Exploring and Modeling Gaze-Based Steering Behavior in Virtual Reality

Xuning Hu
School of Advanced Technology
Xi'an Jiaotong-Liverpool University
Suzhou, China
Computational Media and Arts
The Hong Kong University of Science and Technology (Guangzhou)
Guangzhou, Guangdong, China
xuning.hu22@student.xjtlu.edu.cn

Yichuan Zhang
School of Advanced Technology
Suzhou, Jiangsu, China
Computational Media and Arts
The Hong Kong University of Science and Technology (Guangzhou)
Guangzhou, Guangdong, China
yichuan.zhang22@student.xjtlu.edu.cn

Yushi Wei
Computational Media and Arts
The Hong Kong University of Science and Technology (Guangzhou)
Guangzhou, Guangdong, China
ywei662@connect.hkust-gz.edu.cn

Yue Li
Department of Computing
Xi'an Jiaotong-Liverpool University
Suzhou, Jiangsu, China
yue.li@xjtlu.edu.cn

Wolfgang Stuerzlinger
School of Interactive Arts + Technology (SIAT)
Simon Fraser University
Vancouver, British Columbia, Canada
w.s@sfu.ca

Hai-Ning Liang*
Computational Media and Arts Thrust
The Hong Kong University of Science and Technology (Guangzhou)
Guangzhou, Guangdong, China
hainingliang@hkust-gz.edu.cn

Abstract

Gaze-based interaction is a common input method in virtual reality (VR). Eye movements, such as fixations and saccades, result in different behaviors compared to other input methods. Previous studies on selection tasks showed that, unlike the mouse, the human gaze is insensitive to target distance and does not fully utilize target width due to the characteristics of saccades and micro-saccades of the eyes. However, its application in steering tasks remains unexplored. Since steering tasks are widely used in VR for menu adjustments and object manipulation, this study examines whether the findings from selection tasks apply to steering tasks. We also model and compare the Steering Law based on eye movement characteristics. To do this, we use data on movement time, average speed, and re-entry count. Our analysis investigates the impact of path width and length on performance. This work proposes three candidate models that incorporate gaze characteristics, which achieve a superior fit ($R^2 > 0.964$) compared to the original Steering Law, improving the accuracy of time prediction, AIC, and BIC by 7%, 26%, and 10%, respectively. These models offer valuable insights for game and interface designers who implement gaze-based controls in VR environments.

CCS Concepts

• **Human-centered computing** → **HCI theory, concepts and models**.

Keywords

Gaze Input, Steering Law, Virtual Reality, Modeling

ACM Reference Format:
Xuning Hu, Yichuan Zhang, Yushi Wei, Yue Li, Wolfgang Stuerzlinger, and Hai-Ning Liang. 2025. Exploring and Modeling Gaze-Based Steering Behavior in Virtual Reality. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3706599.3720273

1 Introduction

Advancements in eye-tracking technology have made gaze interaction more prevalent, and it is now considered an intuitive and easy-to-use input method [7, 38]. Modern Virtual Reality (VR) and Augmented Reality (AR) headsets, such as the Quest Pro, Hololens, Apple Vision Pro, and HTC Vive, are equipped with built-in eye-tracking capabilities. Notably, the Apple Vision Pro uses gaze as its primary interaction method, allowing users to gaze at targets and confirm their selection with a pinch. Gaze-based input also addresses various interaction challenges, such as scenarios where hands are occupied or space is limited [40].

Steering, the task of navigating an object from a start to an endpoint along a predefined path, is fundamental in both everyday interactions and virtual environments (VEs). The Steering Law, a well-established mathematical model, accurately predicts movement time (MT) by considering path attributes such as length and width [3]. This model has been validated across various devices and scenarios, including 2D touch screens [36], gaze-controlled hierarchical menus [19, 21], 3D controllers [23], and driving simulators [17, 51]. By exploring the relationship between path characteristics and user performance, the Steering Law provides valuable insights for designing intuitive and efficient interfaces. Extended models have incorporated factors such as path curvature, scale, and device latency, enhancing their predictive power and applicability

*Corresponding author.

ACM ISBN 979-8-4007-1395-8/25/04
https://doi.org/10.1145/3706599.3720273

in various types of interactive systems [2, 29, 48]. In VEs, where steering tasks are essential for menu adjustments and object manipulation, the Steering Law remains a pivotal tool for understanding and optimizing user behavior, ultimately improving interaction efficiency and user experience.

Despite its extensive validation, the applicability of the Steering Law to eye movement input remains underexplored. This study aims to validate the Steering Law for gaze-controlled inputs and enhance its predictive power by integrating eye-specific characteristics. We conducted a user study with 16 participants to examine how path length and path width influence movement time, average speed, and re-entry count in steering tasks (see section 4.4). Based on the collected data, we refined the effects of path width and length on movement time and developed three improved candidate models (see section 4.6). Compared to the original Steering Law, our models achieved a higher prediction accuracy for movement time while reducing the complexity of these models.

In summary, our main contributions include: **(1)** validating the applicability of the Steering Law for gaze-based input, **(2)** determining the impact of path length and path width on various user performance metrics, and **(3)** proposing three candidate models to further predict eye movement time and explain associated behavior patterns. These contributions provide valuable references for future game and interface designers in assessing task difficulty and interface suitability.

2 Related Work

2.1 Modeling User Behavior in Pointing and Steering Tasks

To quantify and predict human performance in pointing or movement tasks, Fitts' Law is a fundamental and widely used probabilistic model based on human behavior patterns [25]. The movement time (MT) in Fitts' law refers to the time required to point and select a target, which is influenced by the index of difficulty (ID). The ID is determined by two basic task parameters: target width and target distance. The equation below expresses the relationship between MT and the task parameters:

$$MT = a + b \cdot ID, \quad ID = \log_2\left(\frac{A}{W} + 1\right) \tag{1}$$

MT refers to the time taken to move from the starting position to the target selection point, which is primarily influenced by the ID value. W represents the width of the target, A denotes the amplitude (distance) between the starting position and the target, while a and b are empirical values obtained through regression analysis.

Inspired by Fitts' law, the Steering Law focuses primarily on interpreting the behavior patterns and performance of individuals in steering tasks. These tasks involve users navigating objects or themselves through paths constrained by width and limited length [4, 51]. Behavior and performance are typically represented by the metric of movement time (MT), which refers to the time required to steer from the start to the end point [1]. The relationship between MT, width (W), and length (A) can be expressed as [1]:

$$MT = a + b \cdot \int_c \frac{ds}{W(s)} \tag{2}$$

where a and b represent empirical constants, s denotes a specific position along path c, and $W(s)$ refers to the width at the position s. Assuming that path c maintains a constant width, eq. (2) can be further simplified to:

$$MT = a + b \cdot \frac{A}{W} \tag{3}$$

Thus, the ds and $W(s)$ can be replaced by the independent value of path length A and constant width W. More relevant to our work, previous research has primarily focused on examining the performance of gaze-based input in selection tasks and how to model it using Fitts' Law. However, the predictive power of Fitts' Law for Gaze input has been less clear. Zhai [54] found a relatively low fit, with a value of 0.75, while Vertegaal et al. [41] reported a higher fit of 0.86 for eye clicks. Miniotas et al. [28] reported the highest fit of 0.98. Based on the characteristics of eye movements, Zhang et al. [55] identified two main factors contributing to the instability of model fitting. The first factor is attributed to the inevitable micro-saccadic movements of the eyes, which prevent the full utilization of the target width. To address this, they proposed to subtract an empirical constant $\mu = 11.2$ from the original target width. The second factor stems from prior research suggesting that the contribution of target distance A to selection time is relatively low. Therefore, they introduced an empirical term $e^{\lambda A}$, with $\lambda = 0.00052$, to reduce the impact of A on selection time. Based on this, they proposed an adapted version of Fitts' Law as follows:

$$MT = a + b \cdot \frac{e^{\lambda A}}{W - \mu} \tag{4}$$

2.2 Gaze-Based Interaction in VR

With the widespread adoption of eye-tracking devices, it is common to find them in VR Head-Mounted Displays(HMDs), including the Apple Vision Pro, Quest Pro, and HTC Vive, which all now offer eye-tracking as an input method. Eye-tracking has been extensively explored and applied in various scenarios as a standalone input method or a collaborative input modality, including in games [9, 16, 42], target manipulation [33, 44, 52], text input and selection [10, 13, 26, 37, 46], user interface design [30, 39], and navigation [20, 22]. Although gaze-based interaction is considered one of the most intuitive and rapid input methods [38] and has the ability to enable interaction with devices even when users' hands are occupied with other tasks [31], there are notable differences compared to traditional cursor movement. Unlike cursor manipulation, users cannot rely on real-time visual feedback for calibration but instead must predict and make anticipatory adjustments [35]. During the correction phase, users must alternate between fixation and saccades [15], maintaining longer fixation durations (ranging from 100 milliseconds to several seconds) to stabilize the cursor's position while using saccades to compensate for positioning errors [31].

3 Research Questions

Although previous studies have explored the optimization and modeling of eye gaze as an input method, they have focused primarily on selection tasks. To gain a deeper understanding of how eye gaze influences user behavior in steering tasks, we address the following research questions under varying path width constraints and path lengths:

RQ1: *How does user behavior in gaze-based cursor control align with the Steering Law?* Unlike mouse cursor movement, eye movements alternate between fixations and saccades [15, 31], which limits the ability to utilize visual feedback for real-time calibration fully, thus requiring predictive adjustments [34]. Our study examines whether the Steering Law, which describes the relationship between path characteristics and movement time, remains applicable to gaze-based steering tasks.

RQ2: *How do path features, such as width and length, influence user behavior in gaze-based steering tasks?* Previous research has shown that movement time in eye-pointing tasks is not directly proportional to movement amplitude [12, 34], suggesting a low contribution of path length A. Zhang et al. [55] adapted Fitts' Law for gaze-based input by applying an exponential transformation to A and adjusting the target width W to account for the stability of eye fixation. Our study investigates how path width and length affect movement time, average speed, and re-entry count in gaze-based steering tasks.

4 User Study

4.1 Participants and Apparatus

Sixteen participants (10 men and 6 women) were recruited from a local university. They came from various academic backgrounds, including mathematics, computer science, and design. Their ages ranged from 18 to 26 years (mean age = 21.56 years, SD = 1.59). Among them, three participants reported having laser-corrected vision, two wore contact lenses during the experiment, six wore eyeglasses, and five did not require correction. Participants rated their familiarity with VR systems on a 7-point Likert scale (M = 5.06, SD = 2.25), with higher scores indicating greater familiarity.

Eye movements were recorded using the integrated eye tracker in the Meta Quest Pro VR headset, offering a resolution of 1800 × 1920 per eye, a horizontal field of view (FoV) of 106°, and a vertical FoV of 95.57°. The eye-tracking hardware, a standard component of Quest Pro, captures positional gaze data at up to 90 Hz via Meta's Unity public eye-tracking API [27]. To minimize extraneous head movement even further [5] and to guarantee that the cursor is operated only by eye movements, participants' heads were stabilized using a chin rest, similar to those used in vision assessments. The software ran on a PC equipped with an Intel Core i9 processor and an NVIDIA RTX 3080 Ti graphics card.

4.2 Experiment Task

In our experimental setup, we adopted a task similar to the Steering Task described in prior VR research [24, 43]. The starting position was marked in green and the ending position in blue [50]. Before each trial, participants pressed a button on the controller to activate the eye-tracking system and control the cursor ball. When the cursor ball overlapped with the starting position for 500 ms, the starting region turned red, signaling the beginning of the task. The participants were then required to control the cursor ball to move a target ball with a diameter equal to the path width along the entire path until it reached the blue end area, marking the completion of a trial. It was considered an error if the cursor ball exceeded the path width limit. They were instructed to prioritize both speed and accuracy throughout the experiment.

4.3 Design and Procedure

The user study employed a 4 × 4 within-subjects design. The design featured four path lengths A (25°, 40°, 55°, 70°) and four path widths W (3°, 5°, 7°, 9°), with *IDs* ranging from 2.77 to 23.33 bits, covering a spectrum from easy to difficult task conditions. Path length was defined as the distance from the starting position to the ending position, while path width referred to the diameter of the target ball (see fig. 1). These four A and four W values were combined into 16 conditions, presented in a randomized order during the experiment. Each condition was repeated five times, resulting in a total of 1280 data points ($4A \times 4W \times 5$ repetitions $\times$ 16 participants).

Participants began by completing a demographic questionnaire. They then adjusted the Quest Pro headset's interpupillary distance (IPD) until the display was clear, followed by eye-tracking calibration. An accuracy test ensured calibration quality; participants with calibration errors greater than 1.5° were required to recalibrate. After (re)calibration, participants engaged in a three-minute practice session to familiarize themselves with the task. Formal trials began after this practice period. During the experiment, participants were instructed to remain seated in a fixed, non-rotating chair, minimize head movement, and focus on speed and accuracy. Each session lasted approximately 30 minutes, with short breaks between trials to prevent eye fatigue.

4.4 Evaluation Metric

Three performance metrics were collected for each trial: movement time (MT), average speed (V), and re-entry count.

- **Movement Time(MT):** The total time taken to complete the steering task from the start area to the endpoint. MT is a standard metric for assessing human behavior patterns and task performance [47, 49].
- **Average Speed (V):** Calculated as path length divided by movement time, average speed offers a stable performance measure by minimizing the variability seen in point-based speed measurements [11, 53]. Higher average speeds indicate better performance [48].
- **Re-entry Count:** The number of attempts made to re-control the cursor and target ball, serving as an indicator of saccadic stability across varying conditions [6, 45].

4.5 Results

We initially collected 1280 records. After excluding 15 trials (1.17%) with movement times exceeding 20 seconds and 27 trials (2.11%) that deviated more than three standard deviations from the mean, we analyzed 1,238 valid records. Repeated measures ANOVA was conducted on Movement Time (MT), Average Speed (V), Success Rate, and Re-entry Count, applying Greenhouse-Geisser correction for sphericity violations and Bonferroni corrections for post-hoc comparisons.

4.5.1 *Movement Time.*

Factors A and W significantly influenced movement time (A: $F_{1.702,25.528} = 46.534$, $p < 0.001$, $\eta_p^2 = 0.756$; W:

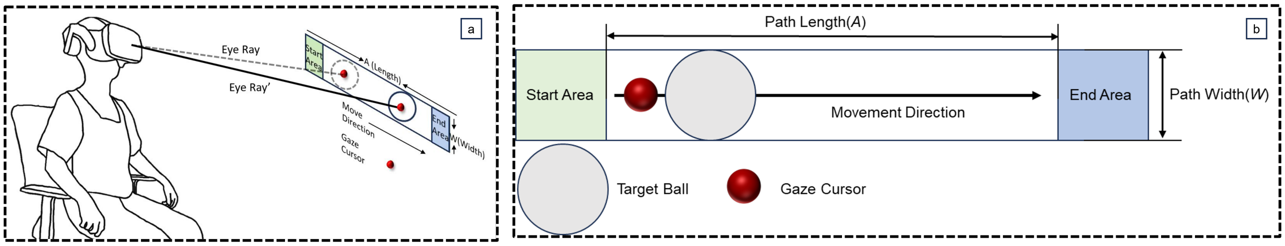

Figure 1: The path width is defined by the diameter of the target ball. Participants operate the Gaze Cursor along the designated movement direction to push the target ball from the starting area to the end area.

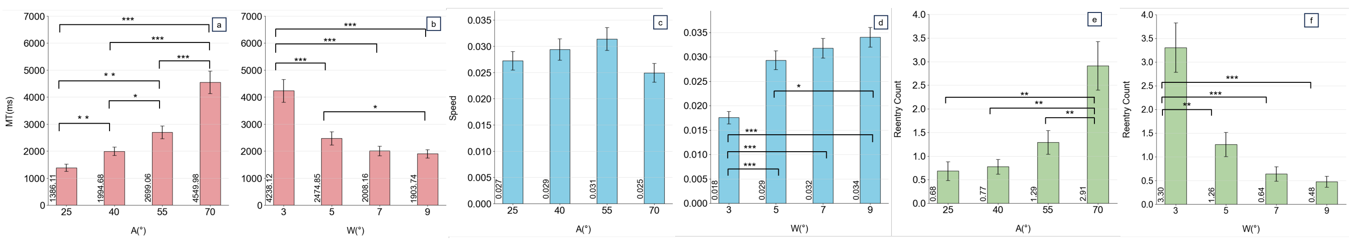

Figure 2: The effects of path length (A) and path width (W) on (a-b) movement time, (c-d) speed, and (e-f) re-entry count. Error bars indicate 95% CIs ($^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$).

$F_{1.727,25.904} = 43.503$, $p < 0.001$, $\eta_p^2 = 0.744$). Their interaction ($A \times W$: $F_{2.269,34.03} = 7.774$, $p = 0.001$, $\eta_p^2 = 0.341$) was also significant. Significant variations were observed among the different conditions within the factor A. Specifically, the 25° A condition exhibited significantly shorter movement times compared to 40° ($\Delta = 595$ ms, $p = 0.008$), 55° ($\Delta = 1311$ ms, $p = 0.002$), and 70° ($\Delta = 3477$ ms, $p < 0.001$). Also, movement time at 40° A was significantly shorter than at 55° ($\Delta = 716$ ms, $p = 0.023$) and 70° ($\Delta = 2882$ ms, $p < 0.001$). Furthermore, the 55° A showed significantly shorter movement times than the 70° ($\Delta = 2116$ ms, $p < 0.001$). Regarding the W factor, significant differences were evident across the various conditions. The 3° W condition resulted in significantly longer movement times than 5° ($\Delta = 1904$ ms, $p < 0.001$), 7° ($\Delta = 2417$ ms, $p < 0.001$), and 9° ($\Delta = 2574$ ms, $p < 0.001$). Finally, the 5° W condition exhibited significantly longer movement times than 9° ($\Delta = 670$ ms, $p = 0.036$).

4.5.2 Speed. Amplitude A did not significantly affect speed (p = 0.057). Speed analysis revealed a significant main effect for factor W ($F_{2.047,30.708} = 32.940$, $p < 0.001$, $\eta_p^2 = 0.687$). The 3° W condition exhibited significantly lower speed compared to 5° ($\Delta = 0.11$ ms/°, $p < 0.001$), 7° ($\Delta = 0.14$ ms/°, $p < 0.001$), 9° ($\Delta = 0.16$ ms/°, $p < 0.001$). These results are visualized in fig. 2.

4.5.3 Re-entry Count. Regarding the number of re-entries, significant main effects were found for factors A ($F_{1.700,20.398} = 22.267$, $p < 0.001$, $\eta_p^2 = 0.650$) and W ($F_{1.655,19.862} = 28.424$, $p < 0.001$, $\eta_p^2 = 0.684$). When A was 70°, the re-entry count was significantly higher than with 25°($\Delta = 1.759, p < 0.001$), 40°($\Delta = 1.601, p = 0.001$), or 55°($\Delta = 1.209, p = 0.002$). When W was 3°, the re-entry count was significantly higher than for 5°($\Delta = 1.497$, $p = 0.002$), 7°($\Delta = 1.933$, $p < 0.001$), or 9°($\Delta = 2.021$, $p < 0.001$) (see fig. 2).

4.6 Models Formulation

In this study, we evaluated three candidate models for predicting Movement Time (MT) and compared them against the baseline model, as summarized in fig. 3 and table 1. We used the original Steering Law proposed by Accot and Zhai [1] as the baseline.

To account for potential gaze stability issues that could have hindered participants from accurately perceiving the impact of target width on MT, we modified path width W by defining $W' = W - \mu$, where μ represents the average gaze deviation due to stability issues (See eq. (4)). This adjustment was made to create Candidate Model 1 (CM1). Furthermore, previous research indicated that target distance has a minimal effect on MT under fixed gaze conditions [55]. Therefore, we applied an exponential transformation to the path length A, defined as $A' = e^{\lambda A}$, resulting in Candidate Model 2 (CM2). Finally, Candidate Model 3 (CM3) combines both the path width adjustment from CM1 and the path length transformation from CM2, utilizing both W' and A' as predictors.

4.7 Model Fitting

We employed non-linear least squares optimization to estimate the parameters of each non-linear model accurately. For each iteration, a distinct set of initial parameters was used to fit the model, and the adjusted corresponding coefficient of determination (R^2) was calculated. The model with the highest adjusted R^2 was selected as the final model.

To thoroughly assess the performance of the models, we used not only the coefficient of determination R^2 but also the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The R^2 metric measures the proportion of variance in the dependent variable explained by the model, with higher values indicating a better fit. Both AIC and BIC balance the fit of a model

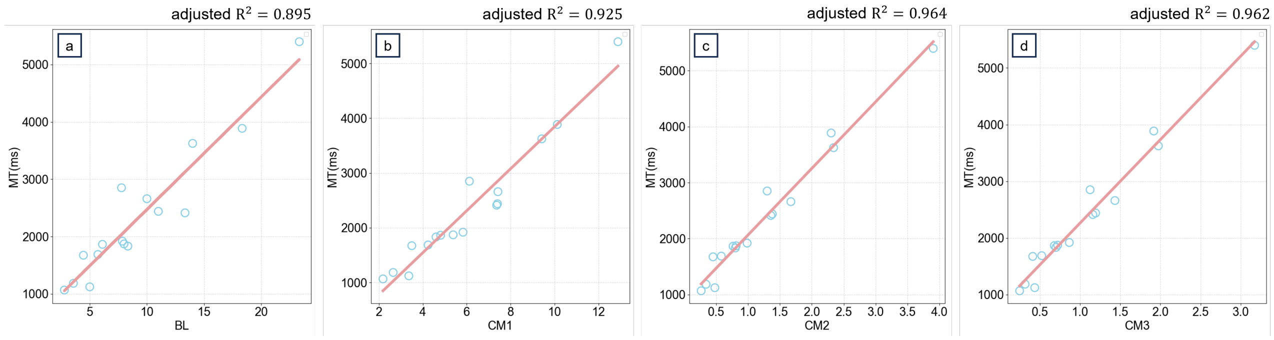

Figure 3: Movement time (MT) model fitting across all conditions (N = 16) using the four candidate models.

Table 1: Model fitting results, where 'BL' denotes the baseline and 'CM' represents our proposed candidate model. Values highlighted in bold signify superior performance. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Name	Model	Adjusted R^2	AIC	BIC	Coefficients	Cross-validation R^2 (SD)
BL	$\mathrm{MT} = a + b\left(\frac{A}{W}\right)$	0.895	236.751	238.296	$a = 508.8$, $b = 196.2$	0.881 (0.062)
CM1	$\mathrm{MT} = a + b\left(\frac{A}{W-\mu}\right)$	0.925	185.4	187.7	$a = 11.8^{***}$, $b = 383.4$, $\mu = -2.43^{*}$	0.916 (0.028)
CM2	$\mathrm{MT} = a + b\left(\frac{e^{\lambda A}}{W}\right)$	**0.964**	**173.5**	**175.8**	$a = 873.2^{***}$, $b = 1190.5^{**}$, $\lambda = 0.035^{***}$	0.959 (0.02)
CM3	$\mathrm{MT} = a + b\left(\frac{e^{\lambda A}}{W-\mu}\right)$	**0.962**	**175.2**	178.3	$a = 788.4^{**}$, $b = 1473.5$, $\mu = -0.30$, $\lambda = 0.033^{***}$	0.923 (0.03)

with complexity to prevent overfitting. Specifically, AIC considers the number of parameters and the goodness of fit, while BIC adds a penalty based on the sample size. Lower AIC and BIC values indicate that a model can achieve a good fit with lower complexity.

4.7.1 Evaluation Results. As shown in fig. 3 and table 1, the original Steering Law model achieved a strong fit with an adjusted R^2 of 0.895. Although the candidate models included additional parameters, due to their consideration of gaze characteristics, they consistently outperformed the baseline model in terms of adjusted R^2, AIC, and BIC. Interestingly, although Zhang et al. [55] suggested that gaze stability issues might limit the utilization of target width in selection tasks, this limitation did not appear in steering tasks. In some instances, the target width exceeded the actual path width, as indicated by negative μ values in models CM2 and CM4. Among all candidate models, CM3 and CM4 not only achieved higher R^2 values but also demonstrated superior AIC and BIC scores.

CM1 has higher AIC and BIC values than CM2 (AIC $\Delta = 11.9$, BIC $\Delta = 11.9$) and CM3 (AIC $\Delta = 10.2$, BIC $\Delta = 9.4$). For AIC, the differences are greater than 10, and for BIC, the differences are greater than 10 and in the 6-10 range. This suggests that CM1 has poorer support compared to CM2 and CM3 [8, 32]. CM2 demonstrates the best adjusted fit with $R^2 = 0.964$, $AIC = 173.5$, and $BIC = 175.8$. CM3 also shows a high adjusted fit with $R^2 = 0.962$, $AIC = 175.2$, and $BIC = 178.3$. When comparing the AIC values, there is no significant difference between CM2 and CM3. However, in the BIC comparison, CM2 has a smaller BIC value than CM3 ($\Delta = 2.5$), indicating better model support. Furthermore, we find that in CM3, μ does not significantly affect the model ($p = 0.659$).

4.7.2 Cross-Validation. We conducted cross-validation tests based on condition grouping to verify the generalizability of the four models. Model coefficients were obtained from 12 randomly selected experimental conditions (levels), and the model fit was tested on the remaining 4 conditions over 100 iterations. Table 1 summarizes the performance results. Overall, our findings indicate that all models achieved accurate predictions in the cross-validation analysis, which were also similar to the original estimates. This suggests that the models are capable of predicting unseen experimental conditions with high accuracy.

5 Discussion

5.1 Applicability of the Steering Law in Gaze-Based Control Tasks (RQ1)

Our findings demonstrate that the original Steering Law model already matches the collected data reasonably closely, achieving an R^2 value of 0.895. This indicates that, even with the transition from manual hand input to gaze input, the Steering Law maintains a robust ability to explain user performance and behavior in gaze-based control tasks.

5.2 Impact of Path Length and Path Width on Steering Performance in Gaze-Based Control (RQ2)

Our results also revealed that both path width and path length have significant effects on movement time ($p < 0.001$). Specifically, users experienced slower movement speeds when navigating highly constrained (narrow) path widths $W = 3°$, whereas speed levels off for moderately narrow widths (7° and 9°). Path length, however, did not significantly influence the speed, which is consistent with findings from previous work [14].

In terms of re-entry time (refer to section 4.5.3), both path width and path length displayed consistent trends: increasing path width constraints and extending path lengths led to higher numbers of user re-entries. However, these increases were only statistically significant for the most challenging tasks.

Interestingly, in our steering tasks, path length had a significant impact on both movement time and re-entry time, as evidenced by pairwise analyses (see section 4.5.1). This result contrasts with previous research on selection tasks, where movement amplitude was found to have minimal effects on time and re-entry time [18]. Previous studies proposed that rapid eye saccades primarily allocate time to calibration phases, thereby reducing the influence of movement amplitude. In contrast, steering tasks require users to maintain continuous and focused control of the cursor to navigate along a predetermined path. We attribute these differences to the increased demands on user attention and gaze stability imposed by the path constraints and temporal requirements inherent in steering tasks.

6 Limitations and Future Work

In our work, we identified several limitations. First, while our model achieved promising results in a controlled, simplified setting with a constant diameter typical of steering tasks, we plan to extend our findings to real-world applications involving targets with arbitrary shapes, curved path features, and complex backgrounds. Second, eye-tracking data requires high device specifications, such as precision, accuracy, packet loss rate, and sampling rate, all of which can impact task performance. However, our study did not account for these variables, which may limit the model's optimal performance across all eye-tracking devices and diverse populations. We plan to explore these variables in future work to better capture their influence.

7 Conclusion

This study investigated the influence of gaze movements as an input modality on user behavior and performance for steering tasks within virtual reality (VR) environments. By analyzing the collected behavioral data, we extended the original Steering Law to incorporate path width and path length, resulting in three candidate models tailored to predict movement time using eye gaze as an input method. Our evaluation demonstrates that the proposed models outperform existing models in predictive accuracy. After addressing potential overfitting risks, we identify two models as the most accurate ones. Additionally, our research enhances the understanding of user behavior patterns in virtual environments, particularly in tasks involving steering tasks, such as constrained object manipulation and navigation along predefined paths.

References

[1] Johnny Accot and Shumin Zhai. 1997. Beyond Fitts' law: models for trajectory-based HCI tasks. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '97)*. Association for Computing Machinery, New York, NY, USA, 295–302. https://doi.org/10.1145/258549.258760

[2] Johnny Accot and Shumin Zhai. 2001. Scale effects in steering law tasks. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Seattle, Washington, USA) *(CHI '01)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/365024.365027

[3] David Ahlström. 2005. Modeling and improving selection in cascading pull-down menus using Fitts' law, the steering law and force fields. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Portland, Oregon, USA) *(CHI '05)*. Association for Computing Machinery, New York, NY, USA, 61–70. https://doi.org/10.1145/1054972.1054982

[4] David Ahlström. 2005. Modeling and improving selection in cascading pull-down menus using Fitts' law, the steering law and force fields. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 61–70.

[5] Samantha Aziz, Dillon J Lohr, Lee Friedman, and Oleg Komogortsev. 2024. Evaluation of Eye Tracking Signal Quality for Virtual Reality Applications: A Case Study in the Meta Quest Pro. In *Proceedings of the 2024 Symposium on Eye Tracking Research and Applications* (Glasgow, United Kingdom) *(ETRA '24)*. Association for Computing Machinery, New York, NY, USA, Article 7, 8 pages. https://doi.org/10.1145/3649902.3653347

[6] Mayra Donaji Barrera Machuca and Wolfgang Stuerzlinger. 2019. The Effect of Stereo Display Deficiencies on Virtual Hand Pointing. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300437

[7] Jonas Blattgerste, Patrick Renner, and Thies Pfeiffer. 2018. Advantages of eye-gaze over head-gaze-based selection in virtual and augmented reality under varying field of views. In *Proceedings of the Workshop on Communication by Gaze Interaction* (Warsaw, Poland) *(COGAIN '18)*. Association for Computing Machinery, New York, NY, USA, Article 1, 9 pages. https://doi.org/10.1145/3206343.3206349

[8] Kenneth P. Burnham and David R. Anderson. 2002. *Model Selection and Multi-model Inference: A Practical Information-Theoretic Approach* (2 ed.). Springer New York, NY. XXVI, 488 pages. https://doi.org/10.1007/b97636

[9] Mark Colley, Beate Wanner, Max Rädler, Marcel Rötzer, Julian Frommel, Teresa Hirzle, Pascal Jansen, and Enrico Rukzio. 2024. Effects of a Gaze-Based 2D Platform Game on User Enjoyment, Perceived Competence, and Digital Eye Strain. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 369, 14 pages. https://doi.org/10.1145/3613904.3641909

[10] Wenzhe Cui, Rui Liu, Zhi Li, Yifan Wang, Andrew Wang, Xia Zhao, Sina Rashidian, Furqan Baig, IV Ramakrishnan, Fusheng Wang, and Xiaojun Bi. 2023. GlanceWriter: Writing Text by Glancing Over Letters with Gaze. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 719, 13 pages. https://doi.org/10.1145/3544548.3581269

[11] K. DeFazio, D. Wittman, and C.G. Drury. 1992. Effective vehicle width in self-paced tracking. *Applied Ergonomics* 23, 6 (1992), 382–386. https://doi.org/10.1016/0003-6870(92)90369-7

[12] Krzysztof Z. Gajos, Jacob O. Wobbrock, and Daniel S. Weld. 2007. Automatically generating user interfaces adapted to users' motor and vision capabilities. In *Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology* (Newport, Rhode Island, USA) *(UIST '07)*. Association for Computing Machinery, New York, NY, USA, 231–240. https://doi.org/10.1145/1294211.1294253

[13] Zhenyi He, Christof Lutteroth, and Ken Perlin. 2022. TapGazer: Text Entry with Finger Tapping and Gaze-directed Word Selection. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 337, 16 pages. https://doi.org/10.1145/3491102.3501838

[14] Errol R. Hoffmann. 2009. Review of models for restricted-path movements. *International Journal of Industrial Ergonomics* 39, 4 (2009), 578–589. https://doi.org/10.1016/j.ergon.2008.02.007 Special issue: Felicitating Colin G. Drury.

[15] Kenneth Holmqvist, Marcus Nyström, Richard Andersson, Richard Dewhurst, Jarodzka Halszka, and Joost van de Weijer. 2011. *Eye Tracking : A Comprehensive Guide to Methods and Measures*. Oxford University Press, United Kingdom.

[16] Xuning Hu, Wenxuan Xu, Yushi Wei, Hao Zhang, Jin Huang, and Hai-Ning Liang. 2025. Optimizing Moving Target Selection in VR by Integrating Proximity-Based Feedback Types and Modalities. In *2025 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*. IEEE.

[17] Xuning Hu, Xinan Yan, Yushi Wei, Wenxuan Xu, Yue Li, Yue Liu, and Hai-Ning Liang. 2024. Exploring the Effects of Spatial Constraints and Curvature for 3D Piloting in Virtual Environments. In *2024 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 505–514. https://doi.org/10.1109/ISMAR62088.2024.00065

[18] Jin Huang, Feng Tian, Nianlong Li, and Xiangmin Fan. 2019. Modeling the Uncertainty in 2D Moving Target Selection. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology* (New Orleans, LA, USA) *(UIST '19)*. Association for Computing Machinery, New York, NY, USA, 1031–1043. https://doi.org/10.1145/3332165.3347880

[19] Yvonne Kammerer, Katharina Scheiter, and Wolfgang Beinhauer. 2008. Looking my way through the menu: the impact of menu design and multimodal input on gaze-based menu selection. In *Proceedings of the 2008 Symposium on Eye*

Tracking Research & Applications (Savannah, Georgia) *(ETRA '08)*. Association for Computing Machinery, New York, NY, USA, 213–220. https://doi.org/10.1145/1344471.1344522

[20] Sei Kang, Jaejoon Jeong, Gun A. Lee, Soo-Hyung Kim, Hyung-Jeong Yang, and Seungwon Kim. 2024. The RayHand Navigation: A Virtual Navigation Method with Relative Position between Hand and Gaze-Ray. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 634, 15 pages. https://doi.org/10.1145/3613904.3642147

[21] Taejun Kim, Auejin Ham, Sunggeun Ahn, and Geehyuk Lee. 2022. Lattice Menu: A Low-Error Gaze-Based Marking Menu Utilizing Target-Assisted Gaze Gestures on a Lattice of Visual Anchors. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 277, 12 pages. https://doi.org/10.1145/3491102.3501977

[22] Jaeyoon Lee, Hanseob Kim, Yechan Yang, and Gerard Jounghyun Kim. 2024. RPG: Rotation Technique in VR Locomotion using Peripheral Gaze. *Proc. ACM Hum.-Comput. Interact.* 8, ETRA, Article 235 (May 2024), 19 pages. https://doi.org/10.1145/3655609

[23] Lei Liu, Jean-Bernard Martens, and Robert van Liere. 2011. Revisiting path steering for 3D manipulation tasks. *International Journal of Human-Computer Studies* 69, 3 (2011), 170–181. https://doi.org/10.1016/j.ijhcs.2010.11.006

[24] Lei Liu, Jean-Bernard Martens, and Robert van Liere. 2010. Revisiting path steering for 3D manipulation tasks. In *2010 IEEE Symposium on 3D User Interfaces (3DUI)*. 39–46. https://doi.org/10.1109/3DUI.2010.5444724

[25] I. Scott MacKenzie. 1992. Fitts' law as a research and design tool in human-computer interaction. *Hum.-Comput. Interact.* 7, 1 (March 1992), 91–139. https://doi.org/10.1207/s15327051hci0701_3

[26] Xuanru Meng, Wenge Xu, and Hai-Ning Liang. 2022. An Exploration of Hands-free Text Selection for Virtual Reality Head-Mounted Displays. In *2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. 74–81. https://doi.org/10.1109/ISMAR55827.2022.00021

[27] Meta. 2024. Eye Tracking for Movement SDK for Unity. https://developers.meta.com/horizon/documentation/unity/move-eye-tracking/.

[28] Darius Miniotas. 2000. Application of Fitts' law to eye gaze interaction. In *CHI '00 Extended Abstracts on Human Factors in Computing Systems* (The Hague, The Netherlands) *(CHI EA '00)*. Association for Computing Machinery, New York, NY, USA, 339–340. https://doi.org/10.1145/633292.633496

[29] Mathieu Nancel and Edward Lank. 2017. Modeling User Performance on Curved Constrained Paths. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 244–254. https://doi.org/10.1145/3025453.3025951

[30] Patryk Piotrowski and Adam Nowosielski. 2019. Gaze-Based Interaction for VR Environments. In *International Conference on Image Processing and Communications Challenges*. https://api.semanticscholar.org/CorpusID:202670633

[31] C. Prablanc, D. Massé, and J.F. Echallier. 1978. Error-correcting mechanisms in large saccades. *Vision Research* 18, 5 (1978), 557–560. https://doi.org/10.1016/0042-6989(78)90202-X

[32] Adrian E. Raftery. 1995. Bayesian Model Selection in Social Research. *Sociological Methodology* 25 (1995), 111–163. https://doi.org/10.2307/271063

[33] Argenis Ramirez Ramirez Gomez, Christopher Clarke, Ludwig Sidenmark, and Hans Gellersen. 2021. Gaze+Hold: Eyes-only Direct Manipulation with Continuous Gaze Modulated by Closure of One Eye. In *ACM Symposium on Eye Tracking Research and Applications* (Virtual Event, Germany) *(ETRA '21 Full Papers)*. Association for Computing Machinery, New York, NY, USA, Article 10, 12 pages. https://doi.org/10.1145/3448017.3457381

[34] Immo Schuetz, T. Scott Murdison, Kevin J. MacKenzie, and Marina Zannoli. 2019. An Explanation of Fitts' Law-like Performance in Gaze-Based Selection Tasks Using a Psychophysics Approach. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300765

[35] Stephen H. Scott. 2004. Optimal feedback control and the neural basis of volitional motor control. *Nature Reviews Neuroscience* 5, 7 (2004), 532–545. https://doi.org/10.1038/nrn1427

[36] Ransalu Senanayake and Ravindra S. Goonetilleke. 2016. Pointing Device Performance in Steering Tasks. *Perceptual and Motor Skills* 122, 3 (2016), 886–910. https://doi.org/10.1177/0031512516649717 PMID: 27216944.

[37] Rongkai Shi, Yushi Wei, Xueying Qin, Pan Hui, and Hai-Ning Liang. 2023. Exploring Gaze-assisted and Hand-based Region Selection in Augmented Reality. *Proc. ACM Hum.-Comput. Interact.* 7, ETRA, Article 160 (May 2023), 19 pages. https://doi.org/10.1145/3591129

[38] Linda E. Sibert and Robert J. K. Jacob. 2000. Evaluation of eye gaze interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (The Hague, The Netherlands) *(CHI '00)*. Association for Computing Machinery, New York, NY, USA, 281–288. https://doi.org/10.1145/332040.332445

[39] Sophie Stellmach and Raimund Dachselt. 2012. Designing gaze-based user interfaces for steering in virtual environments. In *Proceedings of the Symposium on Eye Tracking Research and Applications* (Santa Barbara, California) *(ETRA '12)*. Association for Computing Machinery, New York, NY, USA, 131–138. https://doi.org/10.1145/2168556.2168577

[40] Wen-Jie Tseng, Samuel Huron, Eric Lecolinet, and Jan Gugenheimer. 2023. FingerMapper: Mapping Finger Motions onto Virtual Arms to Enable Safe Virtual Reality Interaction in Confined Spaces. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 874, 14 pages. https://doi.org/10.1145/3544548.3580736

[41] Roel Vertegaal. 2008. A Fitts Law comparison of eye tracking and manual input in the selection of visual targets. In *Proceedings of the 10th International Conference on Multimodal Interfaces* (Chania, Crete, Greece) *(ICMI '08)*. Association for Computing Machinery, New York, NY, USA, 241–248. https://doi.org/10.1145/1452392.1452443

[42] Oleg Špakov, Howell Istance, Kari-Jouko Räihä, Tiia Viitanen, and Harri Siirtola. 2019. Eye gaze and head gaze in collaborative games. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications* (Denver, Colorado) *(ETRA '19)*. Association for Computing Machinery, New York, NY, USA, Article 85, 9 pages. https://doi.org/10.1145/3317959.3321489

[43] Yushi Wei, Rongkai Shi, Anil Ufuk Batmaz, Yue Li, Mengjie Huang, Rui Yang, and Hai-Ning Liang. 2024. Evaluating and Modeling the Effect of Frame Rate on Steering Performance in Virtual Reality. *IEEE Transactions on Visualization and Computer Graphics* (2024), 1–14. https://doi.org/10.1109/TVCG.2024.3451491

[44] Yushi Wei, Rongkai Shi, Difeng Yu, Yihong Wang, Yue Li, Lingyun Yu, and Hai-Ning Liang. 2023. Predicting Gaze-based Target Selection in Augmented Reality Headsets based on Eye and Head Endpoint Distributions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 283, 14 pages. https://doi.org/10.1145/3544548.3581042

[45] Yushi Wei, Kemu Xu, Yue Li, Lingyun Yu, and Hai-Ning Liang. 2024. Exploring and Modeling Directional Effects on Steering Behavior in Virtual Reality. *IEEE Transactions on Visualization and Computer Graphics* 30, 11 (2024), 7107–7117. https://doi.org/10.1109/TVCG.2024.3456166

[46] Wenxuan Xu, Yushi Wei, Xuning Hu, Wolfgang Stuerzlinger, Yuntao Wang, and Hai-Ning Liang. 2025. Predicting Ray Pointer Landing Poses in VR Using Multimodal LSTM-Based Neural Networks. In *2025 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*. IEEE.

[47] Naoto Yamakawa, Tatsuya Maruta, Yuichiro Kinoshita, and Kentaro Go. 2024. Extending Fitts' Law for Tapping on Surfaces Angled in the Depth Direction. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI EA '24)*. Association for Computing Machinery, New York, NY, USA, Article 157, 7 pages. https://doi.org/10.1145/3613905.3650984

[48] Shota Yamanaka. 2019. Steering Performance with Error-accepting Delays. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–9. https://doi.org/10.1145/3290605.3300800

[49] Shota Yamanaka and Homei Miyashita. 2016. Modeling the Steering Time Difference between Narrowing and Widening Tunnels. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 1846–1856. https://doi.org/10.1145/2858036.2858037

[50] Shota Yamanaka and Homei Miyashita. 2019. Modeling Pen Steering Performance in a Single Constant-width Curved Path. In *Proceedings of the 2019 ACM International Conference on Interactive Surfaces and Spaces* (Daejeon, Republic of Korea) *(ISS '19)*. Association for Computing Machinery, New York, NY, USA, 65–76. https://doi.org/10.1145/3343055.3359697

[51] Shota Yamanaka, Takumi Takaku, Yukina Funazaki, Noboru Seto, and Satoshi Nakamura. 2023. Evaluating the Applicability of GUI-Based Steering Laws to VR Car Driving: A Case of Curved Constrained Paths. *Proceedings of the ACM on Human-Computer Interaction* 7, ISS (Nov. 2023), 430:93–430:113. https://doi.org/10.1145/3626466

[52] Difeng Yu, Xueshi Lu, Rongkai Shi, Hai-Ning Liang, Tilman Dingler, Eduardo Velloso, and Jorge Goncalves. 2021. Gaze-Supported 3D Object Manipulation in Virtual Reality. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 734, 13 pages. https://doi.org/10.1145/3411764.3445343

[53] Shumin Zhai, Johnny Accot, and Rogier Woltjer. 2004. Human Action Laws in Electronic Virtual Worlds: An Empirical Study of Path Steering Performance in VR. *Presence: Teleoperators and Virtual Environments* 13, 2 (04 2004), 113–127. https://doi.org/10.1162/1054746041382393

[54] Shumin Zhai, Carlos Morimoto, and Steven Ihde. 1999. Manual and gaze input cascaded (MAGIC) pointing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Pittsburgh, Pennsylvania, USA) *(CHI '99)*. Association for Computing Machinery, New York, NY, USA, 246–253. https://doi.org/10.1145/302979.303053

[55] Xinyong Zhang, Xiangshi Ren, and Hongbin Zha. 2010. Modeling dwell-based eye pointing target acquisition. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '10)*. Association for Computing Machinery, New York, NY, USA, 2083–2092. https://doi.org/10.1145/1753326.1753645