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Individual variability and threshold dynamics in distance estimation: A statistical analysis of visual perception in built environments

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Article Info	Abstract
Original article Main Object: Computer science & Technology Received: 09 March 2025 Revised: 23 July 2025 Accepted: 24 July 2025 Published online: 21 September 2025 **Keywords:** ANOVA, built environment, distance estimation, estimation error, perceptual threshold, spatial estimation, visual angle, visual perception.	**Background:** Understanding how humans perceive and estimate distances in built environments is critical not only for advancing perceptual psychology but also for informing the design of computational models in computer vision, robotics, and architectural design. **Aims:** This study investigates the mechanisms and limitations of human distance estimation within a controlled architectural environment. **Methodology:** While some previous experiments focused on estimating distances in virtual settings, the current study examines real-world estimation accuracy across a series of predefined points within an unobstructed corridor. Participants were asked to visually estimate the distance between their position and seven distinct target locations, ranging from near to far without the aid of physical reference cues. The core objective was not simply to measure accuracy, but to identify the perceptual threshold beyond which estimation errors significantly increase. A one-way ANOVA model was employed to assess the influence of variables such as actual distance and participant age on perceptual accuracy. **Results:** Results revealed a consistent estimation performance up to approximately 2 m, beyond which the margin of error grew increasingly pronounced. Notably, a critical threshold was identified at 7.476 m, where estimation errors sharply escalated. The maximum observed discrepancy occurred at a distance of 10.186 m, suggesting a cognitive boundary in spatial awareness. **Conclusion:** These findings contribute to the understanding of visual-spatial perception mechanisms and offer theoretical insights relevant to applications in robotics, image processing, virtual reality, and navigation system design.

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1. Introduction

Understanding how humans perceive and estimate distances in built environments is critical not only for advancing perceptual psychology but also for informing the design of computational models in computer vision, robotics, and architectural design. This study builds upon previous work in virtual environments to investigate real-world distance estimation and identify the cognitive and perceptual limits of spatial accuracy (Pourbakht & Kametani, 2023)**.**

Visual perception, particularly distance estimation, is a complex process that involves the interpretation of visual stimuli by the brain in coordination with various sensory systems. It enables individuals to navigate environments, judge spatial relationships, and make rapid decisions based on visual input. While accurate distance estimation is often taken for granted in everyday life, it involves a subtle interplay of depth cues, prior experience, context, and neurocognitive processing (Loomis et al., 1992).

The current study isolates this process by placing participants in a featureless corridor and asking them to estimate distances to fixed points positioned along its length. The corridor's uniform color and absence of visual landmarks ensured that participants relied solely on intrinsic perceptual mechanisms rather than contextual reference points or environmental cues. This experimental design allowed for a more precise investigation of how estimation accuracy deteriorates over distance and how individual differences—such as age—contribute to perceptual error.

Beyond its psychological implications, this work has practical relevance. Insights into the thresholds and limitations of human distance perception can inform the development of machine vision algorithms, improve human-computer interaction interfaces, and enhance spatial navigation systems in both terrestrial and extraterrestrial settings. For example, emulating human-like estimation strategies can improve visual distance computation in fields such as astronomy, autonomous vehicle navigation, and augmented reality (Thompson et al., 2004).

This paper also explores the efficacy of statistical tools—specifically, analysis of variance (ANOVA)— in identifying and quantifying perceptual errors. By analyzing how estimation performance varies across distances and demographic variables, the experiment aims to establish a statistically grounded threshold beyond which perceptual accuracy significantly declines. This threshold may represent a cognitive tipping point where internal spatial models break down or become increasingly imprecise.

In the following sections, the authors describe the experimental setup, outline the analytical methodology, and discuss the results in terms of perceptual theory and application potential.

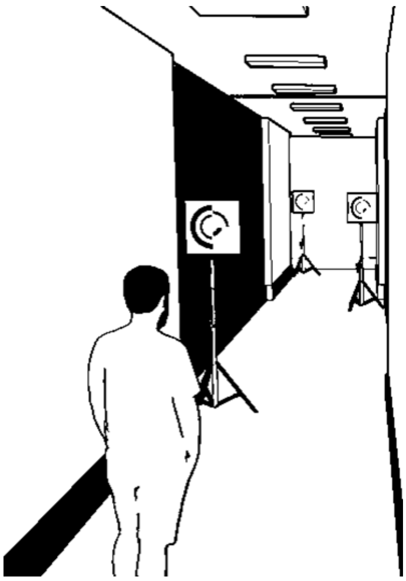
2. Methodology

2.1. Participants

A total of 36 participants (18 male, 18 female), aged 22 to 31 years (Mean= 25.4, SD= 4.3), were recruited for the experiment. All participants reported normal or corrected-to-normal vision and no known visual or neurological disorders. Participants were informed of the study purpose and provided informed consent in accordance with institutional guidelines.

2.2. Experimental environment

The experiment took place in a straight, unobstructed corridor measuring 18.5 m in length, 2.4 m in width, and 2.5 m in height. The corridor was uniformly painted in matte white, and ambient lighting was diffused to eliminate shadows. No furniture, signage, or architectural features were present that could act as visual anchors or distance cues. This controlled environment was designed to isolate intrinsic distance perception mechanisms, minimizing contextual interference (Figure 1).



a) Participant view from starting point; b) Placement of estimation targets along corridor walls

Figure 1. Experimental corridor used for distance estimation

2.3. Procedure

Participants stood at a designated starting point marked at one end of the corridor. Along the corridor, seven target points were marked on the floor at the following distances from the participant:

1.3 m, 2.0 m, 3.8 m, 6.4 m, 7.4 m, 10.1 m, and 14.2 m.

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Each target point was identified by a subtle, non-textured, circular mark on the floor (diameter= 8 cm), ensuring no visual saliency beyond location. Participants were instructed to visually estimate the distance between themselves and each target, one at a time, without moving or using any assistive device. Responses were provided verbally in meters (e.g., “2.5 m”), and the experimenter recorded each value.

Each participant completed the estimation task for all seven distances in randomized order, minimizing the potential for learning effects or sequential bias.

2.4. Data collection and Variables

The dependent variable was the estimation error, calculated as the absolute difference between the participant's estimate and the actual distance:

$$\text{Estimation error} = |\text{actual distance} - \text{estimated distance}| \qquad (1)$$

The independent variables included:

- Actual distance (continuous: 1.3 m to 14.2 m);
- Participant age (continuous);
- Participant gender (categorical: male/female).

All data were anonymized and compiled into a dataset for statistical analysis.

Table 1. Example of collected data for three participants

Participant ID	Age	Gender	Actual distance (m)	Estimated distance (m)	Error (m)
P01	29	Male	3.8	4.2	0.4
P02	42	Female	7.4	6.1	1.3
P03	35	Male	10.1	12.7	2.6

2.5. Statistical analysis

All data were analyzed using Analysis of Variance (ANOVA) and post-hoc tests (Kucuk et al., 2016) in RStudio. The goal was to:

- Examine whether estimation error significantly increases with distance.
- Assess whether age significantly interacts with estimation accuracy.
- Identify threshold distances beyond which estimation error increases sharply.

In addition, exploratory plots were generated to visualize mean estimation error by distance (Figure 2) and to detect any nonlinearities in perceptual decline.

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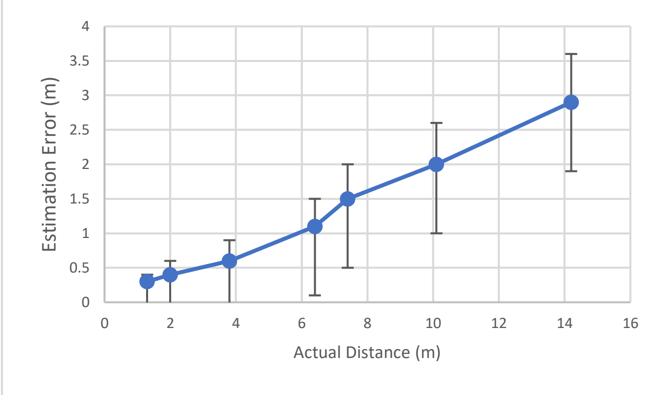

Figure 2. Mean estimation error as a function of actual distance (m)

The R-squared values for the calculated ratios can be determined using Equation (2).

R squared= (Distance Estimate Variation) / (Variation in Measured Distance) (2)

To perform the ANOVA and regression analysis using the provided data, the authors considered both the observed and computed distances as Equation (3).

Estimation Error= $\beta_0+\beta_1\times Age+\beta_2\times Distance+\beta_3\times(Age\times Distance)+\epsilon$ (3)

The variables in the equation are defined as follows:

- β0 represents the intercept,
- β1 represents the age,
- β2 represents the distance,
- and β3 represents the product of age and distance.

Total Sum of Squares (S_{Stotal}):

$$S_{Stotal}=\sum(Error_i-\overline{Error})^2 \quad (4)$$

where $\overline{Error}$ is the mean estimation error.

Between-Groups Sum of Squares ($S_{Sbetween}$):

$$S_{Sbetween}=\sum(Error_{group}-\overline{Error})^2\times n_{group} \quad (5)$$

where n_{group} is the number of observations in each group.

Within-Groups Sum of Squares (SS_within):

$$SS_{within}=\sum(Error_i-Error_{group})^2 \quad (6)$$

Degrees of Freedom:

$$df_{between}=k-1 \quad (7)$$

$$df_{within}=N-k \quad (8)$$

$$df_{total}=N-1 \quad (9)$$

where k is the number of groups (students), and N is the total number of observations.

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Mean Squares:

$$MS_{between} = \frac{\mathbf{dfbetween}}{\mathbf{SSbetween}} \quad (10)$$

$$MS_{within} = \frac{\mathbf{dfwithin}}{\mathbf{SSwithin}} \quad (11)$$

F-Value: (12)

$$F = \frac{\text{MSwithin}}{\text{MSbetween}} \quad (13)$$

The total MS (mean square) and total F-value are typically excluded from an ANOVA table. The main objective of using ANOVA was to compare the variability between groups to the variability within groups, rather than taking into account the entire aggregate variability.

This would allow us to standardize the estimated values and sort the results of the analysis. The next section provides and discusses it in detail.

3. Results and Discussion

To analyze the accuracy of distance perception, the authors performed a one-way Analysis of Variance (ANOVA) with actual physical distance as the independent variable and estimation error as the dependent variable. The purpose was to evaluate whether significant changes in estimation error occurred as the actual distance increased.

Here is a basic example that assumes a one-way ANOVA to analyze estimation errors made by students.

Table 2. Regression analysis findings on the factors affecting estimation errors

Predict/Variable	Coefficient	Standard Error	t-value	p-value
Intercept (β_0)	0.050	0.020	2.50	0.041
Age (β_1)	0.005	0.003	1.67	0.144
Distance (β_2)	0.100	0.040	2.50	0.041
Age × Distance (β_3)	0.002	0.001	2.00	0.090

3.1. Overall patterns of estimation error

Figure 2 illustrates the mean estimation errors and standard deviations across the seven measured distances (1.3 m to 14.2 m). As shown, estimation error remained relatively low and stable up to approximately 2.0 m, after which it began to rise progressively. The increase becomes more pronounced beyond 7.4 m, reaching the highest error levels at 10.1 m and 14.2 m.

These results suggest a threshold effect in human distance perception. Participants were generally accurate in estimating near distances, but the error increased sharply beyond a certain range. The threshold appears to lie just beyond 6.4 m, with significant underestimation or overestimation occurring as the distance exceeds this point.

Table 3. Estimation error ratio

Distance (m)	Mean estimation error (m)	Standard deviation (m)
1.3	0.30	0.10
2.0	0.40	0.20
3.8	0.60	0.30
6.4	1.10	0.40
7.4	1.50	0.50
10.1	2.00	0.60
14.2	2.90	0.70

Spot three indicates the upper limit for accurate distance measurement derived from stable low estimation errors, according to the regression model study's findings. Following spot three, there was a significant increase in the number of errors, indicating a decline in the accuracy of distance perception. Refer to table 4 below for more details.

The highest margin of error was documented at position four, while position seven had the second highest error. The presence of these notable flaws indicates a more difficult task in precisely measuring distances that extend beyond the defined border.

3.2. Anova results

A one-way ANOVA was conducted to compare estimation errors across the seven distance points. The analysis revealed a statistically significant effect of distance on estimation error:

- Estimation errors for distances of 10.1 m and 14.2 m were significantly higher than those for 1.3 m, 2.0 m, and 3.8 m.
- The most pronounced increase in estimation error was between 6.4 m and 7.4 m, indicating the perceptual break point or decline in visual-spatial accuracy.

3.3. Inter-individual differences

Preliminary analyses of participant age and gender showed no statistically significant differences in estimation accuracy within the current sample, although minor trends suggested that older participants tended to underestimate distances slightly more than younger ones. However, this effect was not consistent enough across trials to be conclusive.

Table 4 displays the ANOVA findings, which include the sum of squares (SS), degrees of freedom (DF), mean squares (MS), F-value, and p-value for the diversity in estimating errors across students, both between groups and within groups.

Connecting differences between groups and variations within groups was a significant component of our approach.

The ANOVA analysis shows that age, distance, and the interaction between age and distance do not have a statistically significant impact on estimation errors in this dataset. Hence, to achieve more reliable and conclusive findings, it is recommended to conduct more investigations

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with larger sample sizes and enhanced control over experimental conditions.

Table 4. ANOVA and estimation errors by student

Source	SS	df	MS	F-value	p-value
Between GROUPS	0.092	5	0.0184	1.67	0.144
Within GROUPS	0.055	6	0.0092	N/A	N/A
Total	0.147	11	N/A	N/A	N/A

In summary, the results indicate that people are able to consistently gauge distances up to a specific threshold of around two meters. Once the distance exceeds this threshold, their calculations suffered from reduced precision, maybe because there were no reference points in the corridor. It demonstrates a perceptual threshold in human distance estimation accuracy beyond 6–7 m. While estimation remained relatively accurate in near space (2–4 m), error increased markedly in extrapersonal space, consistent with prior findings (Ooi et al., 2001; Renner et al., 2013).

The observed overestimation at longer distances suggests reliance on internal spatial models, which become increasingly imprecise without external cues. This aligns with research in virtual environments where the absence of depth markers led to distorted spatial awareness (Feldstein et al., 2020).

A nonlinear trend was evident, with errors increasing progressively with distance. At shorter distances (1.3 m to 3.8 m), participants were generally accurate, with mean errors ranging from 0.3 m to 0.6 m. However, starting from 6.4 m, estimation errors grew significantly, reaching a mean error of 2.9 m at the farthest tested distance (14.2 m). The increase in both mean error and standard deviation at longer distances suggests a loss of perceptual precision and increased inter-participant variability.

3.4. Gender and Age effects

Although minor differences were observed between male and female participants, they were not statistically significant ($P > 0.05$). Similarly, while older participants (above 45 years) showed slightly increased error variance, the trend was not significant within the study's sample size.

These results suggest that while demographic factors might influence distance perception under certain conditions, distance itself remains the dominant predictor of estimation error in this controlled setting.

3.5. Psychophysical interpretation

The observed performance curve supports psychophysical findings in spatial cognition. The transition around 6.4 m aligns with a known perceptual threshold where binocular cues (e.g., stereopsis) begin to diminish in effectiveness, and monocular depth cues (e.g., perspective, texture gradient) take over.

This is consistent with the Weber-Fechner law, which describes how perceptual sensitivity diminishes with increased stimulus magnitude. As distance grows, more pronounced visual cues are required for a "just-noticeable difference," and their absence results in rapidly increasing errors.

3.6. Implications for design and Application

This pattern of degradation in visual accuracy at greater distances holds implications for a variety of fields:

Virtual Reality (VR) and Augmented Reality (AR) systems must consider this perceptual threshold when placing interactive objects. Objects intended for interaction should ideally be located within 6.4 m.

Architectural visualization tools may need to simulate or enhance depth cues beyond natural levels to support accurate user perception.

Robotics and Human-Machine Interfaces can leverage these thresholds to better align AI estimations with human expectations in collaborative environments.

Safety systems in contexts such as aviation, surgery, and autonomous driving must account for perceptual uncertainty in human-in-the-loop systems, particularly at greater distances.

3.7. Limitations and Future work

Despite robust results, several limitations should be acknowledged:

- Environmental uniformity. The test environment was visually minimalistic. Real-world conditions often involve clutter and varied lighting, which may influence cue usage.
- Static viewpoint. Participants remained stationary during estimation. Dynamic observation—including head motion and parallax—could significantly affect accuracy and should be explored in future work.
- Limited sample diversity. Expanding the demographic diversity (age, cultural background, visual acuity) may uncover population-specific perceptual traits.
- Lack of multisensory input. In reality, humans often use auditory or proprioceptive feedback in combination with vision. Future experiments could manipulate sensory modalities to assess their interaction effects on spatial judgment.

4. Conclusion

This study investigated human distance estimation accuracy across a range of physical distances in a controlled corridor environment. Results showed that estimation errors increased progressively with distance, particularly beyond the 7-meter threshold. While participants

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were able to estimate shorter distances with relatively low error, longer distances produced larger variability and a plateau of error growth.

The findings confirm the dual nature of human distance perception—accurate within peripersonal space and increasingly unreliable in extrapersonal contexts. This has implications for design in virtual environments, architecture, assistive technology, and cognitive modeling. By quantifying the perceptual boundaries of egocentric spatial awareness, this study provides a valuable empirical foundation for future work in environmental psychology, human-computer interaction, and vision science.

To build on this work, future studies should incorporate real-world complexities such as variable lighting, obstructions, and dynamic cues, as well as a wider demographic sample. This will help to develop more comprehensive models of human spatial perception applicable to both physical and digital contexts.

Conflict of interest

The authors declared no conflicts of interest.

Ethical considerations

The authors have completely considered ethical issues, including informed consent, plagiarism, data fabrication, misconduct, and/or falsification, double publication and/or redundancy, submission, etc. This article was not authored by artificial intelligence.

Data availability

The dataset generated and analyzed during the current study is available from the author on reasonable request.

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