Information Chunk Similarity in Nuclear Power Monitoring: A Cognitive Bias Effect Paradigm

Xiaoli Wu[1], Yiqun Li[1], Yuqi He[1] & Zexi Fang[2]

[1]Nanjing University of Science and Technology, China, [2]Loughborough University, UK

SUMMARY

This study tackles the cognitive bias caused by high similarity among information chunks in nuclear power monitoring systems. A cognitive model was constructed to identify perceptual similarity as the key factor affecting operator cognition. Behavioural experiments using visual search and situational tasks were conducted to quantify chunk similarity and determine the optimal similarity range. Results show that perceptual similarity has a significantly greater impact than semantic similarity. An equation for calculating overall perceptual similarity based on colour, layout, and complexity was developed. The optimal similarity value range ($T_0'' \in [4.624, 5.538]$) was identified, enhancing interface recognizability and cognitive performance. This study proposes a similarity bias effect paradigm for visual tasks, providing a theoretical basis and empirical support for improving nuclear power monitoring interface design.

KEYWORDS

Nuclear power monitoring system, information chunk, similarity bias, perceptual similarity, visual search task

Introduction

In the Main Control Room (MCR) of modern nuclear power plants (NPPs), the transition from analogue to digital interfaces has fundamentally altered the operator's cognitive environment. As the "central nervous system" for operational supervision, MCRs concentrate massive amounts of data into Visual Display Units (VDUs) and Large Display Panels (LDPs) (Wu et al., 2022; Zhang et al., 2019). To ensure logical coherence and minimize learning costs, interface elements are often designed with high structural homogeneity. For instance, functional icons (e.g., valves, pumps) share consistent geometric bases, and subsystem interfaces employ identical layout grids. While this adherence to the "Consistency" usability principle aids in system learning, it inadvertently creates a visual environment characterized by high similarity. Excessive convergence in design can hinder the operator's ability to rapidly discriminate between targets and distractors, potentially inducing "Similarity Bias"—a cognitive error where operators fail to distinguish between visually or semantically analogous elements, leading to operational delays or misjudgements.

To clarify the scope of this study, we introduce the concept of the "Information Chunk." Originating from cognitive psychology, Miller (1956) defined chunking as a process of recoding information into meaningful units to expand working memory capacity, a concept further elaborated by Simon (1974) regarding its dynamic and autonomous nature. In the specific context of NPP monitoring, we define a Nuclear Information Chunk (CNPS) as a discrete visual unit that possesses specific functional meaning and independent structural boundaries. These are categorised into two types: (1) **Graphic-based Chunks**: Symbols and icons representing physical equipment (e.g., valves, sensors) composed of geometric shapes, colour codes, and text labels; (2) **Interface-based Chunks**: Complete monitoring windows or screens composed of multiple graphic chunks and layout elements, serving specific tasks like alarm diagnosis or parameter adjustment. Unlike general UI elements, these chunks exhibit "Dynamic Capacity" (variable information density) and "Autonomy" (independence within the system), making them susceptible to similarity-induced confusion during high-load monitoring tasks.

Current research on visual similarity often relies on qualitative guidelines or focuses solely on computer vision algorithms (Payne & Starren, 2005), lacking a quantitative basis for industrial interface design. This study aims to bridge this gap by: (1) Constructing a cognitive model to explain the mechanism of similarity bias; (2) Quantifying the impact of perceptual versus semantic similarity attributes; and (3) Determining an optimal similarity range (T_0'') that balances the need for systematic consistency with the requirement for visual discernibility.

The Cognitive Model of Similarity Bias

We developed a cognitive model mapping the attributes of nuclear information chunks to the operator's cognitive processing stages, as shown in Fig. 1. Based on the operator cognitive behavior model proposed by Zhang et al. (2019), monitoring tasks involve four stages: Monitoring, Situation Assessment, Response Planning, and Response Execution. Similarity bias primarily occurs during the "Situation Assessment" stage, where operators match visual stimuli with internal mental models. As illustrated in our theoretical framework, the processing of information chunks occurs across three dimensions:

(1) Perceptual Processing: The initial extraction of visual features. We map this to attributes such as **Shape**, **Colour**, **Orientation**, and **Density**. High similarity in these features leads to "Perceptual Similarity Bias" (Treisman & Gelade, 1980).

(2) Semantic Processing: The interpretation of functional meaning. We map this to attributes such as **Subject**, **Usage Scenario**, and **Hierarchy**. Confusion arises when chunks share overlapping semantic categories (e.g., two pumps with different safety classes) (Biggs et al., 2015).

(3) Memory Processing: The retrieval of stored knowledge, mapped to attributes of **Familiarity** and **Complexity**.

We hypothesized that in the rapid scanning environment of the MCR, Perceptual Similarity acts as the dominant factor triggering cognitive bias, overriding semantic distinctions.

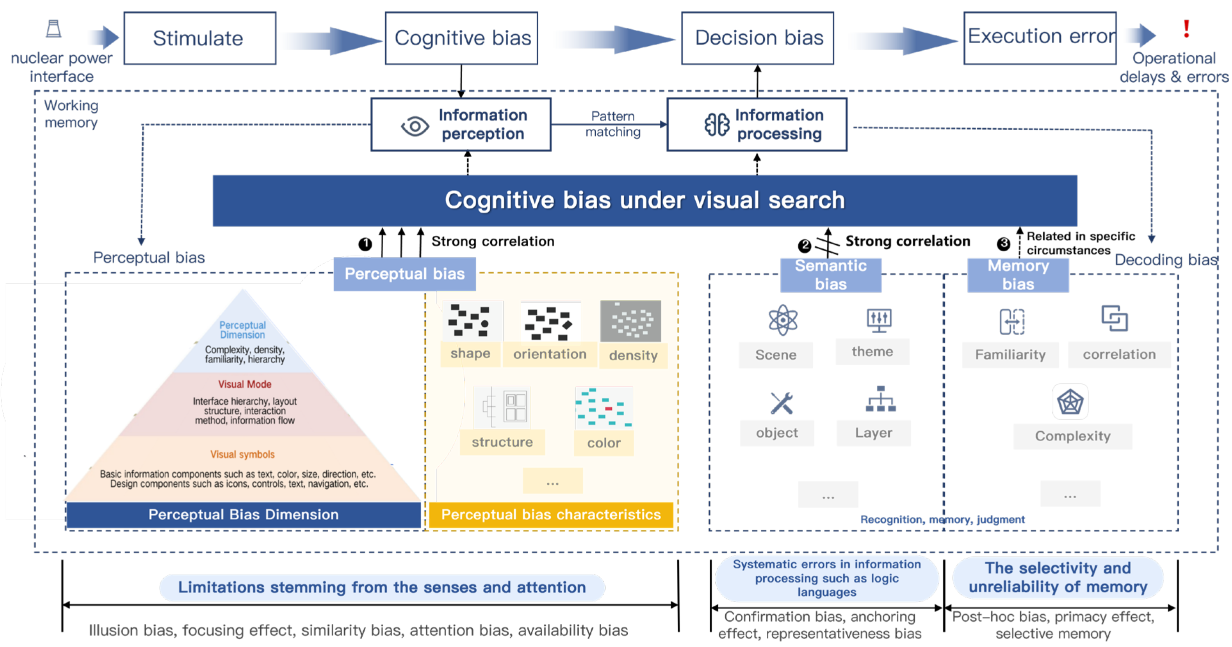


Figure 1. The cognitive model of similarity bias in nuclear monitoring tasks.

Experiment 1: Bivariate Design for Attribute Dominance

To verify the hypothesis derived from the cognitive model, a controlled visual search experiment was conducted using a specific bivariate design.

Experimental Design

A 2 (Information Attribute) × 3 (Similarity Level) mixed factorial design was employed.

(1) Independent Variable 1 (Between-Subjects): Information Attribute Group. Participants were divided into a Perceptual Group (N=10, searching based on visual features without semantic knowledge) and a Semantic Group (N=10, nuclear engineers searching based on functional meaning).

(2) Independent Variable 2 (Within-Subjects): Similarity Level. The target and distractor icons were coded into three levels of similarity, as shown in Fig. 2:

1) Low Similarity: Targets and distractors differed significantly in global shape (e.g., circle vs. rectangle) and orientation.

2) Medium Similarity: Targets shared topological features (e.g., both containing curved elements) but differed in details.

3) High Similarity: Targets and distractors shared identical geometric shapes, differing only in minor internal symbols or rotation

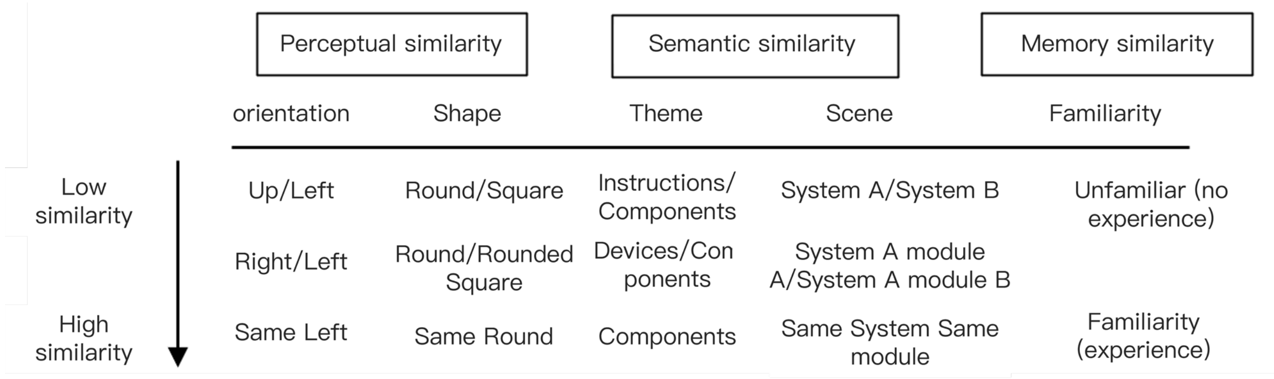


Figure 2: Examples of encoding logic for low, medium, and high similarity graph groups under three similarity dimensions

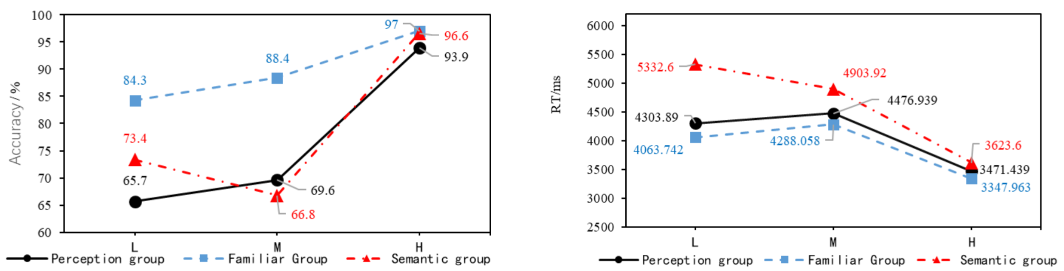
(3) Dependent Variables: Reaction Time (RT) in milliseconds and Error Rate (%).

Task and Procedure

A dual-target visual search paradigm was used. Participants were presented with a 4 × 4 grid of 16 nuclear icons. In each trial, participants had to locate two specific targets amidst distractors. The grid layout simulated the density of a typical simplified monitoring panel. The experiment was conducted using E-Prime software, recording behavioral data to quantify the "Similarity Bias Effect."

Results

A Repeated Measures ANOVA was conducted on Reaction Time (RT) and Error Rate. The results revealed a significant main effect of Similarity Level on RT [$F(2,38) = 25.69, p < 0.001, \eta_P^2 = 0.57$]. Low Similarity Condition: Participants reacted fastest (Mean = 3,899 ms). High Similarity Condition: RT increased significantly (Mean = 4,620 ms), indicating that high visual similarity creates a "search bottleneck." As shown in Fig. 3.



(a) Accuracy line chart (b) Line graph during reaction

Figure 3: Mean visual search accuracy and reaction time for three groups with different similarity levels

Contrary to the intuition that domain knowledge aids recognition, the Semantic Group (Engineers) performed slower (Mean = 4,620 ms) than the Perceptual Group (Novices) (Mean = 4,084 ms). Interpretation: The interaction effect showed that while engineers used semantic cues (functional meaning) to guide their search, this "top-down" processing was slower than the "bottom-up" visual feature matching used by the perceptual group (He et al., 2024). Dominance of Perceptual Attributes: Crucially, when perceptual similarity was high, the error rate for both groups spiked, regardless of semantic differences. This validates Hypothesis: In rapid monitoring tasks, perceptual attributes (what it looks like) override semantic attributes (what it means), making perceptual similarity the primary driver of cognitive bias.

Quantification of Perceptual Similarity

Given the dominance of perceptual factors, we established a mathematical model to quantify the "Overall Perceptual Similarity" (T_0'') of interface chunks.

Variable Extraction and Factor Analysis

Initially, 10 perceptual features (e.g., texture, luminance, contour) were identified via the Delphi method. A Semantic Differential (SD) questionnaire was administered to evaluate 45 pairs of nuclear interfaces. Principal Component Analysis (PCA) reduced these variables to three core dimensions explaining 86.4% of the variance:

(1) Colour Similarity (T_7): Dominant hue and background colour consistency.

(2) Layout Similarity (T_4): Grid structure and spatial arrangement.

(3) Complexity Similarity (T_1): Information density and element count (based on Entropy Theory).

4.2 The Calculation Equation

Using Stepwise Multiple Linear Regression, we derived the unstandardized coefficients for each dimension. The final equation for calculating the similarity between two information chunks is, as shown in Eq. (1):

$$T_0'' = 0.531 \times T_7 + 0.695 \times T_4 + 0.369 \times T_1 - 1.162 \qquad (1)$$

T_0'': The predicted Overall Similarity Value (Range: ~0.4 to 10). T_7, T_4, T_1: Subjective scores (7-point Likert scale) for colour, layout, and complexity differences respectively. Model Fit: The regression model showed high validity ($R^2 = 0.768, F = 46.29, p < 0.001$).

Experiment 2: Optimal Similarity Range

Experimental Design

To determine the optimal T_0'' range, we designed a Scenario-based Task simulating the "Alarm Diagnosis & Parameter Adjustment" sequence.

(1) Independent Variable: Overall Similarity (T_0''). Five sets of interfaces were designed ranging from Level 1 (Extremely Dissimilar/Chaotic) to Level 5 (Extremely Similar/Uniform), as shown in Fig. 4.

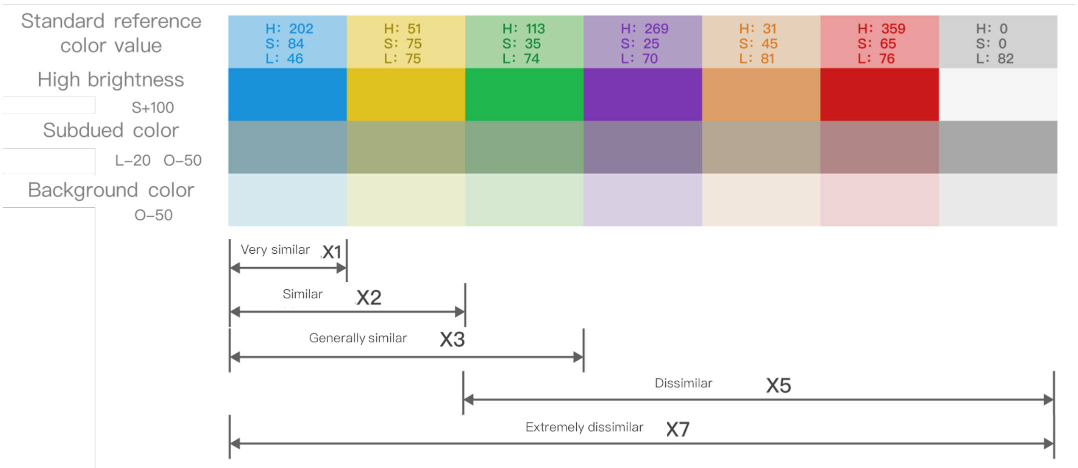


Figure 4: Colour coding results of the experimental drawing group

(2) Dependent Variables: Task Completion Time, Error Rate, and System Usability Scale (Brooke, 1996).

(3) Participants: 27 subjects (12 engineers, 15 trained students).

Results

The relationship between Similarity T_0'') and Performance (Speed/Accuracy) followed a quadratic trend (Inverted U-shape for performance, U-shape for Reaction Time):

(1) Low Similarity Zone ($T_0'' < 4$): Reaction times were slow. The lack of consistency (chaos) increased cognitive load as operators could not predict information location.

(2) High Similarity Zone ($T_0'' > 6$): Reaction times slowed again, and Error Rates peaked. Excessive homogeneity triggered "Similarity Bias," causing target confusion.

(3) Optimal Zone ($T_0'' \in [4.6, 5.5]$): Operators achieved the fastest reaction times and lowest error rates.

Determination of the Threshold

By fitting the behavioural data to a quadratic function ($y = ax^2 + bx + c$), we calculated the stationary point of the curve, as shown in Fig. 5. The mathematically optimal range for similarity was identified as $T_0'' \in [4.624, 5.538]$. Within this range, the interface balances "Systematic Logic" with "Visual Discernibility."

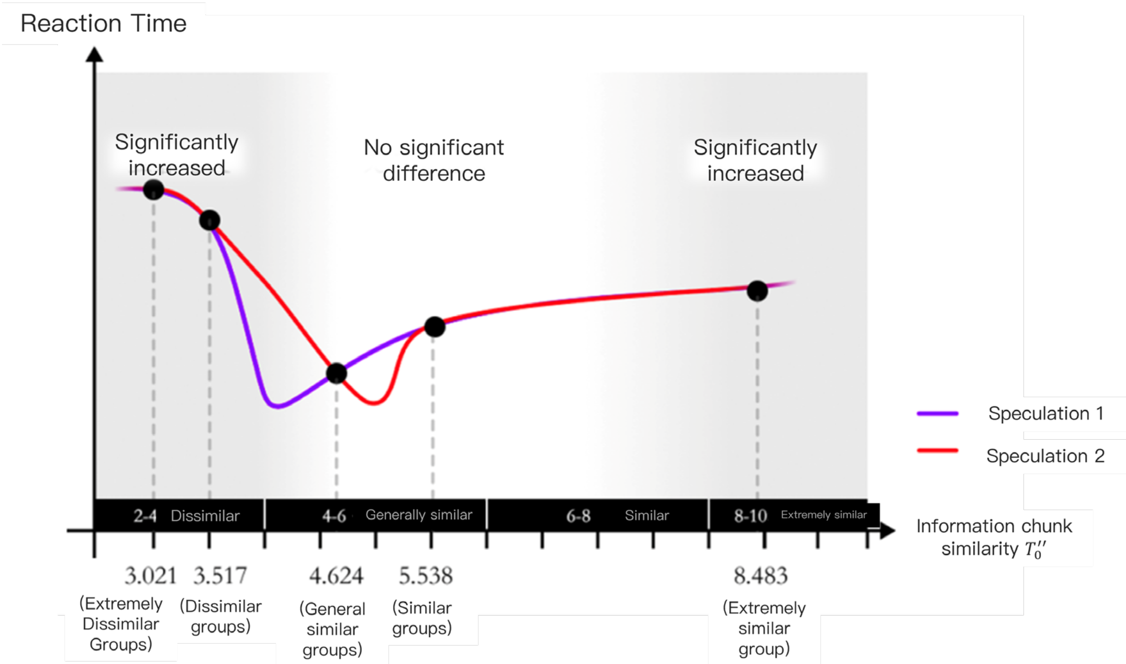


Figure 5: Curve fitting of Reaction Time vs. Overall Perceptual Similarity Value (T_0'')

The Cognitive Bias Effect Paradigm

This study proposes a paradigm to explain how similarity impacts operator reliability. Unlike general UI design, nuclear monitoring requires maintaining attention over long periods, as shown in Fig. 6. Our model suggests that Perceptual Similarity acts as a "double-edged sword": it aids initial learning (memory schema) but hinders real-time discrimination (visual search) when excessive (He, 2025).

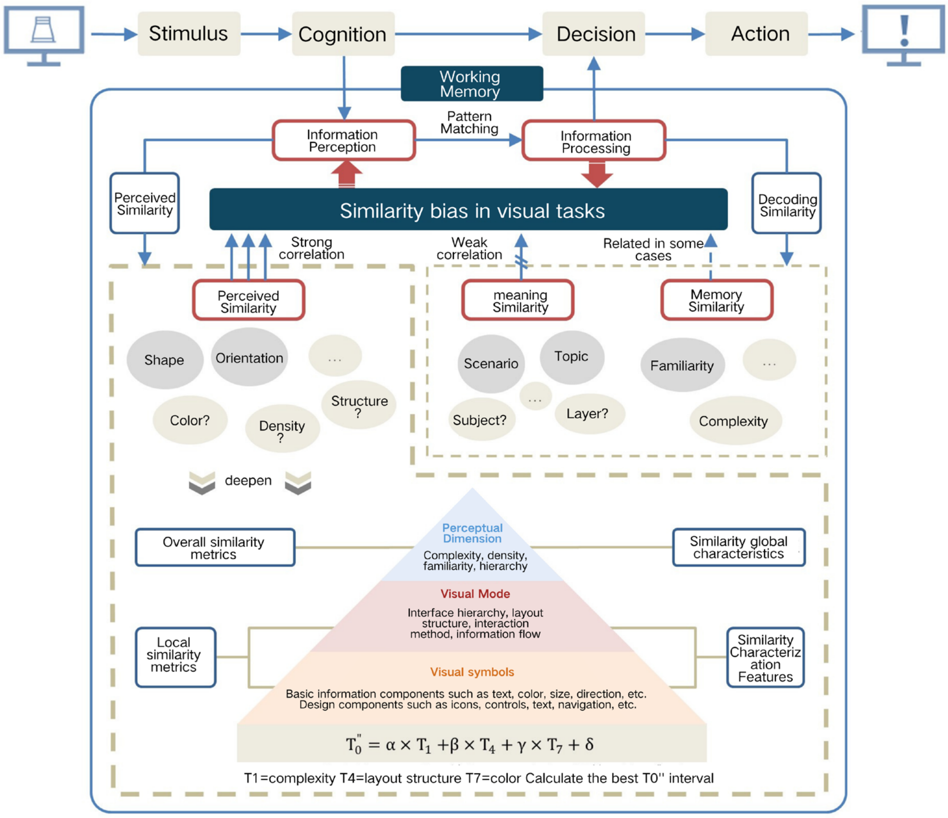


Figure 6: The Cognitive Bias Effect Paradigm

Discussion

Our findings clarify this relationship:

(1) Systematicity (Consistency) is achieved through shared Layout (T_4). Keeping the grid structure constant ($T_4 > 5$) ensures operators know where to look.

(2) Discernibility is achieved through distinct Colour (T_7) and Complexity (T_1). Varying the colour coding or data density allows operators to distinguish what they are looking at.

(3) The "Organic Combination": The optimal range ($T_0'' \approx 5$) represents a state where the interface is structurally consistent but visually distinct. For example, two pump control windows should share the same layout (High T_4) but use different header colours (Low T_7) to prevent mode confusion.

Designers can use the T_0'' equation as a pre-validation tool. If a proposed interface scores $T_0'' > 6$, it is a "High Risk" design. The remedy is not to break the layout, but to introduce "Distinction Tags" (e.g., adding a specific icon or changing the background hue) to lower the T_0'' value back to the safe zone.

Conclusion

This research addresses the critical challenge of "Similarity Bias" in digital nuclear power monitoring. By combining cognitive modelling with empirical experiments, we reached three key conclusions:

(1) Perceptual Dominance: Visual attributes (Colour, Layout, Complexity) are the primary triggers of similarity bias, overriding semantic meaning in rapid search tasks.

(2) Quantification Tool: A validated equation for Overall Perceptual Similarity (T_0'') was established, enabling quantitative evaluation of interface designs.

(3) Optimal Range: A similarity range of $T_0'' \in$ [4.624, 5.538] was identified as the "Safe Zone," where operator performance is maximized.

Future work will explore the impact of mental fatigue on these thresholds and integrate eye-tracking data to further validate the visual search mechanisms.

Acknowledgments

This work is supported by the Jiangsu Provincial Natural Science Foundation (BK20221490), the Open Fund of State Key Laboratory of Nuclear Power Safety Technology and Equipment (K-A2025), and the National Natural Science Foundation of China (52175469).

References

Wu, X. L., Xue, C. Q., Gedeon, T., et al. (2018). Visual Search Experiments of Information Features in Digital Monitoring Task Interfaces. Journal of Southeast University (Natural Science Edition), 48(5), 807-814.

Zhang, L., Dai, L. C., Hu, H., et al. (2019). Human Factors Reliability in Digital Nuclear Power Plants [M]. Beijing: National Defense Industry Press.

Miller, G. A. (1956). The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information. Psychological Review, 63(2), 81.

Simon, H. A. (1974). How Big Is a Chunk? By Combining Data from Several Experiments, a Basic Human Memory Unit Can Be Identified and Measured. Science, 183(4124), 482-488.

Payne, P. R., & Starren, J. B. (2005). Quantifying Visual Similarity in Clinical Iconic Graphics. Journal of the American Medical Informatics Association, 12(3), 338-345.

Treisman, A. M., & Gelade, G. (1980). A Feature-Integration Theory of Attention. Cognitive Psychology, 12(1), 97-136.

Biggs, A. T., Adamo, S. H., Dowd, E. W., & Mitroff, S. R. (2015). Examining Perceptual and Conceptual Set Biases in Multiple-Target Visual Search. Attention, Perception, & Psychophysics, 77(3), 844-855.

He, Y., Wu, X., Yang, X., Fang, Z., Li, Q., Huang, Y., ... & Yu, D. (2024). Research on Similarity Bias in Dual Objective Visual Search Based on Nuclear Power Human-Machine Interface Icons. International Journal of Industrial Ergonomics, 104, 103656.

He, Y.Q. (2025). Research on similarity deviation of information blocks based on intelligent nuclear power monitoring system. Master Thesis, Nanjing: Nanjing University of Science and Technology.

Brooke, J. (1996). SUS-A Quick and Dirty Usability Scale. Usability Evaluation in Industry, 189(194), 4-7.