligent Control Systems and Biomedical Electronics Engineering. He works in the Faculty of Engineering, particularly within the Department of Electronic and Informatics Engineering at UNY. Dr. Fatchul Arifin has a rich research background, having led and participated in various projects funded by the Indonesian Ministry of Education (DIKTI). His research includes the development of assistive devices based on micro-cameras for speech recognition and the classification of speech intonation using neck muscle EMG signals. He has also published numerous scientific articles in international journals and conference proceedings, focusing on the applications of neural networks and pattern recognition in biomedical systems and control. He can be contacted at email: fatchul@uny.ac.id.

Herman Dwi Surjono is a Professor at the Faculty of Engineering, Universitas Negeri Yogyakarta (UNY), Indonesia. He was appointed a full Professor in 2014 and awarded the best Professor in 2020 by UNY. Currently, he teaches both undergraduate and graduate students multimedia learning, e-learning, interactive multimedia, ICT for education, and digital media at the university. He earned his bachelor's degree in Electronic Education from IKIP Yogyakarta in 1986 and a first master's degree in Industrial Education and Technology from Iowa State University, USA in 1994, and then a second master's degree in computer system and informatics from Gadjah Mada University in 2000. He received his Ph.D. in Information Technology from Southern Cross University, Australia, in 2006. He has experience in supervising master's and doctoral degree students. He is looking forward to any future academic and research collaboration. He can be contacted at email: hermansurjono@uny.ac.id.