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The Influence of Personality Traits on Hazard Recognition in Construction Workers

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Abstract

Current construction safety research has paid limited attention to the relationship between stable individual differences and hazard-related visual attention. This study combined personality assessment and eye-tracking technology to investigate visual attention allocation and hazard recognition among construction workers in static work-at-height scenarios. Personality traits were assessed using the Chinese Big Five Personality Inventory Brief Version, and 30 participants with extreme trait profiles were selected for eye-tracking experiments in two representative work-at-height scenarios. Eight eye-tracking indicators were analyzed across four dimensions: attentional span, attentional stability, attentional allocation, and attentional shifting. An AHP-based evaluation framework was further developed to assess visual attention efficacy. The results showed descriptive differences in hazard-related visual attention patterns across personality-trait groups. Individuals high in agreeableness and conscientiousness exhibited more hazard-oriented visual allocation and higher visual attention efficacy, whereas those high in openness and extraversion showed stronger exploratory tendencies and lower efficiency in allocating attention to high-risk areas. Individuals high in neuroticism showed intermediate overall performance but relatively weaker attentional organization. Sensitivity analysis indicated that the ranking results remained stable under moderate weight perturbations. These findings provide a quantitative framework for comparing visual attention efficacy across personality-trait groups and offer preliminary support for differentiated safety training, risk communication, and attentional guidance in construction safety management.

Keywords: construction workers; personality traits; visual attention; hazard recognition; eye tracking

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1. Introduction

Accidents on construction sites typically stem from the coupling and interaction of multiple risk factors [1], with workers' unsafe behaviors acting as a primary direct contributor [2]. While classical research highlighted general human factors in industrial mishaps [3], recent reviews emphasize that unsafe behaviors heavily drive construction

accidents through cognitive errors, poor risk perception, and deficient hazard recognition [4–6]. Under classical human error theory, execution-stage slips and lapses are tightly linked to failures in attentional resource allocation [7]. Consequently, human-factor safety research increasingly focuses on how individual differences, particularly visual attention characteristics, modulate risk-information acquisition and behavioral decision-making.

Construction safety research has gradually expanded from accident causation analysis to risk assessment and risk control. Qualitative and quantitative approaches have been widely applied to hazard identification, classification, and warning in construction processes [8–10], while risk-control studies have mainly focused on safety training, behavioral supervision, site monitoring, warning systems, and intelligent sensing measures [11–14]. These studies have supported construction safety management and promoted a shift toward more standardized and systematic approaches. However, current research still focuses mainly on external environments, management measures, and group-level behavioral characteristics, whereas relatively limited attention has been paid to the individual cognitive mechanisms involved in hazard recognition [5,15]. In particular, systematic quantitative research on the relationship among personality traits, visual attention, and hazard recognition in high-risk scenarios remains limited [16].

Visual attention allocation is a key cognitive process through which individuals select, process, and use risk information in complex environments, and it is shaped by both state-related and trait-related factors [17]. Existing studies have shown that transient states, such as emotional distress, immediate motivation, physiological fatigue, and environmental pressure, can significantly affect attentional engagement and resource allocation [18–22]. In high-risk contexts such as work at height, however, visual attention allocation is not merely a passive response to external stimuli [23,24], but is also influenced by top-down cognitive processing [23] associated with relatively stable individual-difference factors such as personality traits [17]. Although static eye-tracking paradigms have been increasingly used in visual cognition research, most studies still emphasize transient state factors or general static gaze indicators. As a result, how different personality traits shape visual attention allocation in complex hazard-recognition tasks [15], and how these differences further affect hazard-recognition performance, remains insufficiently explained.

The Big Five personality theory provides a useful framework for interpreting the cognition–behavior patterns of construction workers. Neuroticism, extraversion, and conscientiousness are widely regarded as important personality dimensions influencing safety performance [16]. Existing studies have shown that Big Five dimensions are closely associated with workers' safety performance, attention allocation, and hazard-recognition outcomes, and that extraversion, conscientiousness, and openness can affect attentional configuration and hazard-recognition efficiency [24–26]. Work at height requires workers to simultaneously maintain postural control and environmental monitoring, thereby placing higher demands on risk-information acquisition, attention allocation, and hazard recognition [27]. Against this background, examining the relationship between personality traits and visual attention can not only deepen the understanding of the cognitive mechanisms underlying hazard recognition among construction workers, but also promote a shift in safety management from group-based intervention to more targeted and precise intervention [16].

Accordingly, this study focuses on work-at-height scenarios and combines personality trait theory with eye-tracking technology to analyze the visual attention allocation characteristics of construction workers with different personality traits and their influence on hazard recognition. On the basis of risk zoning, the correspondence between visual attention and hazard recognition is further examined. This study is expected to extend construction risk assessment and risk control research from the perspective of individual

cognitive differences and to provide a theoretical basis for personalized safety training, targeted risk control, and the development of intelligent protective systems.

Consequently, this study introduces novelty across two primary dimensions. First, regarding the subject of investigation, it shifts the focus from conventional demographic factors to the inherent psychological domain—specifically, the Big Five personality traits. Second, from a methodological perspective, it advances beyond traditional static images or laboratory-based simulations by deploying wearable eye-tracking technology directly within in-situ work-at-height environments. This approach captures naturalistic visual behaviors under authentic field stressors, thereby achieving robust ecological validity and providing a solid empirical foundation for personalized construction safety management.

The remainder of this paper is organized as follows. Section 2 describes the methodology and experimental procedure. Section 3 presents the eye-tracking results and visual analyses across personality-trait groups. Section 4 reports the AHP-based evaluation, sensitivity analysis, and discussion. Section 5 concludes the paper.

2. Methods

This study used the Chinese Big Five Personality Inventory Brief Version (CBF-PI-B) to assess workers' personality traits and select participants with extreme trait profiles. Representative work-at-height scenarios were used as visual stimuli, and areas of interest were delineated by risk characteristics. Eye-tracking data were collected during scene observation and analyzed using multiple eye-movement indicators and a visual attention evaluation framework to compare attention allocation patterns and hazard-recognition performance across personality-trait groups.

2.1. Participants

Male construction workers aged 21–48 years (Mean = 29 $\pm$ 6) were recruited through recruitment notices distributed by the human resource departments of partner firms. To control for individual differences, baseline data were collected before participant selection. These variables included body mass index (BMI), daily cigarette consumption, years of work experience, education level, and height. Regarding their occupational background, the recruited workers primarily engage in the construction of high-rise residential buildings, large-scale commercial complexes, and municipal infrastructure projects. Their frequent exposure to complex, high-altitude work environments ensures that the sample is highly representative for investigating hazard recognition in work-at-height scenarios. Although this demographic data was recorded during screening, the study adopted an extreme groups design, resulting in a final sample of 30 participants (N = 30). Therefore, to maintain statistical power, these variables were not included as covariates in the final analysis.

To minimize the influence of extraneous variables, all participants were required to meet the following criteria for 24 h prior to the experiment: no sleep deprivation, no alcohol consumption, no use of medication, and no strenuous physical activity [28]. Given the non-invasive and observational nature of this research, all experimental procedures were conducted in strict accordance with the Declaration of Helsinki. Prior to the experiment, participants were fully informed about the study's purpose, the non-intrusive nature of the eye-tracking, and strict data anonymity protocols. Written informed consent was obtained from all subjects. Participation was entirely voluntary, and workers were explicitly assured of their unconditional right to withdraw at any time without facing any negative consequences regarding their employment or compensation.

2.1.1. Measurement of Personality Traits

CBF-PI-B, developed by Wang Mengcheng and Dai Xiaoyang, was employed to assess workers' personality traits across five dimensions: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness. The inventory consists of 40 items, with 8 items per dimension. Within each dimension, 7 items are reverse-scored and 1 item is positively scored (Supplementary Material S1) [29].

A total of 216 workers participated in the survey. Following data screening, invalid questionnaires with evidence of careless responding (e.g., straight-line or inconsistent answers) were excluded, resulting in 209 valid responses. This process ensured the authenticity, reliability, and validity of the personality trait data.

2.1.2. Work Readiness

This study utilized the Chinese Big Five Personality Inventory Brief Version (CBF-PI-B). Developed natively within the Chinese cultural context, this instrument effectively circumvents cross-cultural biases and semantic ambiguities inherent in translated foreign scales, ensuring high alignment with the target population. Its concise 40-item design is well-tailored to the characteristics of frontline construction workers, who often possess varied educational backgrounds and endure high-intensity work environments. This brevity mitigates cognitive fatigue and reduces the probability of careless responding, thereby safeguarding the authenticity and reliability of the data.

Empirical results from this study further substantiate the instrument's applicability. As presented in Table 1, the mean scores (M) for Neuroticism, Openness, and Extraversion were relatively high, suggesting that the sample population generally exhibited heightened emotional sensitivity and susceptibility to negative affect. This observation aligns with theoretical expectations regarding the increased emotional regulatory load experienced by individuals in modern, high-stress societal contexts [30]. Conversely, the mean scores for Conscientiousness and Agreeableness were relatively low. Given the scoring structure of these dimensions, this actually reflects stronger performance within the sample regarding organizational orderliness and interpersonal warmth. Regarding data dispersion, the standard deviations (SD) across all personality traits were closely clustered at 5.878 ± 0.118, with a coefficient of variation (CV) of approximately 2%. These values indicate that the degree of dispersion for each personality trait was consistent across the sample population.

Table 1. Descriptive Statistics and Reliability–Validity Analysis of CBF-PI-B Personality Traits.

Trait	Mean	SD	Cronbach's α	KMO	Bartlett's Test of Sphericity (p-Value)
Neuroticism	27.48	5.95	0.968	0.962	<0.001
Extraversion	27.51	5.67	0.961	0.960	<0.001
Openness	27.57	5.93	0.967	0.961	<0.001
Agreeableness	20.03	5.89	0.963	0.964	<0.001
Conscientiousness	20.15	5.95	0.957	0.960	<0.001
Overall	-	-	0.784	-	-

Note. 1. Measurements were based on the CBF-PI-B. 2. All dimensions were assessed with 8 items rated on a 6-point Likert scale (1 = strongly disagree, 6 = strongly agree). 3. Each dimension contained 7 reverse-scored items and 1 positively scored item. 4. Cronbach's α values were calculated using the 8 items per dimension. 5. SD = standard deviation.

This study systematically evaluated the structural validity of the CBF-PI-B and verified its psychometric properties in conjunction with reliability indicators. As shown in Table 1, the internal consistency reliability of the five dimensions was excellent, with Cronbach's α coefficients ranging from 0.957 to 0.968. This indicates robust item homogeneity within

each dimension and high measurement stability. The overall scale yielded a Cronbach's α of 0.784. This slightly lower value can be attributed to the relative conceptual independence of the five personality dimensions. Nonetheless, it remains well within the widely accepted psychometric threshold (0.70–0.80) and does not compromise the overall reliability of the inventory.

Regarding structural validity, the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy ranged between 0.960 and 0.964, significantly exceeding the 0.70 standard. This suggests strong inter-variable correlations, rendering the data highly suitable for factor analysis. Furthermore, Bartlett's test of sphericity was highly significant ($p < 0.001$), validating the correlations among variables and confirming the appropriateness of the sample data for factor extraction. In conclusion, based on these reliability and validity assessments, the CBF-PI-B fully meets stringent psychometric requirements. It demonstrates robust internal consistency, reliability, and validity, serving as a reliable and effective standardized instrument for evaluating individual Big Five personality traits.

2.1.3. Extreme-Trait Participant Selection

Extreme groups were established based on scores from the five-factor model personality inventory. High-scoring cohorts for each dimension (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness) were defined as participants scoring $\geq$ M + 1 SD. The six highest-scoring individuals from each dimension were selected to form extreme groups, designated as High-Ne, High-Ex, High-Op, High-Ag, and High-Co groups [30].

During recruitment, participants qualifying for multiple groups were assigned using predetermined criteria: (1) assignment to the dimension with their highest standardized score, and (2) random allocation when scores were identical across dimensions. This procedure ensured mutual exclusivity between groups and maintained statistical independence.

The final sample comprised 30 participants, with each individual representing the extreme high-end of their respective personality dimension (see Table 1 for complete sample characteristics).

2.2. Experimental Materials

The experimental materials were developed to reflect typical work-at-height situations characterized by high risk, complex visual information, and clear hazard cues. These materials provided the basis for the presentation of visual stimuli, the delineation of areas of interest, and the subsequent eye-tracking analysis.

2.2.1. Stimulus Materials

This study selected two representative work-at-height scenarios, climbing work and edge work, as the experimental conditions. Participants were tested directly within actual, active work-at-height scenarios to ensure high ecological validity. Specifically, the eye-tracking experiments were conducted in-situ at a real-world high-rise building construction site. The selection was based on both industry risk evidence and task characteristics. As working in high-rise buildings introduces significant objective hazards and elevated psychological stress, it inherently demands a higher level of visual attention and stricter cognitive resource allocation for accident prevention. Falls from height remain one of the leading causes of fatalities in the construction industry, and these incidents commonly involve ladders, scaffolds, openings, and unprotected edges [31]. In addition, both climbing work and edge work require workers to maintain postural stability while monitoring surrounding hazards. As a result, these tasks place high demands on visual attention and hazard recognition. These features make the two scenarios suitable for examining how personality traits are related to visual attention allocation and hazard-recognition

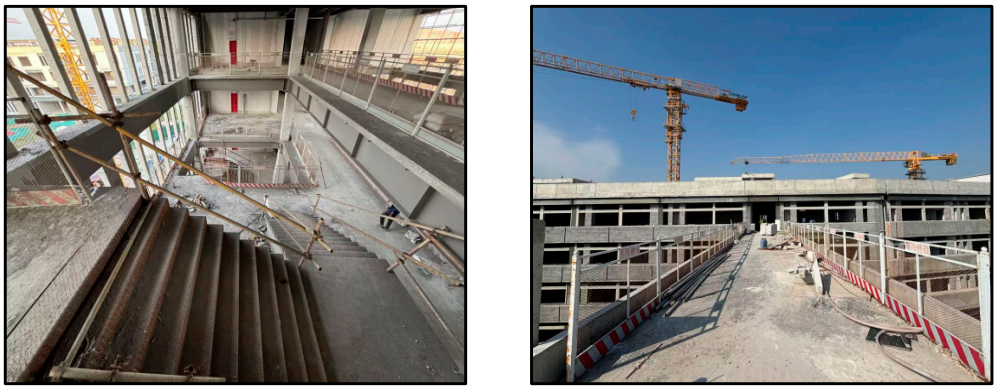
performance in high-risk construction settings. On this basis, corresponding visual stimuli were developed for the subsequent eye-tracking analysis.

2.2.2. Visual Attention Mechanism and Area of Interest Delineation

In eye-tracking studies of aerial work, the definition of Areas of Interest (AOIs) constitutes a critical step for quantifying visual attention and examining its relationship with safety-related behaviors [32]. This study introduced a visual perception factor (V) to enhance the traditional LEC (Likelihood, Exposure, Consequence) risk assessment framework and developed a comprehensive risk evaluation formula through a weighted linear combination model. Based on expert interviews and field survey data, AOIs were classified into three hierarchical risk levels according to their potential hazard severity: Class I (Critical Warning Zones), Class II (Key Protection Zones), and Class III (Routine Attention Zones). The specific operational procedures are as follows:

1. AOIs Delineation Method

To quantitatively assess risks in aerial work scenarios, spatial analysis units were first delineated as fundamental elements for evaluation. The definition of AOIs was conducted by integrating multiple safety zoning principles observable under actual construction conditions, combined with historical accident hotspot distributions and expert evaluations. Based on this synthesized approach, the scene depicted in Figure 1 was partitioned into multiple AOIs reflecting varying risk characteristics. The detailed AOIs demarcation scheme—including the identity of each AOIs and the rationale for its inclusion—is visually presented in Figure 2 and systematically summarized in Table 2.



(**a**) (**b**)

Figure 1. Visual Material. (**a**) Climbing Work at Height. (**b**) Edge Work at Height.



(**a**) (**b**)

Figure 2. Visual Material AOI Delineation Map. (**a**) Climbing Work at Height. (**b**) Edge Work at Height.

Table 2. Visual Material AOIs.

ID	Name
AOI-1	Safety Barrier
AOI-2	Building Materials/Construction Waste
AOI-3	Steel Pipe Handrail
AOI-4	Fire Hydrant Area
AOI-5	Steel Ladder
AOI-6	Tower Crane Area
AOI-7	Building Structure
AOI-8	Steel Beam Installation Area
AOI-9	Scaffolding Erection and Dismantling Area

2. Risk Assessment Factors

This study introduces a visual perception factor (V) into the conventional LEC (Likelihood, Exposure, Consequence) framework, resulting in an enhanced risk evaluation system. The definitions and operationalization of each factor, including the newly incorporated V factor, are summarized in Table 3.

3. Risk Classification and Factor Weight Assignment

To improve the transparency of the risk classification and weight assignment process, this study combined field investigation, expert consultation, and panel discussion. Based on the characteristics of work-at-height construction scenarios, historical accident cases, relevant safety standards, and previous studies, four risk assessment factors were identified, and a 1–10 scoring scale was established.

On this basis, a panel of 16 experts from relevant fields were invited to discuss and evaluate the relative importance of these criteria and the four risk assessment factors across each AOI (Table 4). The 16 consulted experts are evenly distributed across three sectors, comprising academic scholars (n = 6) from universities engaged in construction safety and human factors engineering research, frontline practitioners (n = 5) from large construction enterprises with over 10 years of field experience in work-at-height safety management, and field safety inspectors or infrastructure safety directors (n = 5) from regional transport and shipping development regulatory authorities.

Following the panel discussions, a direct weight allocation method based on expert consensus was employed to systematically synthesize the evaluations into a universally applicable weight vector by calculating the arithmetic mean of the experts' individual scores, thereby mitigating subjective individual biases. The final normalized weights for the four risk factors and their corresponding rationales are summarized in Table 3. Specifically, C was assigned the highest structural weight because the severity of potential loss remains the primary concern in construction safety management, followed closely by L. Conversely, V, functioning as a cognitive modifier rather than a direct physical hazard, was assigned the lowest weight.

Table 3. Modified LEC-V Risk Assessment Factors.

Assessment Factor	Definition	Weight	Evaluation Criterion
L (Likelihood)	Probability of accident occurrence	0.30	Historical accident frequency within the AOIs
E (Exposure)	Frequency of personnel exposure	0.20	Activity frequency of workers within the AOIs
C (Consequence)	Severity of potential outcomes	0.40	Extent of possible casualties, property damage, and environmental impact
V (Visual Perception)	Visual perceptibility of risk cues	0.10	Capacity of visual elements to signal potential hazards

Note. All factors were rated on a 10-point Likert-type scale (1 = Extremely Low, 10 = Extremely High).

Table 4. Risk Assessment Factor.

Integrated Risk Score	AOI-1	AOI-2	AOI-3	AOI-4	AOI-5	AOI-6	AOI-7	AOI-8	AOI-9
L (Likelihood)	7.0	4.0	5.0	3.0	8.0	9.0	2.0	3.0	8.0
E (Exposure)	6.0	5.0	4.0	3.0	7.0	6.0	2.0	3.0	7.0
C (Consequence)	8.0	6.0	7.0	4.0	9.0	8.0	3.0	3.0	9.0
V (Visibility)	5.0	4.0	4.0	5.0	6.0	5.0	3.0	4.0	6.0
R (Integrated Risk Score)	7.0	5.0	5.5	3.6	8.0	7.6	2.5	3.1	8.0

4. Integrated Risk Score

A weighted linear combination model was employed to calculate the comprehensive risk score (Table 4) for each AOIs, expressed as:

$$R_{\mathrm{AOI}-i} = \sum_{k \in \{L,E,C,V\}} k w_k \quad (1)$$

where:

L, E, C, V represent the scores of each risk assessment factor, ω_k denotes the weight coefficient for each risk factor, with the constraint that $\sum w_k = 1, k = L, E, C, V$,the subscript "$i$" indicates different AOIs, where "i" $= 1, 2, \ldots, 9$.

Based on field investigations, expert consultation, and evaluation panel discussions, the final normalized weights were uniformly applied to evaluate all AOIs regardless of their tentative classifications, as detailed in Tables 3 and 4. This standardized approach provides a consistent theoretical foundation for establishing a quantitative model linking visual attention and risk perception.

The AOIs were classified into the following three risk levels based on their integrated risk scores, as detailed in Table 5:

Table 5. AOI Regional Classification for AOIs.

Risk Class	Delineation Criteria	Affected Areas	Management Measures
Class I	R $\geq$ 6	AOI-1, AOI-5, AOI-6, AOI-9	Real-time monitoring, strict control of access
Class II	6 > R $\geq$ 4	AOI-2, AOI-3	Regular inspection, strengthen the protective measures
Class III	4 > R	AOI-4, AOI-7, AOI-8	Routine inspections to maintain clear labeling

2.3. Collection of Eye-Tracking Data

In this experiment, to capture naturalistic visual behaviors, participants wore an aSee Glasses (7invensun, Beijing, China) (Figure 3) wearable eye-tracker directly within the selected real-world construction scenes to collect in-situ eye-movement data. To characterize visual attention during the task, eight eye-tracking metrics were selected and grouped into four dimensions: attention span, attention stability, attention allocation, and attention shifting. All metrics were directly extracted from the raw eye-tracking data or further derived through subsequent processing. In addition, fixation heatmaps and scanpath plots were used to visualize attention allocation patterns and visual search paths. Table 6 summarizes the selected metrics, their units, and their interpretations (Figure 4).



Figure 3. aSee Glasses Eyeglasses Eye Movement Instrument.

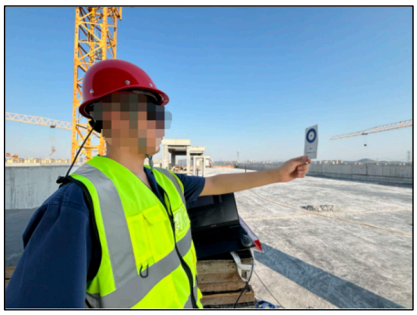


Figure 4. Eye Movement Instrument Calibration.

Table 6. Indicators for Evaluating Visual Attention Efficacy.

Attention Property	Eye-Tracking Metric	Unit	Interpretation of Indicator
Attention Span	Gaze Range Probability	%	Reflects the spatial coverage of visual attention.
	Fixation Count	count	Reflects the frequency of fixation behavior.
Attention Stability	Average Fixation Duration	second (s)	Reflects the duration of sustained attention to target regions.
	Blink Rate	per 15 s	Reflects attentional maintenance and its variation during observation.
Attention Allocation	Heatmap Attention Risk Ratio	%	Reflects attention allocation across regions with different risk levels.
	AOI Fixation Probability	%	Reflects the visual salience of a specific AOI.
Attention Shifting	Time to First Fixation	second (s)	Reflects the early attentional attraction of the target region.
	Number of Transitions	count	Reflects the frequency of attentional switching between AOIs.

2.3.1. Attention Span

Gaze range probability (GRP) was used to quantify the spatial coverage of visual attention within a given time window. This indicator was calculated by generating fixation heatmaps from the raw fixation-point data and then applying an image-segmentation method. GRP was defined as the proportion of the fixation area relative to the total area of the visual stimulus. A larger GRP indicates a broader spatial coverage of visual attention.

Fixation count (FC) refers to the total number of fixations generated by a participant during a given task. This indicator was used to characterize the frequency of fixation behavior during scene observation and may, to some extent, reflect variations in visual search range. In general, a higher fixation count indicates more frequent fixation behavior and relatively more active visual search.

2.3.2. Attention Stability

Average fixation duration (AFD) refers to the mean duration of all fixation events during scene observation and is usually expressed in seconds (s). This indicator is commonly used to reflect the depth of information processing and the degree of sustained attention directed toward target regions. A longer AFD generally indicates that attention is maintained on the corresponding region for a longer period [33].

Blink Rate (BR) refers to the number of eyelid closures per 15-s interval and serves as an important physiological indicator of attentional stability and concentration [34]. Variations in BR are closely associated with cortical activity and can reflect the allocation state of cognitive resources.

2.3.3. Attentional Allocation

1. Heatmap Attention Risk Ratio (HARR)

HARR was used to characterize attention allocation across regions with different risk levels. Based on the color distribution of the eye-tracking heatmaps, the OpenCV library (version 4.5.0) in Python (version 3.10.0) was used to identify and segment regions of different colors and to calculate the area proportion of each color region in the entire image. In this study, red represented high-attention/high-risk regions, yellow represented medium-attention/medium-risk regions, and green represented low-attention/low-risk regions. The area proportions of these regions were used to quantify attention allocation across different risk-level areas.

2. AOI Fixation Probability (AOI FP)

This refers to the likelihood that a viewer fixates within a specific Area of Interest (AOI). A higher AOI fixation probability indicates that the region is more salient or relevant to the participant.

Steps to calculate AOI fixation probability:

(1) Acquisition of Fixation Data: Gaze point data, including fixation coordinates and durations, were recorded using an eye tracker.
(2) Fixation-AOI Mapping: The coordinates of each fixation were compared with the predefined spatial boundaries of the AOIs. Fixations whose coordinates fell within an AOI boundary were assigned to that AOI. This mapping was performed automatically using the eye tracker's native analysis software (Version 1.6.2; 7invensun, Beijing, China).
(3) Probability Calculation: AOI FP was computed using the following formula:

$$\text{AOI fixation probability} = \frac{\text{Number of fixations falling within the AOI}}{\text{Total number of fixations}} \quad (2)$$

(4) Stratified Analysis by Risk Level: The AOI FP values for each of the five high-scoring personality groups were aggregated and analyzed separately across the three risk levels (Class I, Class II, and Class III) according to the classification scheme defined in Table 5.

2.3.4. Attention Shifting

Time to First Fixation (TFF) refers to the time interval between the onset of the stimulus and the participant's first fixation on a target region, usually expressed in seconds (s). This metric is commonly used to characterize the early attentional attraction of a target region. A shorter TFF indicates that the region is more likely to capture attention at an early stage of observation.

Number of Transitions (NT) refers to the number of attentional shifts occurring between different areas of interest. This metric was calculated from scanpath data and was used to characterize the frequency of attentional switching during visual search. A higher NT generally indicates more frequent visual shifts between different regions.

Table 6 summarizes the eye-tracking metrics used to evaluate the four dimensions of visual attention, together with their units and interpretations. These metrics provide a

quantitative basis for evaluating participants' visual attention characteristics during the experimental task.

2.3.5. Visual Representation

Fixation heatmaps were generated from gaze coordinates and fixation durations recorded by the eye tracker. The display area was partitioned into discrete units, and a duration-dependent weighting algorithm was applied to assign intensity values, resulting in a chromatic-encoded visualization. This method utilizes a color gradient in which warm hues indicate regions of high fixation density, while cool tones correspond to areas of lower attentional engagement. Color intensity is proportional to total dwell time, providing an intuitive representation of the spatial distribution of visual attention.

Scanpath plots were used to visualize continuous oculomotor trajectories and the spatial distribution of fixations. The diameter of each fixation marker is scaled proportionally to its duration. These plots allow for quantitative assessment of visual search sequences and attentional strategies, with clustered fixations typically indicating Areas of Interest (AOIs), and sparse distributions reflecting reduced attentional allocation.

2.4. Experimental Procedure

This study adopted a standardized four-stage experimental protocol to ensure methodological rigor and data reliability:

1. Construction workers were assembled to complete the Chinese version of the CBF-PI-B Personality Trait Inventory. The questionnaire was administered via a digital link, with explicit instructions for careful and thorough completion.
2. Participants were then escorted to the preconfigured experimental environment equipped with an eye-tracker. The device was calibrated to ensure accurate capture of ocular movements (Figure 4), after which detailed instructions regarding the visual attention task procedures and precautions were provided.
3. Workers were organized to perform on-site observations at an actual construction site. To maintain consistency, all participants adhered to a uniform viewing angle. Each individual wore the eye-tracking device, and a 15-s data acquisition period was strictly enforced for the real-time recording of eye movement metrics.
4. Upon conclusion of the experiment, raw eye-tracking data were exported and archived. Preliminary data processing was performed, whereby each worker's personality trait inventory data was systematically linked with their corresponding visual attention experiment records using unique identifiers to facilitate subsequent analysis.

To ensure controlled variables, both Scenario 1 and Scenario 2 employed identical observation perspectives. All 30 experimental trials were completed on the same day, with each individual's static data acquisition duration strictly standardized to 15 s. A detailed implementation scheme is provided in Table 7.

Table 7. Data Collection Schedule and Parameters.

Session	Participants (n)	Trials per Participant	Duration (s)
Session 1 (Morning)	30	1	15
Session 2 (Afternoon)	30	1	15

3. Results and Analysis

Given the limited sample size of the extreme-trait groups, the following results mainly reflect trends observed in an exploratory analysis and should be further validated in larger samples.

3.1. Analysis of Eye-Tracking Metrics for Visual Attention

This section describes eye-tracking metrics in relation to different personality traits. Given the preliminary nature of this study, these comparisons are exploratory and aim to identify potential patterns in visual attention rather than establish definitive group effects. We analyze these patterns across four key dimensions: attentional span, stability, allocation, and shifting.

3.1.1. Differences in Attentional Span

Visual attention span was characterized using two metrics, GRP and FC (see Table 8). GRP reflects the spatial distribution range of visual attention, whereas FC indicates the degree of attentional-resource dispersion and the intensity of visual search engagement. Together, these two metrics capture the functional characteristics of visual search strategies.

Table 8. Gaze Range Probability and Fixation Count.

Eye-Tracking Metric	High-Ne	High-Ex	High-Op	High-Ag	High-Co
Gaze Range Probability (%)	38	39	36	33	34
Fixation Count(count)	47.7	32.1	36.9	26.3	21.4

In the present sample, High-Ne showed a relatively high GRP (38%) and FC (47.7), which may indicate broader environmental monitoring together with repetitive and fragmented visual sampling.

High-Ex showed the highest GRP (39%) but the lowest FC (32.1), suggesting a broad but rapid scanning-oriented search pattern.

High-Op showed a relatively broad attentional distribution (GRP: 36%) and a relatively high FC (36.9), which may reflect a breadth-first and detail-oriented search tendency, although attentional dispersion may also have been present.

High-Ag showed intermediate values for both GRP (33%) and FC (26.3), suggesting a relatively balanced attentional allocation pattern.

High-Co showed a lower FC (21) together with a moderate GRP (34%), which may indicate a relatively goal-directed and selective attentional mode.

These descriptive results suggest that broader visual exploration tended to be more evident in High-Ne, High-Ex, and High-Op, whereas relatively more selective visual attention appeared in High-Ag and High-Co. These findings should be interpreted as exploratory given the limited sample size, and their stability across groups remains to be confirmed in larger samples.

3.1.2. Differences in Attentional Stability

AFD and BR were used as physiological indicators of attentional stability (Table 9), jointly reflecting cognitive engagement and resistance to interference during hazard perception across different personality-trait groups. AFD reflects the adequacy of information extraction, whereas BR is closely related to cognitive load and cortical activation. Taken together, these two metrics help characterize differences in cognitive strategies during safety-critical tasks.

High-Ne showed variable fixation patterns across risk levels. In the present sample, their BR was moderate (3.9/15 s), and fixation durations differed across regions, suggesting relatively unstable attentional maintenance and variable processing depth.

High-Ex showed the lowest BR (3.8/15 s), which may indicate relatively stable attentional engagement. However, fixation durations varied across risk levels, suggesting that processing depth also differed across regions.

Table 9. Average Fixation Duration and Blink Rate.

Personality Traits	Average Fixation Duration (s)			Blink Rate (per 15 s)
	Class I	Class II	Class III	
High-Ne	1.87	1.36	2.67	3.9
High-Ex	1.37	1.10	3.06	3.8
High-Op	1.06	1.79	3.71	4.0
High-Ag	2.79	2.64	0.94	4.5
High-Co	1.82	3.49	0.68	4.3

High-Op showed the longest fixation durations in Class III regions, whereas fixation durations in critical areas were relatively shorter. This pattern may reflect greater attention to novel or less critical information, together with relatively weaker sustained focus on safety-critical regions. Their BR was slightly higher (4.0/15 s), which may also indicate greater processing demand.

High-Ag showed relatively long AFD values in critical areas, suggesting relatively deep processing of safety-related information in the present sample. At the same time, this group showed the highest BR (4.5/15 s), which may reflect relatively high cognitive load during task performance.

High-Co maintained relatively long fixations in critical regions, suggesting a more task-oriented attentional pattern. Their BR was also relatively high (4.3/15 s), which may indicate that sustained attention to detailed information was accompanied by increased cognitive demand.

Overall, these descriptive results suggest that attentional stability and processing depth varied across personality-trait groups. In the present sample, High-Ag and High-Co appeared to show relatively greater attentional focus on critical regions, whereas High-Op showed relatively longer fixations in lower-risk areas.

3.1.3. Differences in Attentional Allocation

AOI FP and HARR directly quantify the efficiency of attentional capture by risk. As shown in Table 10, descriptive differences were observed in visual attention allocation patterns among workers with different personality traits, suggesting potentially different risk-oriented attentional distribution patterns across personality dimensions.

Table 10. AOI Fixation Probability and Heatmap Attention Risk Ratio.

Eye-Tracking Metric		High-Ne	High-Ex	High-Op	High-Ag	High-Co
AOI Fixation Probability (%)	Class I	7	9	8	26	24
	Class II	10	12	12	28	38
	Class III	26	34	36	24	15
Heatmap Attention Risk Ratio (%)	red region	19	21	19	23	21
	yellow region	5	3	4	4	3
	green region	14	15	13	6	10

High-Ne exhibited generally low and spatially dispersed fixation probabilities, demonstrating fragmented gaze patterns likely attributable to inefficient emotion regulation and consequent dispersion of cognitive resources. This group's HARR of 19% in red areas further indicates diminished efficiency in risk monitoring.

High-Ex showed a mixed attentional pattern. Fixation probability was higher in Class III areas (34%) than in Class I (9%) and Class II (12%) areas. Their HARR in red areas was 21%, suggesting some attention to critical risks, although overall allocation to high-risk areas remained limited.

High-Op showed a breadth-first attentional pattern. Fixation probability was highest in Class III areas (36%), compared with lower values in Class I (8%) and Class II (12%) areas. Their HARR in red areas was 19%, suggesting relatively broad exploration but weaker attention to safety-critical information.

High-Ag showed a relatively balanced attentional allocation pattern. Their gaze distribution was more consistent with the risk-level hierarchy, and their HARR reached the highest value among all groups (23%), suggesting relatively strong vigilance toward high-risk information.

High-Co showed a relatively risk-focused attentional pattern. In the present sample, they had higher fixation probabilities in Class I (24%) and Class II (38%) areas, but a lower value in Class III (15%). Their HARR in red areas was 21%, suggesting sustained attention to core risk zones.

In the present sample, High-Op and High-Ex appeared to allocate relatively less attention to high-risk areas, whereas High-Co and High-Ag appeared to show relatively more risk-oriented attentional allocation. High-Ne, by contrast, appeared to show a more fragmented attentional distribution.

3.1.4. Differences in Attentional Shifting

Based on the eye-tracking data (Table 11), TFF and NT were used as core metrics of attentional shifting. TFF reflects the speed of attentional orienting, whereas NT indicates the frequency and efficiency of shifts between different regions or AOIs. Taken together, these two measures help characterize visual search strategies and risk-monitoring patterns across personality-trait groups in complex environments.

Table 11. Time to First Fixation and Number of Transitions.

Personality Traits	Time to First Fixation (s)			Number of Transitions
	Class I	Class II	Class III	
High-Ne	0.46	1.37	0.65	18
High-Ex	0.73	0.87	1.12	16
High-Op	0.32	0.56	1.02	14
High-Ag	1.58	1.48	1.21	23
High-Co	1.87	1.67	1.43	21

High-Ne showed an NT of 18. Their longest TFF was observed in Class II regions (1.37 s), whereas shorter TFF values were found in Class I and Class III regions, suggesting differences in attentional orienting across risk levels.

High-Ex showed an NT of 16. Their attention was more frequently directed to Class III regions, indicating a selective attentional pattern across risk levels. Given the limited sample size, however, this shifting pattern should be interpreted cautiously.

High-Op showed the lowest NT (14). Their TFF increased from Class I (0.32 s) to Class II (0.56 s) and Class III (1.02 s), suggesting that attentional orienting varied across risk levels. This group appeared to show broader exploration with relatively slower shifting.

High-Ag showed the highest NT (23). Their TFF values remained relatively high across all risk zones, suggesting a relatively stable distribution of attentional orienting across regions.

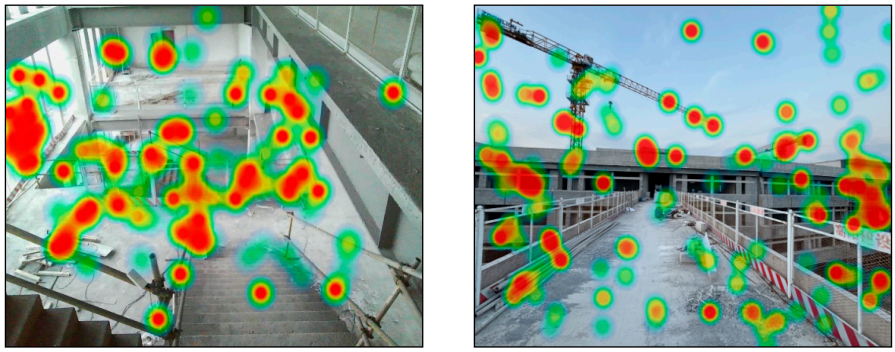
High-Co showed an NT of 21 and the longest TFF in Class I regions (1.87 s). Their attentional allocation appeared to decrease as area priority declined, which may indicate relatively greater attention to higher-priority regions.

These descriptive results suggest that attentional shifting patterns varied across personality-trait groups. High-Ag and High-Co appeared to show relatively greater attention to critical regions, whereas High-Op showed relatively longer fixations in lower-risk areas.

3.2. Visual Attention Visualization Analysis

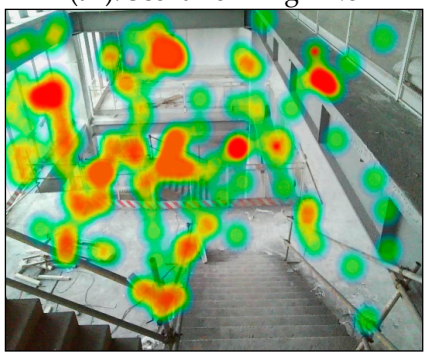
3.2.1. Fixation Heatmaps

Figure 5 presents superimposed fixation heatmaps illustrating the visual attention patterns of construction workers across five personality-trait groups. These visualizations are intended to serve a heuristic purpose by identifying potential trends and generating hypotheses regarding personality-related attentional patterns for further examination in future research.

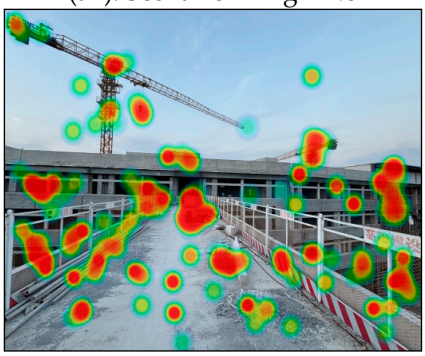


(**a1**). Scenario 1 High-Ne

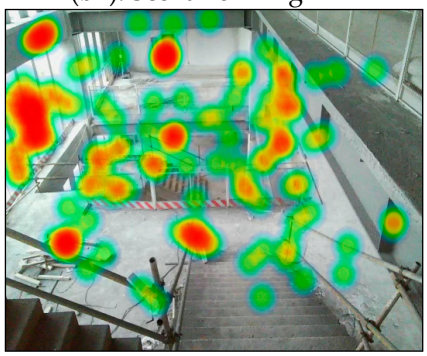
(**a2**). Scenario 2 High-Ne



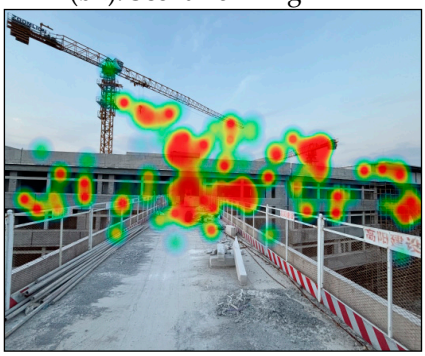
(**b1**). Scenario 1 High-Ex



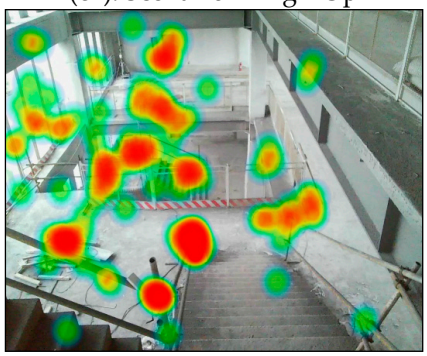
(**b2**). Scenario 2 High-Ex



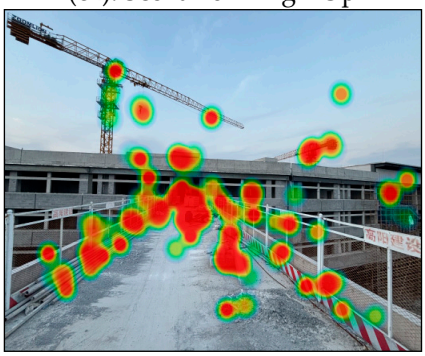
(**c1**). Scenario 1 High-Op



(**c2**). Scenario 2 High-Op

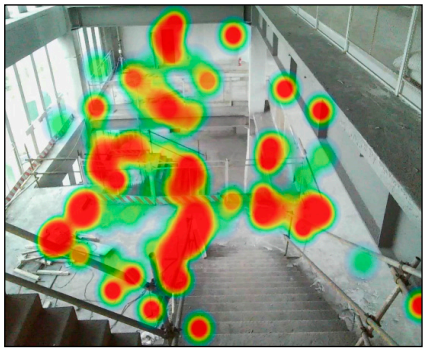


(**d1**). Scenario 1 High-Ag

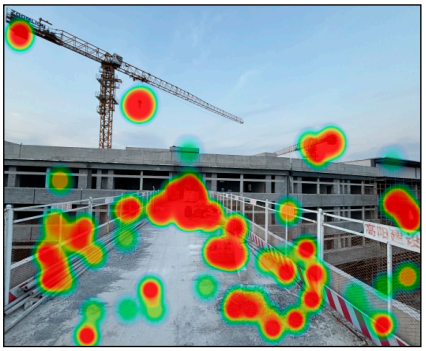


(**d2**). Scenario 2 High-Ag

Figure 5. *Cont.*



(**e1**). Scenario 1 High-Co



(**e2**). Scenario 2 High-Co

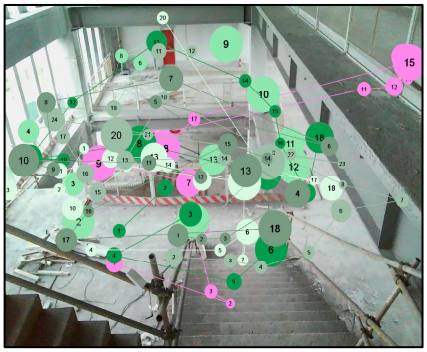
Figure 5. Superimposed Fixation Heatmaps (red, yellow, and green represent high-, medium-, and low-attention/risk regions, respectively). Schematic representations of the aerial work scenarios (Scenario 1 and Scenario 2) are provided in Figure 1.

High-Ne showed a dispersed fixation pattern, with relatively limited attention to critical hazard zones. In the present sample, this group appeared to show reduced stability in attention to safety-related information. High-Ex showed fixation distributions across multiple AOIs, suggesting broad visual search coverage and rapid information sampling. However, their relatively short fixation durations may indicate limited depth of processing of risk-related information. High-Op showed distributed visual attention and relatively strong exploratory behavior toward novel environmental stimuli, such as dust-proof nets. This pattern may reflect broad exploration, but it may also be associated with reduced vigilance toward immediate hazards. High-Ag showed a visual pattern that combined attention to safety monitoring with attention to socially relevant information, suggesting relatively balanced monitoring of environmental and social cues in the present sample. High-Co maintained visual focus on safety-critical areas, such as guardrails and warning signs, suggesting a relatively more systematic hazard-oriented pattern in the present sample.

3.2.2. Scanpath Plot

Figure 6 presents superimposed scanpath plots for five groups of construction workers with distinct personality traits following exposure to two visual stimulus scenarios.

High-Ne showed disorganized scanpaths, dispersed fixations, and relatively unstable attentional organization. Their visual trajectories involved frequent shifts between areas and limited sequential structure. In the present sample, this pattern was associated with reduced attention to critical hazard information.

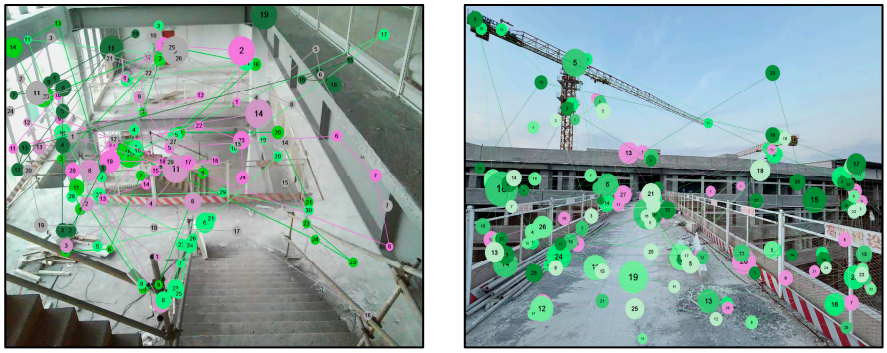


(**a1**). Scenario 1 High-Ne

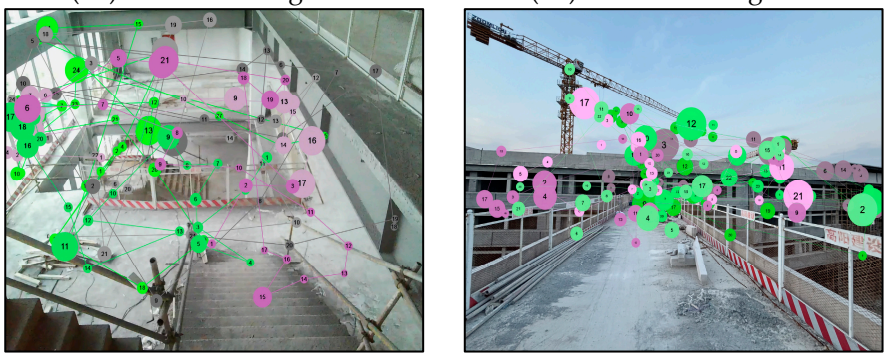


(**a2**). Scenario 2 High-Ne

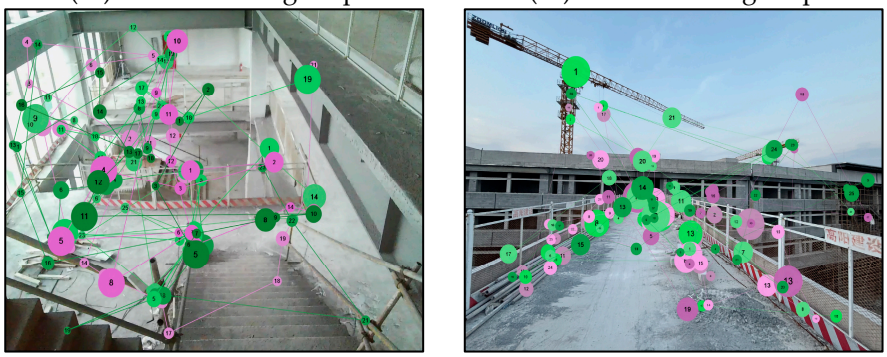
Figure 6. *Cont.*



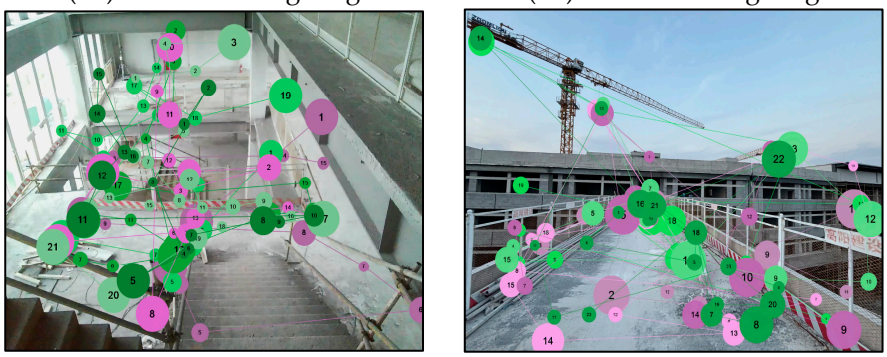
(**b1**). Scenario 1 High-Ex (**b2**). Scenario 2 High-Ex



(**c1**). Scenario 1 High-Op (**c2**). Scenario 2 High-Op



(**d1**). Scenario 1 High-Ag (**d2**). Scenario 2 High-Ag



(**e1**). Scenario 1 High-Co (**e2**). Scenario 2 High-Co

Figure 6. Superimposed Scanpath Plot (Numbers indicate fixation sequence order or individual participants; circle size is proportional to fixation duration; connecting lines represent saccadic movements between successive fixations; colors are software-generated for visualization only and do not represent additional analytical variables) Schematic representations of the aerial work scenarios (Scenario 1 and Scenario 2) are provided in Figure 1.

High-Ex showed complex and extensive visual trajectories. Their scanpaths suggested a broad scanning pattern from the overall scene to specific areas of interest. However, their short fixation durations may indicate limited sustained processing of hazard-related information.

High-Op showed strong exploratory attention to novel elements and often fixated on unconventional areas, such as dust nets outside windows. Their scanpaths showed repeated inspections, high fixation density, and prolonged fixation in these areas. This pattern may reflect broad exploration together with reduced attention to immediate hazards.

High-Ag distributed visual attention across broader areas while maintaining attention to potential hazards. Their scanpaths showed relatively concentrated fixation on hazard-related regions, suggesting balanced monitoring of the environment.

High-Co rapidly oriented to safety-critical areas, such as warning signs, and showed repeated checking thereafter. Their scanpaths were organized around safety-related regions while also incorporating surrounding areas, suggesting a relatively systematic hazard-oriented visual pattern.

The scanpath results suggest that different personality-trait groups may adopt different visual search strategies in hazardous environments. In the present sample, High-Op and High-Ex appeared to show broader exploratory tendencies, whereas High-Co and High-Ag appeared to show relatively more hazard-oriented visual allocation. By contrast, High-Ne appeared to show less stable attentional organization.

4. Evaluation and Discussion

4.1. AHP-Based Evaluation Framework and Weight Determination

The present study used the Analytic Hierarchy Process (AHP) [27] to construct a three-level evaluation index system consisting of the objective layer, criterion layer, and indicator layer (Table 12), and to determine the weights of the selected indicators. In this system, visual attention efficacy was defined as the objective layer. Attentional span, attentional stability, attention allocation, and attention shifting were defined as the criterion layer. Eight eye-tracking indicators were defined as the indicator layer. The relative importance of these indicators could not be determined directly from the observational data alone. Therefore, structured expert judgment was introduced. Within this hierarchical framework, AHP converts qualitative judgments into quantitative results through pairwise comparisons among indicators. Consistency testing was also used to improve the rigor and rationality of the weighting process.

To determine the indicator weights, three rounds of Delphi consultation were conducted with 16 experts from construction safety, civil engineering, and related research fields. Using the Saaty 1–9 scale, the experts performed pairwise comparisons of the elements at the criterion and indicator levels, constructed the judgment matrices, and used them for weight calculation and consistency testing. The detailed procedure is provided in Supplementary Materials S2 and S3.

In this evaluation system, the weights at each level were calculated using the geometric mean method followed by normalization.

1. Geometric Mean Method: Calculate the geometric mean of each row element.

$$w'_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \tag{3}$$

where w'_i denotes the initial weight of the i-th indicator; a_{ij} represents the element in the i-th row and j-th column of the judgment matrix, indicating the relative importance comparison value between indicators i and j; and n is the order of the judgment matrix, where $i, j = 1, 2, \ldots, n$.

2. Normalization:

$$w_i = \frac{w'_i}{\sum_{j=1}^{n} w'_j} \tag{4}$$

where w_i is the normalized weight of the i-th indicator; w'_i is the initial weight calculated via the geometric mean method; and n is the order of the current judgment matrix, where $i, j = 1, 2, \ldots, n$.

3. Eigenvalue Calculation: Solve for the maximum eigenvalue.

$$Aw = \lambda_{\max} w \tag{5}$$

where A is the original judgment matrix; w is the eigenvector; and $\lambda_{\max}$ is the maximum eigenvalue of matrix A, which is used for consistency verification.

4. Consistency Test:

$$\begin{aligned} \mathrm{CI} &= \frac{\lambda_{\max} - n}{n-1} \\ \mathrm{CR} &= \frac{\mathrm{CI}}{\mathrm{RI}} \end{aligned} \tag{6}$$

where CI is the consistency index; n is the order of the matrix; CR is the consistency ratio, and RI is the random consistency index. A judgment matrix was considered acceptable when CR < 0.10. In this study, both the criterion-layer and indicator-layer judgment matrices satisfied the consistency requirement.

Hierarchical total ordering represents a crucial procedure in the AHP, serving to determine the global weights of all indicators within the evaluation system through iterative layer-wise aggregation and normalization. The composite weight of each underlying indicator is computed by multiplying the weight of the corresponding criterion (Bi) by the weight of the sub-criterion (Cj), as expressed by the formula:

$$\text{Composite Weight} = W(B_i) \times W(C_j) \tag{7}$$

where $i = 1, 2, 3, 4$ represents the indices of the four evaluation criteria in the criterion layer; and $j = 1, 2, \ldots, 8$ denotes the indices of the eight underlying indicators in the sub-criterion layer.

The resulting combined weights of the Visual attention efficacy evaluation index system are systematically presented in Table 12.

Table 12. Combined Weights of the Visual Attention Efficacy Evaluation Index System.

Objective Layer	Criterion Layer	Weights	Indicator Layer	Weights	Combined Weights	Overall Sorting
Visual attention efficacy (A)	Attentional Span (B1)	0.24	Gaze Range Probability (C1)	0.78	0.187	3
			Fixation Count (C2)	0.22	0.053	8
	Attentional Stability (B2)	0.25	Average Fixation Duration (C3)	0.75	0.188	2
			Blink Rate (C4)	0.25	0.063	7
	Attention Allocation (B3)	0.28	Heatmap Attention Risk Ratio (C5)	0.76	0.213	1
			AOI Fixation Probability (C6)	0.24	0.067	6
	Attention Shifting (B4)	0.23	Time to First Fixation (C7)	0.64	0.147	4
			Number of Transitions (C8)	0.36	0.083	5

4.2. Comprehensive Evaluation Results of Visual Attention Efficacy

1. Data Processing

Eye movement metrics of construction workers with different personality traits were integrated and averaged. Min–max normalization was applied to eliminate dimensional differences (Table 13),

$$X^* = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{8}$$

where X^* is the normalized (dimensionless) value of the indicator; X is the original data value; $X_{\min}$ is the minimum value of the indicator; and $X_{\max}$ is the maximum value of the indicator.

Table 13. Indicator Level Dimensionless Data.

Indicator Layer	High-Ne	High-Ex	High-Op	High-Ag	High-Co
Gaze Range Probability (C1)	0.000	0.125	0.001	1.000	0.903
Fixation Count (C2)	1.000	0.474	0.389	0.000	0.080
Average Fixation Duration (C3)	0.257	0.128	0.000	1.000	0.960
Blink Rate (C4)	0.000	0.103	0.577	1.000	0.103
Heatmap Attention Risk Ratio (C5)	0.118	0.000	0.011	1.000	0.861
AOI Fixation Probability (C6)	0.000	0.067	0.089	0.822	1.000
Time to First Fixation (C7)	0.358	0.000	0.273	0.820	1.000
Number of Transitions (C8)	0.655	1.000	0.414	0.104	0.000

2. Evaluation of Visual Attention Efficacy Across Personality Traits

The visual attention efficacy score for each personality trait was calculated by multiplying the comprehensive weight of each indicator by its corresponding normalized value under that trait, yielding the indicator-specific contribution. The overall efficacy score for a given trait was then obtained by summing the contributions from all indicators. This computation was performed across all personality traits, with the results summarized in Table 14.

Table 14. Visual Attention Efficacy.

Personality Traits	High-Ne	High-Ex	High-Op	High-Ag	High-Co
Visual Attention Efficacy	0.230	0.163	0.137	0.839	0.765

Visual attention efficacy appeared to vary across personality-trait groups. In the present sample, the High-Ag group showed the highest visual attention efficacy, followed by the High-Co group. This pattern may be related to traits such as cooperativeness, patience, organizational ability, and sense of responsibility. By contrast, the High-Op and High-Ex groups showed relatively lower visual attention efficacy, suggesting that their cognitive processing may have been more prone to attentional dispersion. The High-Ne group showed an intermediate level of visual attention efficacy, which may be related to relatively lower emotional stability.

4.3. Sensitivity Analysis of Ranking Stability

Given that the criterion-layer weights directly affect the overall contribution of each indicator, the present study prioritized examining the influence of criterion-layer weight variation on the ranking results. To test the sensitivity of the evaluation results to weight settings and the robustness of the ranking pattern, a sensitivity analysis was conducted based on the original criterion-layer weights. Specifically, each of the four criterion-layer weights was perturbed by $\pm 10\%$ and $\pm 20\%$, while the remaining weights were proportionally adjusted and normalized to ensure that the total weight remained equal to 1. A total of 16 perturbation schemes were generated. The detailed perturbation schemes, corresponding Visual Attention Efficacy values, and ranking results are presented in Supplementary Material S4 Table S8. The results showed that, although the Visual Attention Efficacy values of the five personality-trait groups changed slightly across the tested schemes, the overall ranking remained unchanged, namely: High-Ag > High-Co > High-Ne > High-Ex > High-Op. These results indicate that the ranking pattern remained stable under moderate perturbations of the criterion-layer weights, suggesting that the current evaluation results were not sensitive to such weight variation.

4.4. Interpretation of Results and Practical Implications

The eye-tracking metrics indicate that visual attention patterns varied across personality-trait groups in the present sample. Across attentional span, stability, allocation, and shifting, High-Ag and High-Co generally showed greater attention to safety-critical regions, whereas High-Op and High-Ex showed broader exploratory patterns. By contrast, High-Ne showed less stable attentional organization. These findings suggest that personality-related differences may be associated with the visual sampling and processing of hazard information in work-at-height scenarios.

The visualization results provide further descriptive support for these patterns. The fixation heatmaps and scanpath plots showed that High-Co and High-Ag tended to maintain greater attention to safety-related areas, whereas High-Op and High-Ex more often showed broader or more exploratory visual trajectories. High-Ne showed more dispersed fixations and less stable visual organization. Although these visualizations should not be treated as definitive evidence on their own, they were broadly consistent with the metric-based results and helped illustrate how different personality-trait groups distributed attention across the same hazardous scenes.

These trait-specific visual behaviors can be interpreted through the theoretical framework of Attentional Control Theory (ACT) [35]. According to ACT, elevated anxiety impairs the efficiency of the goal-directed (top-down) attentional system while increasing susceptibility to the stimulus-driven (bottom-up) system. Applied to the current work-at-height scenarios, this framework provides a plausible mechanistic explanation for the divergent attentional patterns. Specifically, the fragmented and unstable visual organization observed in the High-Ne group yields empirical support for ACT in a field setting: heightened trait anxiety likely compromises top-down cognitive control, rendering visual resources more susceptible to diversion by task-irrelevant ambient distractors. Conversely, the sustained focus on safety-critical areas among High-Co and High-Ag workers suggests a highly efficient, goal-directed attentional system capable of suppressing irrelevant environmental stimuli. The visualization results offer corroborating descriptive evidence for these patterns. Fixation heatmaps and scanpath plots demonstrate that the High-Co and High-Ag groups maintained concentrated visual attention on safety-related zones, whereas the High-Op and High-Ex groups exhibited broader, exploratory visual trajectories. While these visualizations are inherently qualitative and should not be interpreted as standalone definitive evidence, they align robustly with the quantitative metrics. Collectively, these findings illustrate how varying personality traits may differentially modulate the balance between top-down goal execution and bottom-up stimulus processing during hazard recognition.

Taken together, the Visual Attention Efficacy results were generally consistent with the findings from the eye-tracking metrics and visualization analyses. In the present sample, High-Ag showed the highest Visual Attention Efficacy, followed by High-Co, whereas High-Op and High-Ex showed lower values, and High-Ne remained at an intermediate level. This convergence across multiple forms of evidence provides preliminary support for the current evaluation framework as a reasonable approach to characterizing group-level differences in visual attention under hazardous construction conditions. However, this interpretation should remain cautious. The present study used a relatively small extreme-group sample and was conducted under static visual conditions. Therefore, the current results should be regarded as preliminary and exploratory rather than conclusive. From a practical perspective, the findings may provide a preliminary reference for future safety communication and training design, but they do not directly validate the effectiveness of personality-informed intervention strategies.

5. Conclusions and Limitations of the Research

5.1. Conclusions

This study used eye-tracking experiments under static work-at-height scenarios to examine the relationships among personality traits, visual attention allocation patterns, and hazard recognition in construction workers. The main conclusions are as follows:

1. In the present sample, different personality-trait groups appeared to show different visual attention patterns during hazard-related information processing. The High-Co tended to maintain more sustained attention to safety-critical areas, e.g., higher AOI FP and longer AFD in Class I and Class II zones. In contrast, the High-Ag appeared to balance broader environmental monitoring with attention to hazard-related cues, with the highest HARR for critical risks observed in the present sample. The High-Op and High-Ex showed broader exploratory tendencies, e.g., higher GRP but lower AOI FP in high-risk AOIs; this pattern suggests a less concentrated allocation of attention to high-risk areas. High-Ne showed an intermediate pattern, accompanied by relatively less stable attentional organization indicated by dispersed scanpaths and fluctuating fixation times. These findings suggest that personality-related differences may be associated with hazard-information processing and hazard-recognition performance in work-at-height scenarios.
2. The AHP-based Visual Attention Efficacy evaluation system provided a quantitative framework for comparing the overall performance of different personality-trait groups. The results showed that High-Ag (0.839) and High-Co (0.765) obtained relatively higher Visual Attention Efficacy scores, whereas High-Op (0.163) and High-Ex (0.137) obtained relatively lower scores. High-Ne (0.230) remained at an intermediate level. In addition, the sensitivity analysis showed that the overall ranking pattern remained unchanged under moderate perturbations of the criterion-layer weights, which provided supplementary support for the robustness of the current evaluation framework.
3. The present study provides exploratory evidence that personality-related differences may be relevant to visual attention allocation and hazard recognition in hazardous construction contexts. These findings may provide a preliminary reference for future safety communication and training design in construction safety management. However, the results should be interpreted with caution because the study was conducted under static visual conditions and involved a relatively small sample.

5.2. Limitations

While this study yields valuable insights, several methodological limitations must be acknowledged. First, the small, exclusively male cross-sectional sample (N = 30) lacks a control group, which hindered the statistical isolation of covariates like work experience and restricted both cross-cultural generalizability and causal inferences to mere correlational associations. Second, the 15-s static observation paradigm captures only initial visual orienting; by excluding dynamic variables such as environmental fluctuations and prolonged fatigue, it serves primarily as a foundational baseline rather than a reflection of dynamic operational realities. Furthermore, the single-modal reliance on eye-tracking prevents the direct quantification of higher-order cognitive operations, and the lack of concurrent physiological and psychometric data constrains the empirical validation of the underlying cognitive mechanisms. Finally, the AHP framework's weights, derived from a restricted panel of 16 institutional experts, require further empirical validation before being extrapolated to diverse corporate safety cultures.

5.3. Future Research Directions

Future investigations should proceed along four critical trajectories:

1. Future research must incorporate larger, diverse samples (e.g., female workers, cross-cultural cohorts, control groups) to evaluate the generalizability and gradient effects of trait-behavior patterns. Collaborating with cognitive neuroscientists and psychologists is imperative to validate the underlying psychological mechanisms.
2. To overcome static constraints, studies must integrate temporal dimensions via mobile eye-tracking and dynamic simulations (e.g., VR). This enables the continuous evaluation of how physical distractions, environmental shifts, and cumulative fatigue impact working memory and risk decision-making over time.
3. Experimental designs must transition to multi-modal data. Concurrently recording eye-tracking, neurological (e.g., EEG), physiological (e.g., heart rate), and psychometric data will explicitly map the mediating cognitive and affective mechanisms bridging personality traits with hazard recognition.
4. Subsequent research should empirically test personality-informed safety interventions. Evaluating customized, trait-specific training protocols in real-world settings is essential to validate their value in personalized proactive safety management.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings16132495/s1, File S1: Chinese Big Five Personality Questionnaire (Bilingual Version); File S2: Questionnaire on the Importance of Evaluation Indicators for Visual Attention Efficacy of Construction Workers; Table S1: Pairwise comparison matrix for the criteria-layer dimensions (B1–B4); Table S2: Pairwise comparison matrix for the indicator-layer metrics (C1–C8); Table S3: Criterion Layer A Judgment Matrix; Table S4: Indicator Level B1 Judgment Matrix; Table S5: Indicator Level B2 Judgment Matrix; Table S6: Indicator Level B3 Judgment Matrix; Table S7: Indicator Level B4 Judgment Matrix; Table S8: Sensitivity Analysis of Ranking Stability under Criterion-Layer Weight Perturbations.

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Institutional Review Board Statement: Ethical review and approval were waived for this study due to its non-interventional and non-invasive nature. The research involved a completely anonymous questionnaire survey for participant screening and a subsequent non-intrusive field eye-tracking experiment that posed zero physical or psychological risk to the workers, with strict data anonymity protocols enforced throughout the entire process.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Written informed consent was obtained from all construction workers prior to both the questionnaire screening and the eye-tracking experiment, and they were fully informed of the study's purpose and their unconditional right to withdraw at any time.

Data Availability Statement: The original contributions presented in this study are included in the article/Supplementary Materials. Further inquiries can be directed to the corresponding author.

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Co., Ltd. Author Xinen Pan was employed by the company Guangxi Transport Science & Technology Group Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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