Analysis of Electroencephalogram and Fear of Crime Perception in Virtual Reality: Examining the influence of illuminance variations on Pedestrian Experience

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Abstract

This study examines the relationship between fear of crime emotions, Electroencephalogram (EEG) reactions, and variations in nighttime illuminance within a virtual environment. The study analyzed the perceptions of participants in diverse nighttime illuminance scenarios in Seoul using EEG analysis and fear of crime surveys to uncover new insights. This study aims to understand the influence of biological responses on fear perception in virtual reality (VR) by integrating EEG data. Illuminance levels were measured at four locations, followed by environmental recordings using 360-degree cameras. Ninety-five participants evaluated fear of crime in ten randomly selected VR videos experienced through head-mounted displays. This study examines the correlations between fear of crime in virtual reality (VR) environments and EEG measurements using cross-classified multilevel analysis. The results show that illuminance affects both fear of crime and EEG. Furthermore, the study finds that EEG significantly impacts fear of crime, indicating its usefulness as a complementary perceptual scale. The analysis also reveals that the Valence index of EEG significantly influences fear of crime. It highlights the potential application of EEG in urban design practices. This study provides insights into the relationship between architectural environmental factors, survey responses, and biological responses in virtual environments. The results demonstrate the compatibility of EEG with survey responses and underscore the value of EEG in urban design.

Keywords: Virtual Reality (VR), Electroencephalogram (EEG), Fear of Crime, Urban Safety

Introduction

Urban development plays a significant role in creating safer environments. In particular, urban illumination, which improves with development, facilitates safe activities after dark (Hu et al., 2020). Cozens and Sun (2019) cited Maslow's hierarchy of needs to argue that safety is a fundamental human requirement after physiological needs, encompassing protection from harm, law and order, and freedom from fear. Safety is broadly divided into actual and perceived social safety, the latter measured by perceived personal danger, risk, and fear of crime (Boomsma & Steg, 2014a). Safety and fear of crime are critical issues that can directly or indirectly affect various aspects of life, including nocturnal activities (Evans & Fletcher, 2000). Therefore, illuminance is an effective means of reducing fear of crime, which has a significant impact on daily life (Boyce et al., 2000). Previous studies have analyzed the effectiveness of illumination in preventing crime and its correlation with fear of crime (van Osch, 2000; Wu, 2014). However, these studies have not systematically examined how safety perceptions vary according to the spatial characteristics of different environments and the brightness levels of installed illuminance. This gap exists because it is challenging to create varied experimental environments in actual urban areas and conduct participant-based experiments. Virtual reality (VR) can be used to address this issue. Studies utilizing VR technology (Boomsma & Steg, 2014a, 2014b; Nasar & Bokharaei, 2017; van Rijswijk & Haans, 2018) have investigated how illuminance affects perception. They have shown that brightness levels influence individuals' sense of prospect, refuge, and concealment, ultimately affecting safety perceptions. However, some studies have used virtual environments (Boomsma & Steg, 2014a, 2014b; Nasar & Bokharaei, 2017; van Rijswijk & Haans, 2018; Kim & Noh, 2018). It has been noted that relying solely on traditional visual cues to simulate an authentic presence has limitations (Mouratidis & Hassan, 2020; Kim & Lee, 2022).

Furthermore, surveys conducted in virtual environments may be limited by subjective participant responses. To address this limitation, it is necessary to develop a method for dynamically detecting users' emotional states during surveys (Martinez-Tejada, 2021), as well as an objective measure of the sense of presence experienced by participants. In the realm of built environments, research is currently being conducted using EEG technology based on biosignals (Ji, 2020; Olszewska-Guizzo, 2020). Perceptions in fear-inducing environments can elicit a combination of positive and negative emotions (Bower, 2019). EEG technology is considered essential in such studies to provide an objective assessment of how environmental or personal characteristics influence survey responses (Son et al., 2023). However, measuring EEG directly in outdoor settings is impractical due to contact issues and numerous external variables (Marin-Morales, 2018). This study comprehensively examines the effects of illuminance on fear of crime and electroencephalogram using virtual reality (VR) technology in Seoul, South Korea. Participants experience a sense of presence similar to being at the actual site through VR. To examine the correlation between illuminance and fear of crime, a cross-classified multilevel analysis model was utilized. In addition, we used EEG data for cross-validation to overcome the limitations of subjective responses.

This research goes beyond examining the impact of illuminance on the fear of crime to understanding how illuminance influences electroencephalogram and, in turn, how these electroencephalograms affect the fear of crime. The study investigates whether illuminance affects not only subjective fear responses but also objective biosignals such as electroencephalogram. Finally, we aim to clarify the correlation between illuminance and fear of crime by elucidating the relationship between the physical environment or personal characteristics and EEG data. Our goal is to broaden the application of VR technology in urban design and safety by integrating it with biosignal data and exploring EEG indices and their potential applications in mitigating fear of crime. This approach bridges architecture, neuroscience, and criminology.

Literature Review

Crime fear and illuminance levels

The fear of crime experienced by people is difficult to precisely define because its nature is ambiguous, but researchers generally define it as "perception of potential victimization" (Yin, 1980). Fear of crime is defined as the fear of harm from strangers in everyday life (Conklin, 1975). The causes of fear of crime include both individual and environmental dimensions. Early studies on fear of crime suggested that individuals' direct experiences of crime victimization influence fear of crime (Skogan, 1986). However, findings suggesting that women or the elderly experience higher levels of fear compared to men (Warr, 1984; Ferraro, 1996) led to the emergence of vulnerability theories, which discuss vulnerability in terms of individuals' susceptibility and fear manifestation through information networks. Subsequently, theories relating fear of crime to community social control (Shaw and McKay, 1942) expanded fear of crime theories to include neighborhood dimensions. In summary, fear of crime is measured through emotions, and it can be influenced by individual characteristics as well as neighborhood characteristics, particularly physical environments. Considering environmental factors as causes of fear of crime, studies analyzing the relationship between physical space and fear of crime have been conducted. These studies aim to identify factors that people consider when perceiving space or experiencing emotions in space.

During nighttime, illumination plays a significant role, with Loewen et al. (1993: 324) mentioning that the level of illumination is included in the characteristics of the physical environment. Illumination studies are mostly conducted through field-based experiments. Boyce et al. (2000) conducted experiments in urban and suburban areas, including roads and parking lots, to analyze the relationship between perceived safety and illumination levels to identify the brightness of illuminance perceived as safe by participants. Mattoni et al. (2017) conducted similar experiments on 10 similar roads to identify the brightness of illuminance perceived as safe. Subsequent studies targeted roads (Haans & de Kort, 2012), bridges, and spaces (Kim & Noh, 2018), with some studies measuring objective heart rate (Castro-Toledo et al., 2017) rather than subjective perceptions through surveys. Illuminance-related meta-analysis conducted by Ceccato (2020) among 37 illuminance studies showed that 72% of them demonstrated the positive effects of illuminance on crime prevention. Field experiments are conducted because the most basic method to measure fear of crime is to directly experiment in places where fear of crime is expected.

However, there may be various uncontrollable variables in actual spaces. Due to these limitations, there are studies using virtual environments (Simulated VR) or photographs. Boomsma and Steg (2014a) conducted experiments using five virtual simulation environment photographs with varying illuminance levels, finding that participants felt safer in brighter photographs. Boomsma and Steg (2014b) analyzed differences in people's perceptions of safety using parameters such as level of entrapment in risky situations in addition to differences in illuminance levels, yielding significant results. Nasar and Bokharaei (2017) created virtual spaces based on brightness and uniformity of illumination, while van Rijswijk and Haans (2018) used 100 photographs of actual locations to identify the impact of factors related to safety on people's safety perceptions. They found that illuminance quality directly affects safety perceptions but to a lesser extent, and illuminance quality affects parameters such as prospect, refuge, and escape, which in turn strongly influence safety perceptions. This study showed similar results to the field-based study by Haans and de Kort (2012). Son et al. (2023) adopted a quasi-experimental approach using Recorded VR to analyze perceptions of fear of crime under various illumination conditions. They found that as illumination increased, fear of crime tended to decrease, and this change was more significant in areas with large differences in illumination between day and night. However, previous studies on illumination had the limitation of subjective data analysis based on surveys.

EEG analysis to measure fear of crime

To objectively analyse emotional aspects, biometric data can be used. Virtual environments have the advantage of being able to control the environment, which allows participants' biological responses to be seen without external interference (Choi, et al. 2023), making VR surveys in a laboratory setting an ideal environment for utilising biometric data (Marin-Morales et al., 2013). In particular, advances in EEG measurement technology have made it possible to measure human emotions more accurately and reliably (Cohen et al., 2017). EEG is an electrical phenomenon determined by the coupling and activity between nerve cells in the brain, also known as electroencephalogram (EEG), which is the amplification and recording of electrical potentials induced by electrodes attached to the top of the head (Teplan, 2002). The recorded electrical signals can be transformed and represented on a frequency axis, and human brain waves are mostly between 0.5 and 60 Hz and are classified into 5 waves according to their frequency (Table 1) (Siirtola et al., 2023).

Valence and Arousal have been commercialized as methods to identify emotions through EEG (Martinez-Tejada, 2021; Siirtola, 2023). Valence is the difference between the left and right brain. To be precise, emotional valence is expressed as the difference between the right posterior superior temporal sulcus and the medial prefrontal cortex (Kliemann et al. 2016). The ratio of beta waves to alpha waves represents arousal. Arousal is the degree of excitement (Jebelli et al., 2018). Table 2 summarizes the literature on EEG analysis of human emotions in VR. We found that EEG was used to measure the emotions of subjects in various fields. The emotional information measured through EEG was Valence, Arousal, etc. and to support this, the method of asking the experimenter through questions by an assistant such as Self-Assessment Manikin and Survey was mainly used. This demonstrated the utility of EEG, and in previous studies, the number of participants measured after EEG cleaning averaged 30, the average number of scenarios was 5.7, and the total number of scenarios (N) measured across participants averaged 180.5.

Method

Overview

This study builds upon the foundational research conducted by Son et al. (2023), titled "Analysis of the relationship between nighttime illuminance and fear of crime using a quasi-controlled experiment with recorded virtual reality." While Son et al. concluded that higher illuminance levels are associated with reduced fear of crime, our research seeks to provide a more nuanced understanding of this relationship by incorporating the analysis of electroencephalogram (EEG) data. This approach aims to bridge the gap between environmental psychology and physiological responses, offering insights into the embodied cognition of fear in urban settings. The primary objective of our study is to investigate the influence of nighttime illuminance on pedestrians' fear of crime and to examine how this relationship is mediated by physiological responses, as measured by EEG. By integrating EEG data, we aim to assess whether the reduction in fear of crime attributed to increased illuminance is directly reflected in the brain's electrical activity, thereby providing a more objective measure of fear. Our methodology involves a quasi-controlled experiment using virtual reality (VR) to simulate various street environments in Seoul with differing levels of illuminance. Participants were exposed to four scenarios, each designed to vary in illuminance and environmental characteristics. Horizontal and vertical illuminance data were meticulously measured and recorded as 360-degree videos, which were then post-processed to match the perceived illuminance in the VR videos with that of the actual environments. EEG data were collected to examine participants' neurological responses to these environments.

To ensure a comprehensive analysis, specific EEG metrics were chosen for their relevance to emotional and cognitive processing, including alpha, beta, and theta wave activities. These metrics were selected based on their established associations with attention, arousal, and emotional states in existing literature. Our study is anchored in the theoretical frameworks of environmental psychology and embodied cognition, positing that our perceptions and emotional responses to environmental stimuli are not only processed cognitively but are also manifested physiologically. This theoretical grounding informs our hypothesis that changes in environmental illuminance can modulate the physiological markers of fear. A total of 101 adults in their twenties were recruited for this study. This demographic was specifically chosen due to their high likelihood of engaging with VR technology and their potential variability in responses to fear of crime. The selection rationale is based on literature suggesting that younger adults may exhibit distinct physiological responses to fear stimuli compared to other age groups. The analysis revealed that EEG responses, particularly in terms of alpha and beta wave activities, varied significantly with changes in illuminance, suggesting a physiological basis for the reduced fear of crime at higher illuminance levels. These findings support the hypothesis that environmental design, through illuminance, can influence emotional states at a neurological level. All participants provided informed consent. The study was conducted following ethical guidelines, ensuring the confidentiality and anonymity of participant data. Measures were also in place to monitor participant well-being throughout the experiment, with the option to withdraw at any point.

Our study contributes to the understanding of the complex interplay between urban design, particularly illuminance, and the subjective experience of fear of crime. By incorporating physiological measures, we offer a more objective perspective on how environmental factors influence emotional responses, providing valuable insights for urban planning and public safety strategies. This research not only extends the work of Son et al. (2023) but also opens new avenues for exploring the physiological dimensions of environmental psychology, highlight the importance of considering both psychological and physiological responses in the design of safer urban environments.

Study areas for the controlled experiment

According to data provided by Numbeo (2021), South Korea's crime index is recorded at 26.68, which ranks 20th out of 137 countries in terms of safety. Seoul's score is 26.18, placing it 52nd out of the world's 427 largest cities. Despite these relatively high levels of safety, South Koreans have a relatively high fear of crime. In the 2022 Social Safety Awareness Survey conducted by Statistics Korea, 39.1% of respondents said they did not feel safe from crime, the third highest rate after fear of emerging diseases and national security (war) in the wake of the COVID-19 pandemic. In particular, 29.6% of respondents felt unsafe walking at night and 44.0% of women felt unsafe. When asked why they were afraid to walk at night, 19.5% cited "lack of safety facilities such as street illuminance and CCTV" as the reason for their concern, meaning that one in three people aged 13 and over in South Korea are afraid to walk at night.

The methodology for measuring illuminance and recording the virtual environment was as follows. The study was conducted using an omnidirectional virtual reality (VR) video recording of a narrow alleyway in a relatively crime-free area of Seoul. However, Seoul has a large cluster of low-rise mixed-use residential and commercial buildings, which are generally classified as residential in terms of land use and are subject to the nighttime light pollution standard (illuminance $\leq$ 10 lux). In addition, narrow streets without sidewalks, shared by pedestrians and vehicles, are widespread in Seoul. This makes pedestrians vulnerable to crime. The criteria for selecting specific sites were as follows: Sites currently undergoing illuminance improvement projects were excluded to prevent skewed results. Furthermore, we prioritized sites with similar physical characteristics—such as building usage, spacing between buildings, and overall enclosure—to minimize the variability of external parameters. Following these criteria, seven locations within Seoul were initially considered. After conducting field surveys both during the day and at night, Sangdo 1-dong was ultimately chosen as the study area (Figure 1). The Sangdo 1-dong area encompasses all four types of environments outlined by the Korean Standard for Roadway Illuminance (KS A 3701, 2019), which includes: (A) residential areas with high pedestrian traffic, (B) residential areas with low pedestrian traffic, (C) commercial areas with high pedestrian traffic, and (D) commercial areas with low pedestrian traffic. To align with regional classifications specified in CIE-115:2010, pedestrian traffic volumes—originally detailed in the Ministry of Land, Infrastructure, and Transport's Road Safety Installation Guidelines—were categorized into two groups. Since the standard does not define thresholds for low vs. high pedestrian traffic, this classification was based on interpretations of the Korean Pedestrian Level of Service (PLoS) guidelines. All selected sites are narrow, mixed-use streets without dedicated sidewalks, featuring an average width ranging from 3.7 to 7.6 meters. Illuminance levels were measured across these four sites over four non-consecutive days in April 2021 (refer to Table 3). A total of 13 measurements were taken at 15-minute intervals around sunset—a period marked by rapidly decreasing illuminance levels. Subsequent measurements were recorded at intervals ranging from 30 to 60 minutes. During the measurement period, the weather remained cloudy, with negligible temperature fluctuations. Illuminance at each site was evaluated in terms of both vertical and horizontal illuminance (Figure 2).

Controlled experiment with instrument

For this study, 360-degree cameras were utilized to immerse participants in a realistic street-side environment of the selected study sites. Two distinct types of video recordings were produced: Initially, videos showcasing the study sites at specific times—corresponding with the illuminance level measurements—were played back for durations of three to six minutes, resulting in a total of 13 recordings per site. The camera, equipped with a lens positioned at a height of 160 cm, was stationed in pedestrian zones to minimize vehicle interference. These recordings were captured using two Panasonic GH5S cameras, each fitted with an Entaniya HAL200 3.6 MFT wide-angle lens. The raw footage was recorded in 4K 10-bit at 30 frames per second, compatible with the specifications of the head-mounted displays (HMDs) used in the VR experiments. LOG mode was enabled for recordings made after sunset, in complete darkness.

The selection of videos and footage for the VR survey involved a rigorous post-processing phase. Initially, videos from periods with negligible illuminance changes (specifically, the 8th, 10th, and 12th measurements in Table 3) were discarded to streamline the video editing and survey process. The remaining footage was then condensed into 30-second clips, with additional edits made to correct motion inconsistencies among people and objects (e.g., vehicles). Manual video stitching was employed to synchronize clips from both cameras, with a professional video editor addressing any automatic stitching errors. Unwanted elements, such as tripods, were removed, and sharpening effects were applied to enhance video clarity. Color adjustments and noise reduction were also performed to correct for color discrepancies inherent in log shooting, resulting in a final product that closely mimics the human visual experience. These video recording, editing, and post-processing tasks were carried out by a VR video production specialist.

In the experiment, EEG signals were captured using the commercially available Interaxon MUSE2 headband (Model ID: MU-03), as per Krigolson et al. (2017). The reference electrode FPz (CMS/DRL) was placed on the forehead, with input electrodes positioned at the front (AF7 and AF8, made of silver) and back (TP9 and TP10, made of conductive silicone-rubber) over each ear, as detailed by Silvia Angela Mansi et al. (2021) (see Figure 3). The device recorded signals at a 256 Hz sampling rate, with raw EEG data and sensor connectivity monitored through the Mind Monitor application, connected to a tablet PC via Bluetooth Low Energy (BLE). Given the susceptibility of EEG recordings to various types of noise and artifacts, meticulous processing and denoising were imperative. A lab assistant was on-site to oversee EEG measurements and ensure sensor connectivity. To refine data accuracy, a notch filter (50/60 Hz) was applied to eliminate electrical noise, a high-pass filter (0.1 Hz) to remove DC offsets and low-frequency artifacts, and a low-pass filter (45 Hz) to filter out high-frequency noise. Channels or segments exhibiting abnormalities or artifacts were identified and excluded from analysis. Furthermore, data affected by eye movement noise (EOG) or signals exceeding power thresholds of ± 100 uV were omitted. Post-denoising, EEG data was recorded in one-second intervals, with the relative (%) power spectral density (PSD) for theta, alpha, beta, and gamma frequency bands calculated via fast Fourier transform (FFT).

Data files from the MUSE device with unrecorded or anomalous readings from any of the four sensors were discarded. Participant data was also excluded if the recorded duration was less than 45 seconds or if EEG values remained constant for over 10 seconds (see Figure 4). After the cleaning process, a final review of anomalous channels and artificial segments was conducted through graphical analysis of trends for each channel and sensor.

Experiment procedures and survey questionnaire

Participants were equipped with an HMD device and EEG measurement equipment and were provided with a narration by a survey assistant: "You are walking down the street after leaving your home to go out for the day." A total of 40 VR videos were randomly selected, with 10 from each of the four destinations, for participants to experience. They were then asked questions by the research assistant. To prevent participants from predicting the context of the next video, all 40 videos were fully intermixed. Additionally, to enhance immersion, the survey guide provided narration each time a VR video played:

"You are on your way home from an appointment, and now you are stopping to look around."

After experiencing each video, participants were asked to rate their fear of two types of crime on a Likert scale from 1 to 7. The specific questions were:

"1. In the situation you are in right now, how much do you fear that a crime such as theft, violence, sexual assault, robbery, or murder could happen to you?

2. In the situation you are in now, how much do you fear that a crime such as theft, violence, sexual assault, robbery, or murder could happen to someone else?"

This process was repeated for a total of 10 videos to complete the VR experience. Participants then responded to a post-survey, rating the validity of the VR experience on a 5-point Likert scale (1-not at all to 5-very much). This survey was based on Lessiter et al.'s (2001) realism measure, which included aspects such as physical spatiality/reality, immersion, ecological feasibility, and occurrence of adverse health effects. To ensure accuracy and minimize survey time, software was developed to automatically transmit a random sequence of videos based on each participant's identification number. Additionally, the software recorded information such as the duration of the participant's experience.

Analysis method, variables, and model specification

The data collected from the virtual reality (VR) experiments in this study possess a hierarchical structure. This is because the data are grouped at the rater level, meaning individual perceptions for the same rater are internally correlated, with the perceived fear of crime evoked by each video serving as the unit of analysis. After excluding 6 participants with inadequate EEG measurements across all scenarios, and those with poor scenario-specific EEG measurements, a total of 95 participants and 622 video scenarios were included in the analysis. The analysis of hierarchical data necessitates the application of multilevel models. However, the experimental data in this study are grouped not only by rater but also by video. Participants were asked to respond to the degree of fear of crime evoked by 10 randomly presented videos out of 40, and each video was rated by an average of 24 different participants, indicating a correlation between individual perceptions of the same video. In essence, the VR experimental data in this study form a hierarchical structure in a cross-classification design for two different superordinate groups (raters and videos). Consequently, this study adopts a cross-classification multilevel model(Table 4). The analysis model utilized a pooled sample model that combined all four sites, which were divided into residential and commercial areas within a neighborhood with average foot traffic. This allowed for the variation of validation variables through sites with varying illumination and foot traffic within an area with a similar physical environment. The dependent variables, Fear of Self-Victimization (FSV) and Fear of Others (FOV), cannot be analyzed simultaneously, so they were analyzed in separate models. Additionally, the average fear of FSV and FOV was analyzed, meaning there are three types of fear corresponding to the dependent variable.

Valence was also calculated from the EEG data. As seen in previous studies, Valence is a measure of the degree of positivity or negativity and is determined by the difference between the left and right brain. However, individuals have different Valence levels when they begin participating in the experiment. Therefore, instead of the absolute numerical value of Valence, the change in Valence value that the participant experienced during the experiment was identified. For convenience, this was termed Valence Fluctuation and used as a dependent variable. A total of three dependent variables were entered into each model, with EEG as the dependent variable and fear as the dependent variable, resulting in a total of six models. The main test variable, illuminance, consists of three components: horizontal average illuminance, vertical minimum illuminance, and vertical uniformity (minimum illuminance/average illuminance). However, since horizontal average illuminance is closely correlated with vertical minimum illuminance, and uniformity is also calculated using these two variables, it is challenging to establish their conceptual independence. Therefore, separate models were built to validate these three test variables, applying logarithmic values for horizontal average illuminance and vertical minimum illuminance to the model through linear transformation, as described in the "Cross-classified multilevel analysis" section below. As outlined above, the analyzed model consists of a total of 18 models. To summarize, the 18 models are divided according to the 3 types of the dependent variable "fear", in each case the dependent variable is divided into "EEG" or "fear". Furthermore, the models are conditioned on the 3 types of the validation variable "illumination". For this reason, the 18 models are organized as 3 (types of fear) * 2 (EEG, fear) * 3 (types of Illuminance) = 3 * 2 * 3 = 18 models.

To determine the relationship between illuminance and fear of crime, a preliminary survey was conducted on personal characteristics. Personal characteristics include gender, age, and experience of other crimes. Other preliminary surveys were conducted, such as living arrangements and family members. The impact of personal characteristics on this relationship was also assessed. Other variables were also included in the models to test the adequacy of the experimental controls. First, a variable called 'current video presentation order' was included in all models to control for the potential effect of the presentation order of the 10 VR videos experienced by each participant on perceived fear of crime. Second, the warm-up task, which was provided to increase familiarity with the VR device and increase immersion in the VR experiment, was controlled for in which of the four sites the warm-up task was experienced, with site D as the baseline variable and the other three sites as dummy variables. Third, to control for differences between sites in the full-site models, a dummy variable was applied to each site, with site D as the baseline variable. Table 4 summarizes the definitions and levels of the variables. "Pedestrian and two-wheeler traffic" is a variable measured in units of footage (BETWEEN), meaning the number of all pedestrians, motorcycles, motorized scooters, etc. (excluding vehicles) that appear in the footage, regardless of whether there is vehicular traffic. The purpose of this variable is to capture the impact of the presence of moving people in a dark space late at night on fear of crime.

Results

Association between illuminance and perceived fear of crime

Using EEG, we measured indices of arousal and valence fluctuation, and arousal fluctuation together with valence, and plotted them against horizontal mean illuminance and vertical minimum illuminance (Figure 5-10). The study used EEG to measure arousal and valence fluctuation and arousal fluctuation. The scatter plot showed a negative correlation between both illuminance levels and valence fluctuation. Therefore, valence fluctuation was chosen as the variable for all EEG and valence indices in the subsequent analysis (Figure 5). The box plots in Figures 6,7 show the time-varying values of fear of self-crime and fear of acquaintance-crime, as well as their valence and valence fluctuation, as illuminance varied with time. Fear increased as illuminance increased, while valence and valence fluctuation, which represent the degree of positivity, tended to decrease. The decrease in valence fluctuation was more pronounced.

Figures 8 through 10 depict the fear response and EEG response to different types of illumination. The Valence Fluctuation, which measures changes in positive emotion, is positively correlated with illumination and negatively correlated with fear response. In other words, participants experienced less fear of crime with higher illumination, and the EEG response was positively affected. Figure 8-10 shows that Valence did not change significantly with changes in illumination value, unlike horizontal and vertical illumination. To investigate the relationship between illuminance and the average fear of crime at different times of the day, we used the logarithm of illuminance to represent a negative linear function graph. The perceived fear of crime decreased rapidly as the illuminance increased. Under illuminance conditions below a certain threshold luminance, the fear of crime decreases significantly as the illuminance increases. However, once the threshold luminance is reached, the fear of crime does not decrease significantly. This pattern was observed across all sites, even when vertical minimum illuminance was applied instead of horizontal average illuminance. Therefore, for a cross-classification multilevel analysis, it is preferable to linearly transform the main test variable, illuminance values, to set the model in linear logarithmic form. However, in the case of uniformity, it was not transformed linearly in the model because it showed a linear relationship with fear of crime (see Figure 10). The results indicate that uniform street illuminance reduces the perceived fear of crime, which supports the findings of Fotios et al. (2019) who used both surveys and EEG measurements with VR.

Cross-classified multilevel analysis

In this study, cross-classified multilevel models were used to analyze the relationship between fear of crime (FSV, FOV) and various factors, with fear of crime serving as the dependent variable. The models produced posterior predictive p-values (PPP-values) greater than 0.05, indicating a strong overall fit, with PPP-values ranging between 0.4 and 0.5. The analysis showed that Valence Fluctuation (Kliemann, 2016; Cho, 2022), a metric derived from EEG data, has an inverse impact on fear of crime, indicating a negative correlation(Table 5). At the same time, illuminance has a dual effect: it positively influences EEG activity while inversely affecting fear of crime. These findings support the hypothesis that positive valence and higher illuminance levels are associated with reduced fear of crime (Boyce et al., 2000; Kim & Noh, 2018; Mattoni et al., 2017; Son et al., 2023). The results highlight the importance of uniformity in average horizontal and minimum vertical illuminance in mitigating fear of crime, as evidenced by physiological responses. Further analysis showed that illuminance has a direct impact on EEG valence, which in turn affects fear of crime. Additionally, we investigated how personal characteristics modulate these effects(Table 6). The study evaluated the impact of variables such as gender, prior crime experiences, sense of presence/immersion, and adverse physiological reactions on EEG responses and fear of crime. The results showed that sense of presence/immersion was a significant factor in 16 out of 18 models, affecting both Valence and Fear of Crime. Higher levels of presence and immersion in VR environments are closely linked to more pronounced EEG responses and increased fear of crime. This highlights the critical role of realistic VR environment development for accurate simulation of crime fear responses. However, gender, experience of other crimes, and adverse physiological reactions did not significantly influence EEG responses. This indicates the challenges in using EEG to assess individual-level variables such as gender and experience. Therefore, while EEG can be a reliable measure of the physical environment's impact on fear of crime, its utility in capturing individual differences is limited.

In summary, our cross-classified multilevel analysis model findings suggest that higher illuminance levels are associated with positive changes in EEG valence and reduced fear of crime. This supports the idea that illuminance has a direct impact on EEG activity, which in turn reflects subjective perceptions of crime fear. These results underscore the interconnectedness of environmental factors, physiological responses, and subjective experiences in the context of urban safety.

Conclusion

This paper demonstrates that illuminance levels not only affect fear of crime but also EEG. Therefore, EEG can be used as a valid tool for measuring fear of crime, complementing the limitations of surveys with objective data. The study also quantified participants' perceptions as the virtual environment changed in a non-survey way. This study is the first attempt to analyze the relationship between illuminance and fear of crime by applying a quasi-controlled experiment based on recorded VR with EEG. The research conclusively shows that changes in illuminance can elicit measurable changes in brain activity associated with fear, suggesting a direct link between environmental illuminance and the fear of crime. This information is crucial for urban planning and public safety strategies, as it emphasizes the significance of taking psychological comfort into account when designing public spaces.

Although our findings are significant, it is important to note that they have limitations. The use of recorded VR environments, instead of live experiences, may not fully capture the nuances of real-world fear responses. This limitation suggests that while EEG responses provide valuable insights, they may differ in real-world scenarios where unpredictable elements are present. Future research should aim to incorporate more realistic or live environmental conditions to better simulate real-world responses. This study examines the impact of illuminance on reducing fear of crime, using the term 'fear of crime' instead of 'reassurance' as used in CIE (236-2019) and recent studies (Fotios et al., 2019). While 'fear of crime' is a widely accepted term in the field, it has been criticized for potentially triggering such fear (Farrel et al.1997; Boyce, 2019). Individual perception may be a factor and can reflect sociodemographic situations (Painter, 1996; Svechkina et al., 2020; Portnov et al., 2020; Fotios et al., 2022). Additionally, this study aimed to minimize the experiment time for each participant. Therefore, specific types of fear of crime, such as fear of theft, violence, sexual assault, robbery, or murder, could not be considered.

Furthermore, the survey questionnaire did not account for potential errors in human perception that could result in range-bias, as addressed by the day dark approach suggested by Boyce et al. (2000). Given these limitations, future research should investigate more advanced VR technologies that provide greater realism. Expanding the range of biological responses measured, such as incorporating pupil dilation, heart rate, and galvanic skin response, will provide a more comprehensive understanding of fear reactions. Additionally, enhancing the diversity of participants and settings will improve the generalizability of our findings across different socio-cultural contexts. The use of emerging game engine technologies that simulate dynamic changes in illuminance within virtual reality (VR) environments could greatly enhance experimental realism. These advancements would not only strengthen empirical evidence, but also provide more nuanced insights into the psychological effects of illuminance on fear.

In conclusion, this study represents a significant advancement in comprehending the psychological effects of urban lighting. By addressing the limitations and incorporating the suggested future research directions, we can deepen our understanding of how environmental design influences human emotions and behaviors. This research not only contributes to academic discourse but also has practical implications for creating safer and more psychologically comfortable urban environments. This paper demonstrates that illuminance levels significantly impact EEG responses, establishing EEG as a valid tool for objectively measuring fear of crime. The research goes beyond previous perceptions of illuminance levels, providing a novel approach to understanding the interplay between environmental factors and psychological responses.

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Table 1. Types of EEG and their features

Wave	Features	
	State of consciousness	*Frequency (Hz)*
δ	Unconscious level	0–4
θ	Subconscious level	4–7
α	Consciousness and subconscious level	8–12
β	Level of consciousness	13–17
γ	Level of consciousness	31–50

Table 2. Previous papers using VR and EEG

Article	VR	Emotional Information	Participants	Scenario (N)
1	O	Valence / Arousal / Self-Assessment Manikin	38 (60)	4 (N = 152)
2	O	Frontal alpha asymmetry (FAA) / Survey(after experiment)	22	9 (N = 198)
3	X	Valence / Arousal /Survey / Self-Assessment Manikin	28	4 (N = 112)
4	O	Arousal (RAB indicators)/ Survey(after experiment)	33	1 (N=33)
5	X	Valence / Arousal /Survey / Self-Assessment Manikin	12	4 (N=48)

Note. 1) Morales et al., 2018 2) Guizzo et al., 2020 3) Alakus et al., 2020 4) Kim et al., 2021 5) Cho et al., 2022

Table 3. Date and time of measuring the illumination of each site

Division	[Site A] Residential, High pedestrian volume	[Site B] Residential, Low pedestrian volume	[Site C] Commercial, High pedestrian volume	[Site D] Commercial, Low pedestrian volume
Day	April 26th, 2021 (Mon)	April 30th, 2021 (Fri)	April 28th, 2021 (Wed)	April 29th, 2021 (Thu)
Weather	Cloudy	Cloudy	Generally Cloudy	Cloudy
Minimum temperature	10°C	11°C	13°C	12°C
Maximum temperature	21°C	16°C	20°C	21°C
Sunset[1]	19:17	19:21	19:19	19:20
1st	18:00	18:04	18:02	18:03
2nd	18:30	18:34	18:32	18:33
3rd	19:00	19:04	19:02	19:03
4th	19:15	19:19	19:17	19:18
5th	19:30	19:34	19:32	19:33
6th	19:45	19:49	19:47	19:48
7th	20:00	20:04	20:02	20:03
8th	20:15	20:19	20:17	20:18
9th	20:30	20:34	20:32	20:33
10th	20:45	20:49	20:47	20:48
11th	21:00	21:04	21:02	21:03
12th	22:00	22:04	22:02	22:03
13th	22:30	22:34	22:32	22:33

[1]) Sunset time is based in Seoul(GMT +9)

Table 4. Definition and level of the variables in the analysis

Variable	Note	Level
Dependent variables		
Fear of self-victimization (FSV)	7-point Likert scale	Within (person*video)
Fear of others' victimization (FOV)	7-point Likert scale	Within (person*video)
Valence Fluctuation (EEG)	Direct measurement	Within (person*video)
Test variables		
ln (horizontal mean luminance)	Direct measurement	Between (video)
ln (vertical min. luminance)	Direct measurement	Between (video)

Vertical uniformity	Vertical min/avg luminance	Between (video)
Control variables		
Valence Fluctuation (EEG)	Direct measurement	Within (person*video)
Pedestrian/two-wheeled vehicle traffic*	Those appearing in the video	Between (video)
Age		Between (person)
Gender	Male = 1	Between (person)
Education	Postgraduate or higher =1	Between (person)
Residential type		
- detached/multi-family**	Multifamily, townhouse	Between (person)
- apartment house**	Apartment, multi-use, officetel	Between (person)
Household size		
- one-person household	Ref.: 3+	Between (person)
- two-person household	Ref.: 3+	Between (person)
Familiarity with the area	Familiar = 1	Between (person)
1-week back alley walk		
- 3–4 days	Ref.: less than 3 days	Between (person)
- 5–7 days	Ref.: less than 3 days	Between (person)
Avg. returning home time		
- 8–10 pm	Ref.: before 8 pm	Between (person)
- 10 pm or later	Ref.: before 8 pm	Between (person)
Experience of other crimes	Yes = 1	Between (person)
Risk of FSV	4-point scale (1 = very low, 2 = low, 3 = high, 4 = very high)	Between (person)
Self-defense level		Between (person)
Severity and continuity of harm (self)		Between (person)
Past experience of VR	Yes = 1	Between (person)
- sense of presence/immersion	Cf. Factor analysis result	Between (person)
- adverse physiological reactions		Between (person)
- ecological validity		Between (person)
Order or presentation of the current video	On value out of 1 to 10	Within (person*video)
Current video (Site A)	Ref.: Site D	Between (video)
Current video (Site B)		Between (video)
Current video (Site C)		Between (video)

* All pedestrians, motorbikes, and electric kickboards appeared in the video
** Ref. variable is other residential types (dormitories, tiny studios, etc.)

Table 5. Total effects of EEG and illuminance on fear of crime

	Ln (horizontal mean illuminance)		Ln (vertical min illuminance)		Vertical uniformity	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
EEG						
Valence Fluctuation Affects FSV	-0.241	0.000	-0.240	0.000	-0.250	0.000
Valence Fluctuation Affects FOV	-0.309	0.000	-0.307	0.000	-0.316	0.000
Valence Fluctuation Affects Average FC	-0.274	0.000	-0.273	0.000	-0.282	0.000
Illuminance						
Illuminance Affects Valence Fluctuation	0.081	0.000	0.074	0.000	0.626	0.001
Illuminance Affects FSV	-0.267	0.000	-0.255	0.000	-2.807	0.000
Illuminance Affects FOV	-0.344	0.000	-0.329	0.000	-3.525	0.000
Illuminance Affects Average FC	-0.306	0.000	-0.292	0.000	-3.168	0.000

Table 6. Total effects of personal characteristics on valence and fear of crime

	Valence Fluctuation		Fear of Crime*		Valence Fluctuation		Fear of Crime **		Valence Fluctuation		Fear of Crime ***	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gender	0.051	0.341	**-1.112**	**0.000**	0.049	0.346	-0.414	0.102	0.049	0.349	**-0.763**	**0.004**
	0.052	0.339	**-1.111**	**0.000**	0.049	0.346	-0.414	0.102	0.050	0.346	**-0.761**	**0.004**
	0.054	0.331	**-1.125**	**0.000**	0.050	0.343	-0.412	0.103	0.053	0.333	**-0.777**	**0.003**
Experience of other crimes	0.054	0.331	**-1.125**	**0.000**	-0.057	0.291	0.408	0.077	-0.054	0.302	0.468	0.028
	-0.056	0.294	**0.529**	**0.009**	-0.057	0.291	0.408	0.077	-0.055	0.298	0.465	0.029
	-0.065	0.264	**0.532**	**0.008**	-0.058	0.287	0.405	0.079	-0.064	0.265	0.470	0.027
Sense of presence/immersion	**-0.102**	**0.012**	**0.199**	**0.018**	**-0.107**	**0.009**	**0.280**	**0.011**	**-0.104**	**0.010**	**0.237**	**0.012**
	-0.101	**0.013**	**0.196**	**0.019**	**-0.107**	**0.000**	**0.280**	**0.011**	**-0.104**	**0.011**	**0.234**	**0.013**
	-0.106	**0.009**	**0.203**	**0.015**	-0.106	0.009	0.277	0.012	**-0.108**	**0.007**	**0.241**	**0.010**
Adverse physiological reaction	-0.040	0.198	**0.219**	**0.014**	-0.040	0.199	0.178	0.081	-0.040	0.198	0.199	0.035
	-0.041	0.193	**-0.087**	**0.014**	-0.040	0.199	0.178	0.081	-0.041	0.193	0.198	0.036
	-0.046	0.164	**0.221**	**0.012**	-0.041	0.194	0.177	0.083	-0.047	0.155	0.202	0.032

Note. Shading: Not Include "0" within 95% confidence interval, * Fear of self-victimization (FSV) **Fear of others' victimization (FOV) ***Average Fear of crime, In a row, from top to bottom, ln(horizontal average illuminance), ln(vertical minimum illuminance), vertical uniformity

Figure 1. Site location and day/night view

Note. Evaluation ratings were made during the 2014 fall academic term.

Figure 2. Illuminance measurement method and procedure

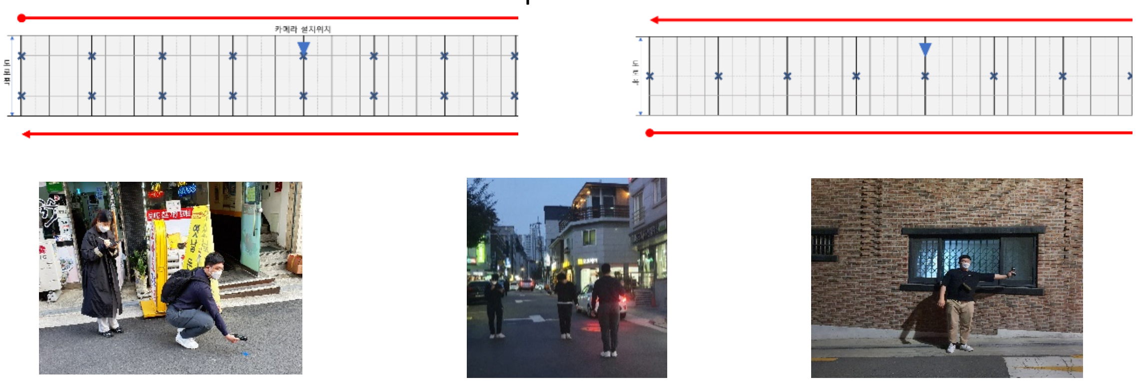


Figure 3. Muse2 (Left), Electrode Position (Right)

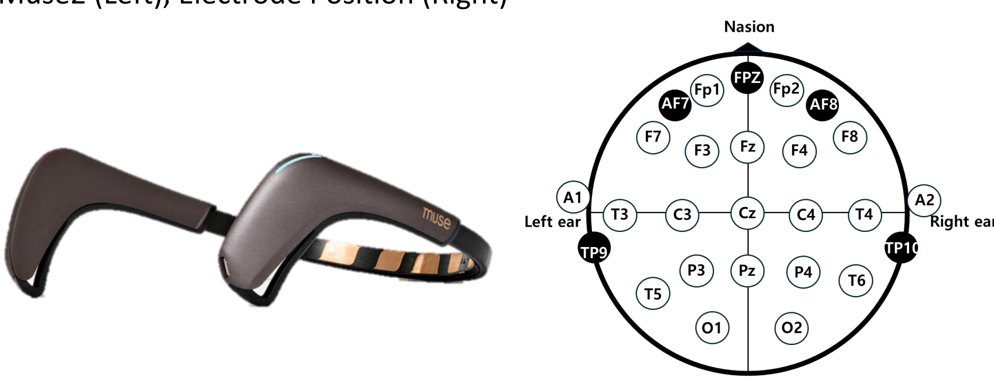


Figure 4. Before refinement (left) After refinement (right)

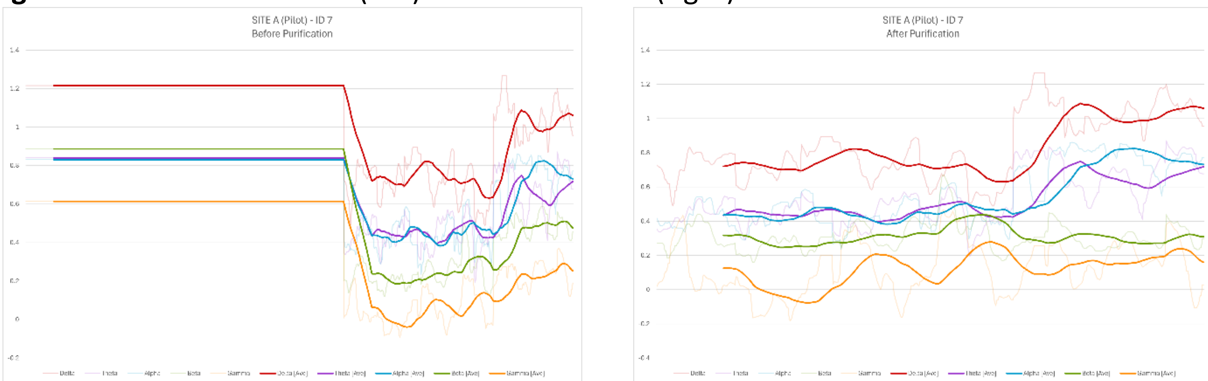


Figure 5. Scatterplot of Valence and Arousal as a function of illuminance

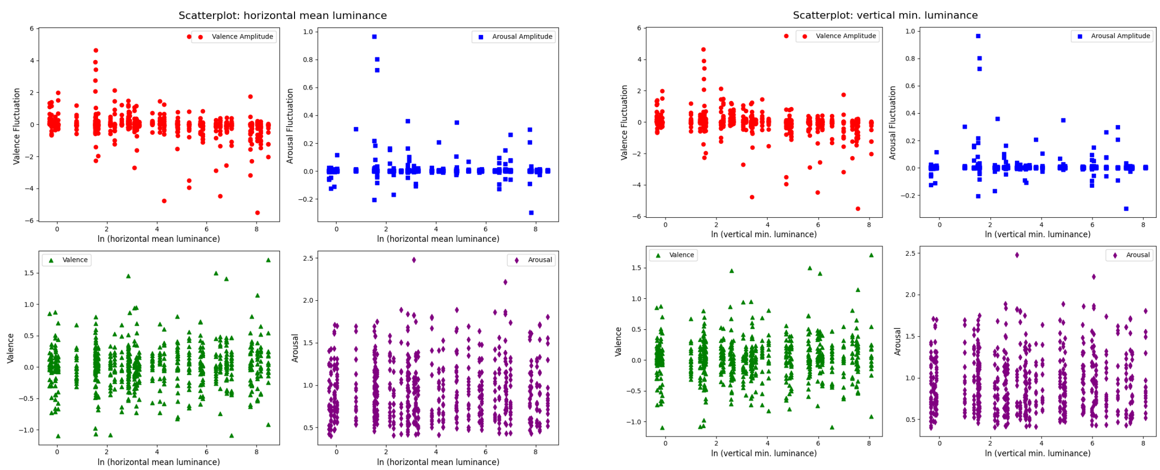


Figure 6. Fear of crimes by time

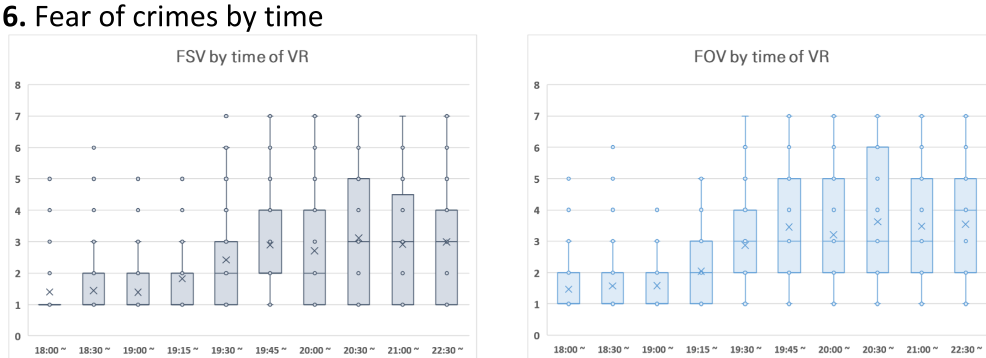


Figure 7. Valence and Valence Fluctuation by time

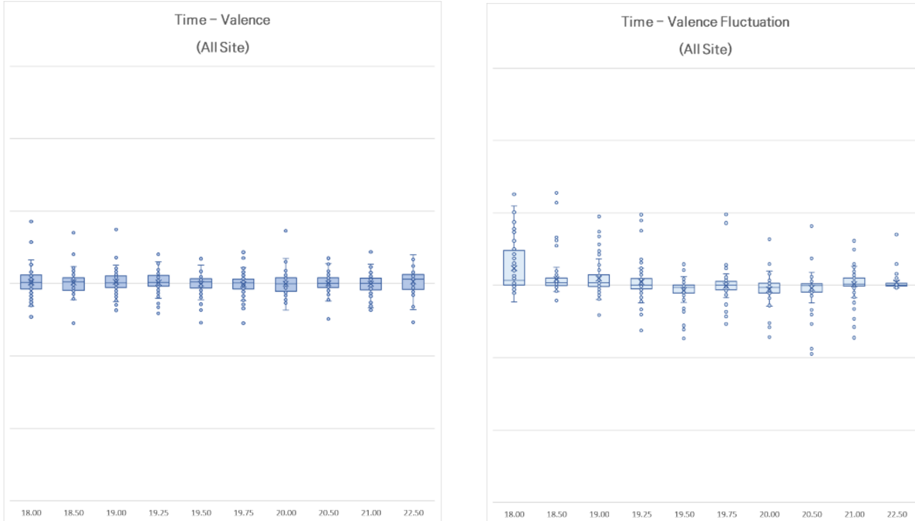
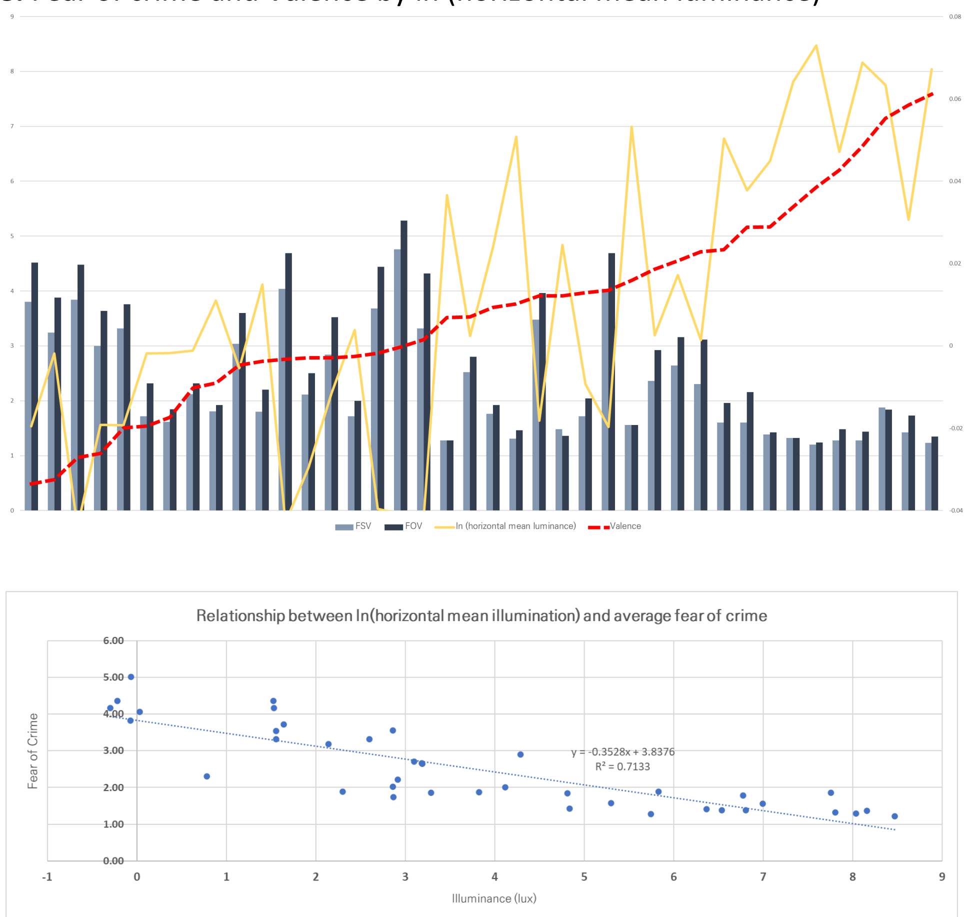


Figure 8. Fear of crime and Valence by ln (horizontal mean luminance)



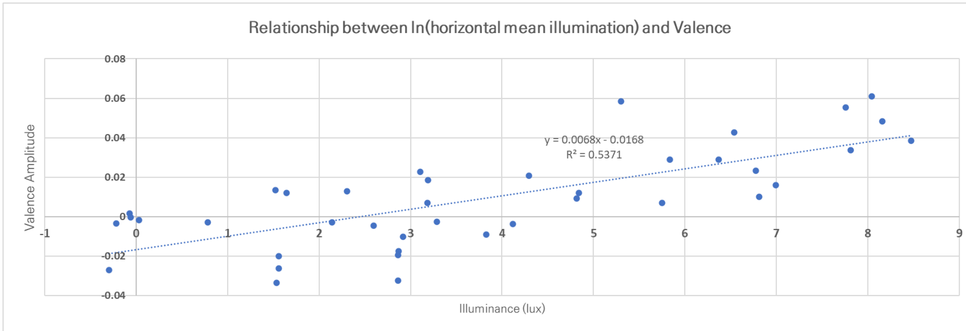
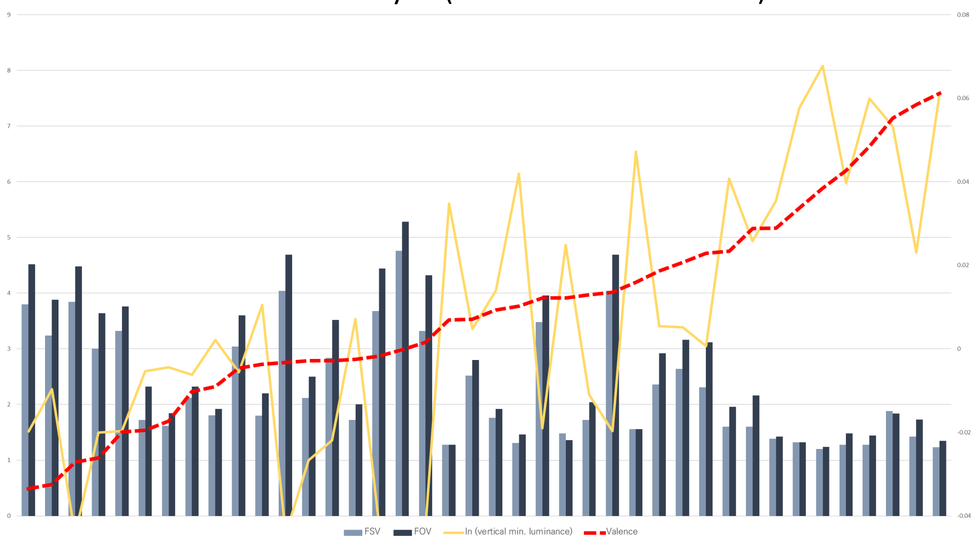
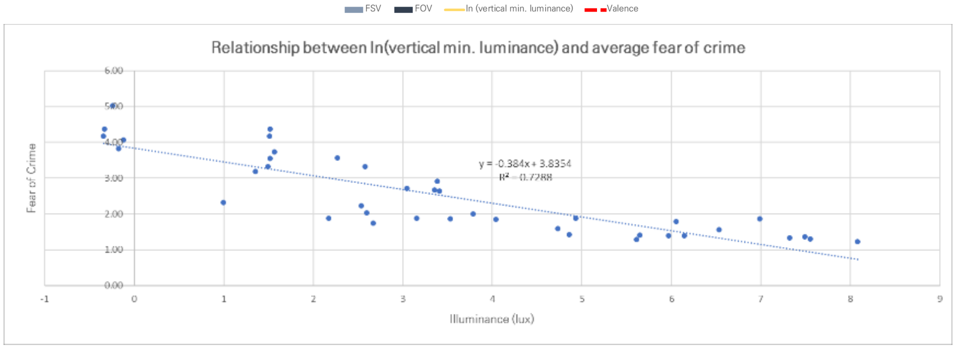


Figure 9. Fear of crime and Valence by ln (vertical min. luminance)





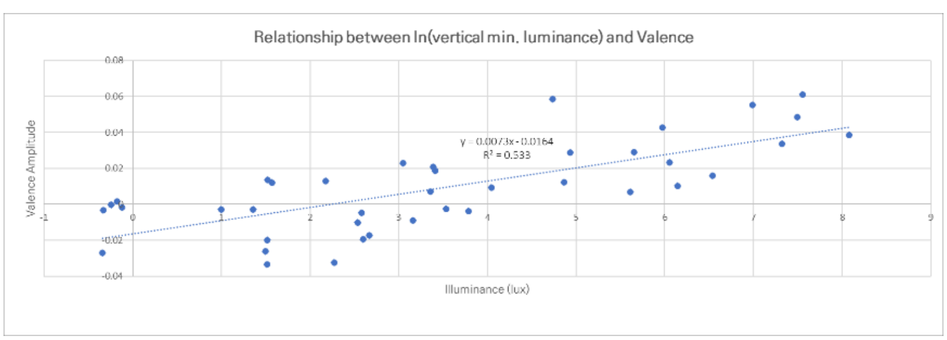


Figure 10. Fear of crime and Valence by Vertical uniformity