THE SCENE DYNAMISM AS AN ASPECT OF RATING INDOOR VIEW QUALITY

by

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THESIS ABSTRACT

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The Scene Dynamism as an Aspect of Rating Indoor View Quality

Views through windows provide a visual connection to the outdoors, information about weather and time, and indoor environments. Observers looking through a window perceive dynamic scene content, but the associated benefits are difficult to quantify. To better understand these benefits we employed an online survey (n=59) whereby subjects ranked scenes associated with window views having differing levels of dynamism. The rankings were compared against numerical measurements of motion derived from scene recordings using OpenCV with Python. Results show statistically significant differences among high, medium, and low dynamism for each of the twelve views. Among 100% natural views, high dynamism scenes were most preferred. When comparing three levels of dynamism in views with human activity, the medium level of dynamism was most preferred indicating a potential desire for moderate activity while avoiding sparsely occupied “ghost towns” or the chaos associated with heavy vehicular traffic.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

I.1. Introduction

Office workers spend a large part of their day at their desk with a fixed viewpoint. If they are fortunate, they have a window that provides a view to the outdoor environments. While the value of view is anecdotally understood, and in some cases specifically studied (Turan et al., 2021) , there is a need to better understand the variables that serve as indicators of view preference. Several studies have demonstrated the desire to have a view outdoors in different settings such as office buildings (Boubekri & Haghighat, 1993; Butler & Biner, 1989; Belinda Lowenhaupt Collins, 1975; Markus, 1967; Wells, 1965), schools (Benfield et al., 2015; Belinda Lowenhaupt Collins, 1975; Glen P. Nimnicht, 1966), residential buildings (R. Kaplan, 2001), and hospitals (R. S. Ulrich, 1984; Wilson, 1972). Still further investigation is warranted to better understand the variables that drive preference. We choose to focus on office settings due to the impact of view on real estate value (Turan et al., 2021). Office employees have consistently indicated their disdain for working in windowless offices (Belinda Lowenhaupt Collins, 1975), and they also have indicated a desire to let sunlight into their office if it can be accomplished without increasing glare (Van Den Wymelenberg et al., 2010). It is likely that occupants' desire for view is coupled, or confounded with their desire for daylight, sunlight, and access to information about weather condition s and time of the day. The specific view content has also been showing to impact workplace satisfaction with people preferring nature as opposed to urban content. Anecdotal information suggests that people enjoy movement, expected or unexpected movement, within their view, but this has not been explicitly investigated. Urban activity, including movement of people and cars, contribute to dynamic content in views from windows, such as trees moving in wind, animals running or flying, and clouds floating by in the sky. We aim to explore the preference associated with differing degrees of moving objects within a view, a metric we characterize as “view dynamism”.

View content and its impact on human subjects’ preference has been investigated by many researchers but we still believed that some gaps within this topic need to be covered by adopting a new research method that eliminates the limitations in previous related research studies. This research study specifically investigates the impact of the level of scene motion in view content on our preference. Including examples of scene motion, which makes a scene look dynamic, such as people, cars, water flows, trees, etc. may impact our satisfaction with a view. All of the dynamic elements mentioned above, either urban or natural, are not static but dynamic.

The present thesis is formatted in the style of a journal to which results and papers will be submitted. The advent of COVID-19 made a halt in the research project since the campus went on a complete shutdown for several successive terms and the recruitment of the human subjects became almost impossible. The researchers altered the previous research method used in the pilot study to overcome challenges the virus made for the project completion. Chapter 2 comprise the paper that summarizes research methods and key findings of this research project. It also describes the aims, methodology, and results of the research project with 59 human subjects.

Chapter 3 reviews the aims, hypotheses, and key findings of the project. The last chapter relates the findings to the research hypotheses and discusses the theoretical and methodological shortcomings and limitations of the study. within chapter 3, researchers suggest further research studies in the area based on a similar methodology.

CHAPTER II

II.1. Introduction

II.1.1. Why people value view through windows

Americans typically spend most of their lives (90% on average) in indoor spaces (Rudd & Bergey, 2014). Because a large part of the modern world's population is city habitants, a lot of people work in offices and administrative buildings (Al Horr et al., 2016). This becomes more intense for office workers who spend their working hours in a fixed position with a changeless viewpoint. The worst-case belongs to some office workers who are confined to work in office spaces without any apertures through the outdoor environment. Office workers have strongly reported their desire to have view and window close to their work station (Boubekri & Haghighat, 1993). This makes sense, due to two common opinions that people do not like to work in windowless offices and almost any kind of view is preferred to having no view (Belinda Lowenhaupt Collins, 1975). People normally prefer rooms with windows and tend to have view to the outside (Butler & Biner, 1989; Markus, 1967; Wells, 1965). In some modern office settings with deep floor layouts, not all employees have equal access to windows and views. View through outdoor environment endows employees with assets such as having more job satisfaction, less depressed mood, and less job stress which can positively impact employees' mood (An et al., 2016; Finnegan & Solomon, 1981; Leather et al., 1998). Lack of view and window, as a potential source for sunlight, in office spaces, however, will lead to a negative impact on employees' workability (Ruys, 1970) and a less positive attitude on their job satisfaction (Finnegan & Solomon, 1981). Office workers strongly showed their desire to let sunlight into their office when available since this might improve employees' satisfaction(Van Den Wymelenberg et al., 2010). Even those office workers working in windowless offices tend to compensate for lack of window by mounting natural images and landscape photos (Sommer, 1974) and having plants in their offices (Bringslimark et al., 2011). However, office workers still desire to see outdoor environment even if the their visual contact with natural work has been substituted with posters and paintings (Heerwagen & Orians, 1986). Peeping through windows and looking at few natural elements such as several trees can significantly benefit office workers who became tired of working in their work station and help them restore their attention (R. Kaplan, 1989, 1993; S. Kaplan, 1995). Access to window and view is not only matter of preference or positive attitudes on job satisfaction but also of health, well-being (Raanaas et al., 2012; Trøstrup et al., 2019; R. S. Ulrich, 1984; Roger S. Ulrich et al., 1991), stress reduction (Cole & Hall, 2010; Hartig et al., 1996; Ward Thompson et al., 2012) and being more psychologically comfortable in office spaces (Heerwagen & Orians, 1986). These impacts on health, stress and well-being can even be more serious in office spaces because according to Bureau of Labor Statistics 123 million full time employees in the United States spend 44 hours per week in their offices sitting at their desks (*American Time Use Survey Charts Page*, n.d.; *U.S.*, n.d.). In this case, view may be the only possible way to have a short term visual contact with outdoor environment to gain knowledge of the weather and time of the day and also bring micro-restorative setting as one's attention is worn out (R. Kaplan, 2001). Research studies strongly suggest that having view and window is an essential part of office spaces especially in the modern world's offices where workers are becoming less active and more stationary at their workstations for prolonged hours every day.

II.1.2. View Content & View Satisfaction

In this part we briefly review previous research studies investigating view satisfaction by focusing on the content of view in different settings. Our unbounded desire to have window through outdoor environment suggests that even a brick wall outside the window is preferred over the same brick wall inside the same room (Belinda L. Collins, 2016). Kaplan in 2001, investigated the impact of view content on satisfaction of residents in a residential complex. In her study, the survey was sent to residents along with 40 scenes as images of potential views from the windows of the residential community. Participants in the survey, who were residents of the apartment community, were asked to first “rate images in terms of similarity to the view from their apartment”, second “indicate how much they would like such a view if it was their view from their window”. In this case, subjects have to imagine the static black and white photographs as the view from their home. Consistent with findings of other research studies, in Kaplan study, natural scenes were preferred the most in comparison to urban scene occupied with cars and structures (R. Kaplan, 2001; Kfir & Munemoto, 2003; Shafer & Brush, 1977; Tuaycharoen & Tregenza, 2005; Roger S. Ulrich, 1981). Although it has been said that natural scene is preferred over buildings and built environment, preference varies among different buildings’ design. In a survey among 601 participants who were shown 64 color slides of different buildings, it was revealed that people normally like modern buildings over old buildings unless old buildings are well-maintained. The maintenance of old buildings will alter the relationship (Herzog & Gale, 1996; Herzog & Shier, 2000). Other scholars, investigated the view satisfaction by exposing human subjects to real scene through outdoor environment. In particular, they investigated view satisfaction among office workers working in a multi-story building. Since the research setting was a deep-layout office, not all the employees had the same access to windows and the view content varied significantly depending on their location in the office. Participants were asked to rate the view from their workstation in the office. Office workers who had natural elements such as trees and hills in their view were significantly more satisfied with their view content in comparison to their peers who had view of nearby buildings and built environment (Markus, 1967). Other researchers investigated scene preference by using 56 slides with different contents which were categorized into four groups as follows, “man”, “man and some nature”, “some man and nature” and the last one was “nature”. These slides were rated by 88 human subjects for preference, complexity and excitement-intrigue. Their experiment had three results as follows: natural scene slides were vastly preferred over urban scene slides, complexity was positively correlated with subjects’ preference within natural scenes and urban scenes, level of informational content is playing a role subjects’ preference on slides (S. Kaplan et al., 1972). With respect to the fact that natural scenes are rich in complex fractal patterns, people show aesthetic preference for natural scene with visual mid-complexity of fractal patterns within nature (Spehar & Taylor, 2013; R. Taylor et al., 2011; R. P. Taylor, 2006). A view with a diverse content which gives more detailed information about an outdoor environment is most preferred over others (R. Kaplan et al., 1989). it might be safe to say that the more view extends to include exterior areas, the more informative that view will be. Outdoor areas, visible through a window, consist of layers including ground level, sky level and greenery features. Each of these gifts the viewer with abundant information, and so may be strongly preferred as facets of favored views (Keighley, 1973a, 1973b; Markus, 1967). Another comprehensive study investigated the impact of building location and floor number on view preference in Japan and its results showed that these two independent variables strongly affect view assessment by respondents. This means that people who lived in upper floors assessed the view from their dwelling more positively than residents living in lower floors. Researchers of the research study determined the potential relationship between distance of objects visible through the view and view satisfaction. The result also revealed the importance of living room view for residents. Views including the residential buildings in the close zone to the window were the most important determinants of a negative assessment of the view. when the portion of residential buildings increased in a closer distance to windows, respondents negatively assessed their view through outdoor environment. On the other hand, sea view was the most significant determinants of a positive assessments (Kfir & Munemoto, 2003). A group of researchers administered a survey by ordinary office workers in the Netherlands by adopting an assessment method which looks at the assessors' opinion on several different factors to evaluate the quality of view based on their satisfaction. They designed a series of questions asking about items visible in the view. Depending on existence of each natural or manmade item, each question had a score. By scoring 23 images, view quality was calculated. To test the applicability of their designed method, scores derived from the questionnaire was compared to office workers' ratings who were asked to indicate how much they would like these pictures to be the view from their workplace. Consistent with findings with previous research studies, office workers rated images dominated by nearby greenery, distant landscape, sky and water (Hellinga & Hordijk, 2014). Preference for the existence of water in views such as lake or the sea, invariably is emphasized by other researchers

(Kfir & Munemoto, 2003; Shafer & Brush, 1977; Tuaycharoen & Tregenza, 2005; Roger S. Ulrich, 1981). View content is not the only factor impacting view quality and subjects' assessment. In an investigation about the impact of sunlight pattern in three different conditions (fractal pattern, striped pattern and clear sky) on view quality based on 33 office workers' assessment. The result indicated that subjects with clear sky condition rated view quality based on their preference significantly higher than fractal patterns and striped pattern. In the same study, it is also reported that the influence of desk layout and subjects' position was significant with higher view quality ratings for participants perpendicular to window compared to participants parallel to window (Abboushi et al., 2020).

II.1.3. View Motion & View Satisfaction

Motion, as a factor impacting our surrounding environment, has been investigated in other research studies. Other research studies suggested that motion influenced judgment of scenic beauty by human subjects within a landscape with significant dynamism and motion related to a river (Hetherington et al., 1993). Other scholars conducted a research study on comparison between on-site scenic beauty ratings and photo-based ratings. The result indicated that there were differences observed at an individual (person) level for scenic beauty ratings (Hull & Stewart, 1992). Another comprehensive study on perception of scenic beauty of a river showed that public perception of scenic beauty increases with increasing flow to a point and then starts decreasing for further increases in flow (Brown & Daniel, 1991). There exists ample empirical evidence suggesting that exposure to view is associated with increased health and well-being. People also claim greater satisfaction with preferred view. The most consistent finding in the literature is the comparison between built and unbuilt environment and their impact on view preference (R. Kaplan, 1993, 2001; Kfir & Munemoto, 2003; Shafer & Brush, 1977; Tuaycharoen & Tregenza, 2005; Roger S. Ulrich, 1981; Velarde et al., 2007). Since judgment of photographs highly correlates with on-site judgment (Stewart et al., 1984), a great proportion of past studies employed static photos of natural and built environment (Al-Akl et al., 2018; R. Kaplan, 1989, 2001; Tuaycharoen & Tregenza, 2005) as proxies for the actual, physical settings. However, static photos do not reflect our experience from view, since natural elements, people and cars are not static but dynamic, and might give a different interpretation of previous results. Additionally, looking at static images is not similar to being exposed to a real, physically present view, since humans are able to explore through their eyes in four dimensions and follow dynamic elements of a view. Movement improves the process of perceiving our environment and it is a critical part of the perceptual process (Gibson, 1979). Since humans and other animals are mobile organisms, the way that an individual perceives an environment by being shown in a static picture from a fixed viewpoint, is not comparable with the way individuals experience the present moment, dynamic, real environment (Heft & Nasar, 2000). Including examples of dynamic natural elements such as trees, clouds, water flows and animals in a viewscape may impact our satisfaction with a view. Perhaps, view content does not entirely consist of natural scene and built environment; there are other elements that have been neglected. For instance, when looking through a window, different items appear in the frame, such as people, cars, natural activity like birds in the sky, each adding to the level of dynamism in the view. This illustrates that dynamism in view is as an important factor that has been neglected by previous researchers. Particular interest is the relationship between dynamism in view content and satisfaction with a view. There is no record of a systematic study on view content and satisfaction based on dynamism visible through the window. An important innovation of this study is to consider how view dynamism affects satisfaction of participants from given points of view.

II.1.4. Relevant View Quality Research Methods

Research studies suggest that view and window impact office workers from different aspects, such as health, job satisfaction, well-being and stress reduction, view content and its impact on preference have been investigated. Previous practices in research studies on the impact of view content on subjects' satisfaction investigated by different strategies have two challenges. One of the challenges within research studies on view might be lack of control over view content which undergoes dynamic changes all the time. Having human subjects exposed to real views/real outdoor environment as a method to carry out research studies on this topic makes less control on objects visible through the window. Weather condition may change during different days that the research study goes on and it might lead to different impact on satisfaction of human subjects participating in different days. Daylight itself is dynamic as a light source, producing diverse visual patterns in both space and time, and increasing natural activity/interest (Rockcastle & Andersen, 2014). Urban atmosphere contains dynamic items such as cars, bickers and pedestrians who make dynamic changes in the view. These constant changes might affect satisfaction with a view with different aesthetic qualities. Assessing view under different conditions for the same scene might give biased results. Another challenge in view satisfaction studies is the use of photos and/or static rendered images of outdoor environment, such as urban scene or natural scene, by computer software. This challenge originates from the nature of photos which are not dynamic but static. In this case subjects are asked to assess their satisfaction by looking at images with diverse content. We might perceive the content of a real view in a different way other than looking at static images with no dynamic objects which compose a great portion of outdoor real scenes. Our world is being perceived more through its dynamic rather than static qualities. It continually undergoes dynamic changes both from physical processes in the world itself and from visual changes caused by our own activities such as loco-motion. With all those points in mind, we set out to design an experiment that introduces "view dynamism" as a method for evaluating view quality through windows. Adding dynamism into view research may shed additional light on view preference, increasing the knowledge base related to the impact of dynamism on satisfaction with view. The main objective of this research is to seek data related to human subjects' preference by implementing a dynamic view methodology in view preference research. The method used in this research study made an attempt to overcome challenges in previous research projects on satisfaction with views through windows.

We designed an online survey to investigate participants' satisfaction with targeted views that vary in both content and dynamism. This new method may give researchers a better understanding about relationships between view satisfaction (dependent variable) and scene dynamism (independent variable). To do so, three videos were recorded in 12 locations, for a total of 36 videos, each demonstrating different level of activity, or "dynamism". Videos and the designed questionnaire were uploaded to a Qualtrics survey, and disseminated on social media to recruit potential participants around the world. The research protocol was reviewed by the Institutional Review Board (protocol number: 05292020.029).

Level of dynamism of views through windows (independent variable), and ranked preference among presented views (dependent variable), were investigated. The following are hypotheses that were tested:

1. H1: View preference will be statistically differentiated by level of view dynamism.
2. H2: Scenes with high view dynamism will be statistically least preferred among urban views with vehicular traffic.
3. H3: Scenes with high view dynamism will be statistically most preferred among views with 100% natural content
4. H4: Scenes with high view dynamism will be statistically most preferred among urban views without vehicular traffic.

II.2. Methodology

The study comprised subjective ranking evaluations of three recorded scenes within each of 12 unique views. The three scenes within each view were recorded and clipped to 10 seconds in duration such that they intentionally include different levels of activity for content within the scene. The scene activity was numerically characterized by a computational image analysis algorithm to define a specific value of scene "dynamism". Participants were recruited via social media and asked to rank the three scenes within each view: (3) most preferred, (2) neither most or lease preferred and (1) least preferred. The following section provides the methodological details for the study.

II.2.1. Selecting Views and Recording Scenes

The majority of the previous research on view preference employed static photos and/or slides as stimuli. Photo-based illustrations may depict implied motion ensued from human activity, city activity, and natural activity. In this case, there should be a subtle difference between images that illustrate implied motion versus real motion. Some research shows that people are able to perceive movement from statics images (Di Dio et al., 2016), however emerging research suggests that static images with implied motion are not perceived equally with videos showing real motion (Sgouramani et al., 2019). One of the differences between the real environment and photo-based materials is the scene dynamism that exists in our real world. Differences between on-site scenic beauty ratings and photo-based ratings were observed at an individual (person) level (Hull & Stewart, 1992). Video could overcome the challenge with pictures and be more compatible with the research hypothesis. To test the research hypotheses, a sizable pilot data set was captured by recording 12 views with different levels of scene motion, a range of natural and human fabricated content, and a range of human and automobile activity. 12 different views were recorded 3 times for total of 36 recorded video scenes. A Canon EOS-Mark 5D SLR with a frame rate of 59.94 frames per second and a Canon Zoom Lens EF 16-35 mm 1:28 was fixed at an average, typical eye level of seated occupants in an office (1.20 m above the floor). The camera was held in a fixed position throughout the entire video recording process to record videos from the same viewpoint. All videos were recorded with the same resolution (1280× 720) and trimmed into 606 frames (10 seconds) by VSDC that is a free video editing software.

II.2.2. Coding View Content

Recorded videos were categorized based on the percentage of area covered by greenery and natural elements. Adobe Photoshop was employed to calculate the number of pixels quantitatively in areas covered with natural elements for all views with 300 dpi resolution and 1488 x 1024 pixels. Figure 1 shows the process and final masked image in which natural and built environment elements became white and black respectively.

Figure 1. Pixel measurement by adobe Photoshop that was applied to all 12 views. The process of selecting natural covered areas such as greenery and sky by quick mask mode in the software. Black and white represent "human fabricated" and "nature" respectively.

Once the pixel measurements were done for all 12 views, a wide spectrum of different view content from Urban with very low area covered by natural elements to 100% natural view was provided. Note that these numbers define the percentage of area covered with natural elements in each scene. The closer the value is to 100, the more naturally covered in the scene. According to figure 2, the spectrum starts from 23% covered by natural content and ends with 3 natural views with 100% green areas. Figure 2, starts with the least percent natural content and ends with the greatest natural content measured in 12 views. Given that the hypotheses differentiate between views that are primarily natural and those that are primarily human fabricated (urban), coding the view content was necessary (figure 1).

II.2.3. Coding Scene Dynamism

OpenCV (*OpenCV*, n.d.) is a library of programming and computer vision were used extensively for video analysis and motion detection in this research study. Python 3.8.2 (*Download Python*, n.d.) was used to develop a code that could detect motion in videos in a qualitative approach. Motion detection was designed based on the contours of moving elements in the videos. Contour is defined as a curve along the boundary of an object. First, all 36 videos were imported into Pycharm IDE to apply the motion detection code on them. Second, by adding a while loop in the code, the differences between each consequent frame were detected. Once the difference was detected between the two consequent frames, the moving objects were recognized, and the contours were drawn around the dynamic elements which could be cars, people, branches of a tree, or birds in the sky. Figure 2 shows four scenes when the code was run to detect dynamism objects and measure the boundary of the moving elements. In each scene, the dynamic objects are indicated by a green boundary around them. As shown, the dynamism ensued from the traffic flow of a street, people passing by our window or bickers.

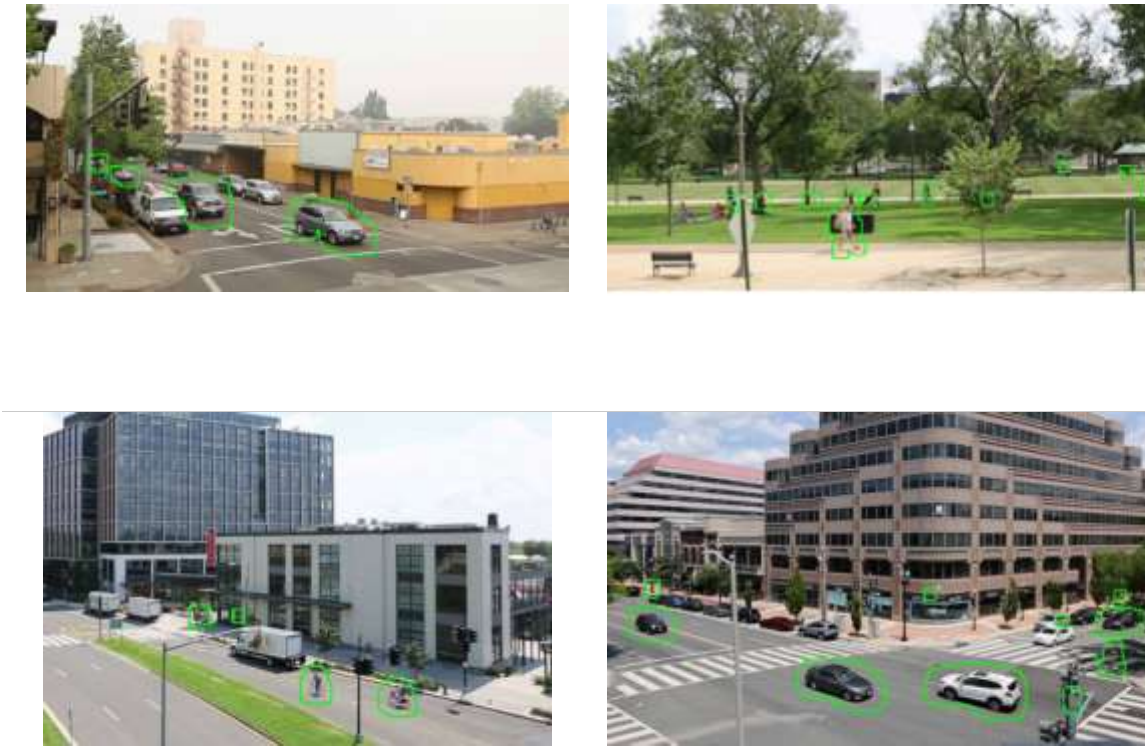


Figure 2. Examples of 4 views when the code was applied to videos. The green boundary line around the objects show the dynamic object which can be either cars, people or natural elements.

Once the dynamism is detected, the area of the dynamic objects' boundary was measured by counting the pixels surrounded in that area. Python counts the pixels that underwent dynamic changes. All measurements were done from frame to frame and appended into a list. Dynamism was rank ordered for each scene such that there were 3 ranked levels: High, Middle and Low scene dynamism for each of the 12 views, all baes upon the sum of contour area method. Since 3 videos were recorded for each view, there were 3 sums of contours obtained for each view. For example, figure 3 indicates one of views with the correspondent sums of contours for each High, Middle, and Low dynamism rank by scene.

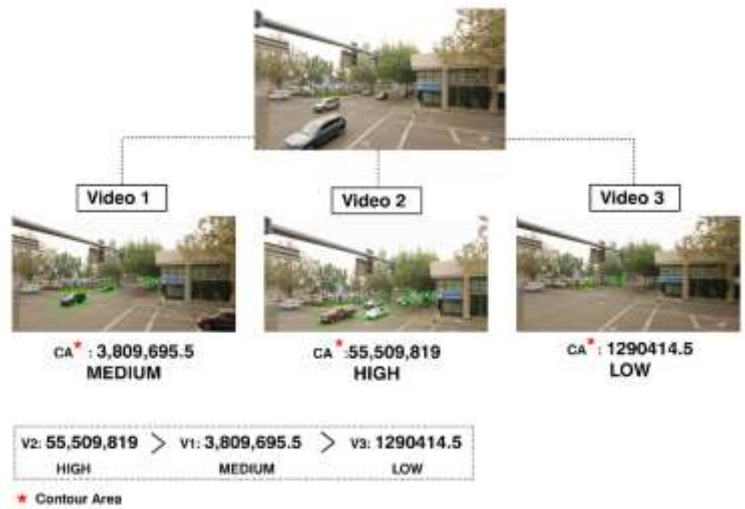
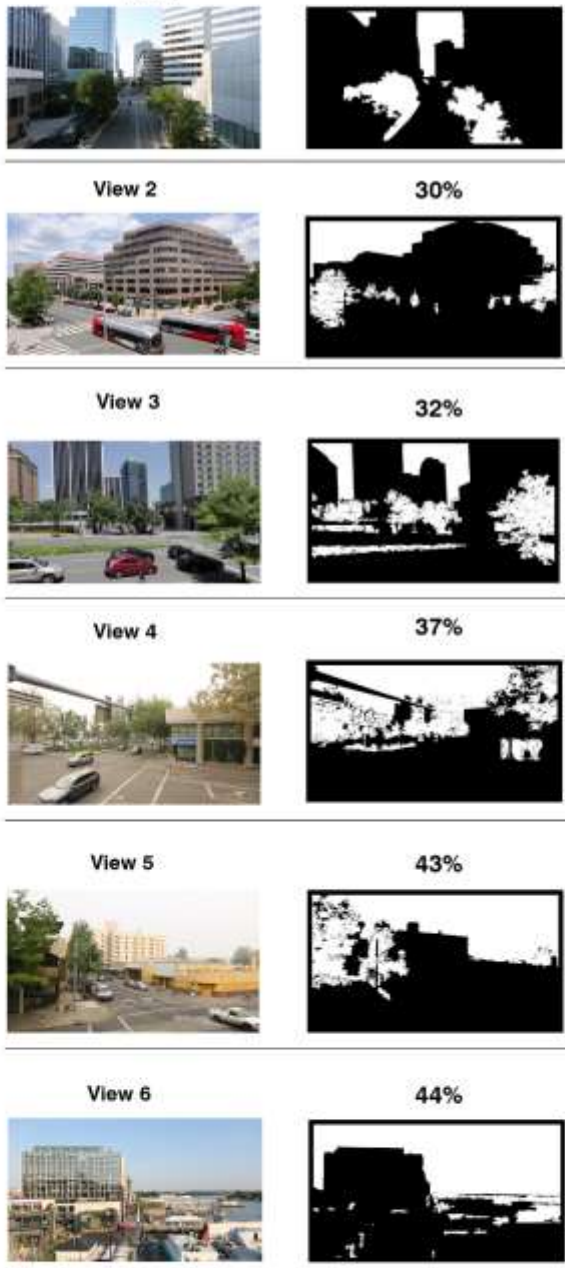


Figure 3. Process of categorizing views with

Figure 4 and 5 summarizes sum and mean of all measure contours for all scene dynamism within each view in this experiment. Views are ordered based on a rank order starting from the least percent nature and ending with the highest percent nature.

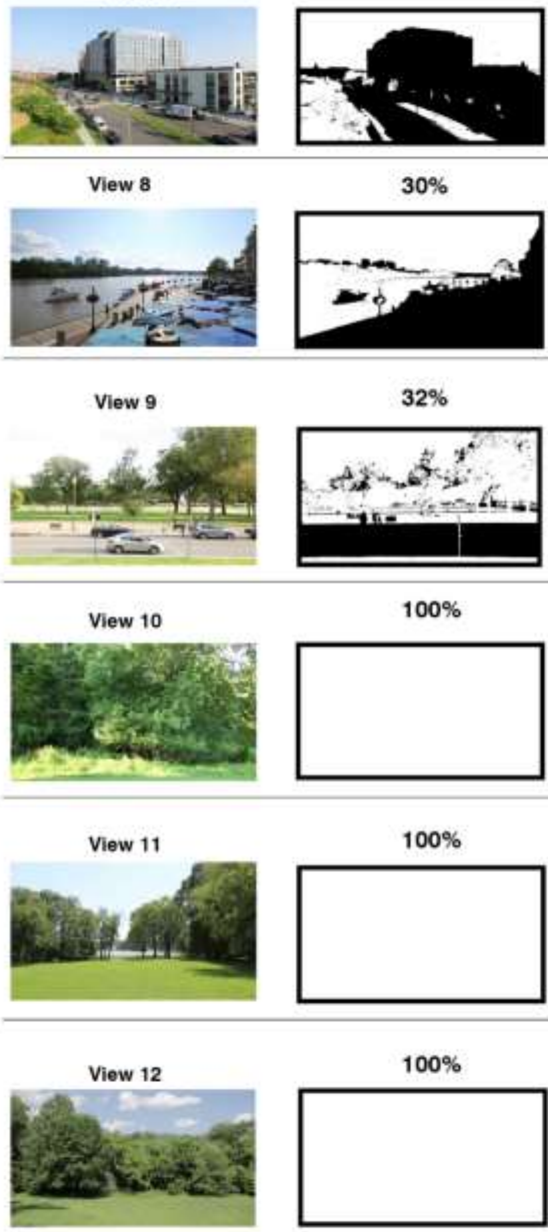
II.2.4. Participants and Recruitment

A total of 59 people (28 male, 31 female) participated in the survey within 5 age ranges (18-29: 34%, 30-39:37%, 40-49:15%, 50-59:9% & 60 or more: 5%) from October 13th, 2022 to December 15th, 20220. Participants who were under 18 years of age were excluded from the research study due to the policy and regulations of research compliance service at the University of Oregon. The institutional review board at the University of Oregon reviewed and approved the research protocol (IRB Protocol Number: 05292020.029). There was no compensation for taking the survey. Participants had access to the survey via a link that was available on several social networks.



View		Level	Sum of Contours	Mean of Contour
View 1	23%	High	16,708,035	1865
		Medium	7,166,304	1227
		Low	789,381	617
View 2	30%	High	20,054,030	4016
		Medium	6,962,686	1806
		Low	3,265,408	1533
View 3	32%	High	19,247,106	3504
		Medium	11,536,081	1807
		Low	1,553,410	1233
View 4	37%	High	55,509,819	6597
		Medium	3,809,695	3802
		Low	1,290,414	2198
View 5	43%	High	18,952,975	7857
		Medium	9,573,937	8289
		Low	770,593	1157
View 6	44%	High	6,073,085	795
		Medium	1,935,999	591
		Low	965,581	797

Figure 4. Reported contour areas and contour mean value by Python for pixel measurement along with pixel analysis for identifying view content by Adobe Photoshop. The black pixels imply human fabricate content and white pixels indicate nature.



View	Natural content	Level	Sum of Contours	Mean of Contour
View 7	23%	High	12,641,068	2940
		Medium	7,879,428	2039
		Low	2,134,737	1254
View 8	30%	High	69,877,639	1690
		Medium	65,069,625	2260
		Low	35,335,277	1616
View 9	32%	High	17,991,149	1938
		Medium	13,152,749	1769
		Low	937,753	679
View 10	100%	High	190,318,481	1209
		Medium	37,064,894	922
		Low	435,436	484
View 11	100%	High	77,469,897	1184
		Medium	10,099,687	649
		Low	508,907	617
View 12	100%	High	1,656,699	585
		Medium	1,376,417	549
		Low	20,491	418

Figure 5. Reported contour areas and contour mean value by Python for pixel measurement along with pixel analysis for identifying view content by Adobe Photoshop. The black pixels imply human fabricated content and white pixels indicate natural content.

To make people willing to take the survey, an advertisement video was accompanying the survey link on social media. This paved the path to having more human subjects recruited by making participants willing to take the survey. Concerning the focus of the study and the visual characteristic of the questionnaire, the online survey was only dedicated to desktop users so that videos could be presented on a large screen. Consequently, researchers had to select social platforms that are commonly viewed on a desktop by users. Another factor in social platforms' selection was the popularity of them in North America. Among different social platforms, Instagram, Linkedin, Twitter, and Facebook were selected. according to table 1, as of the 3rd quarter of 2019, for Facebook, Linkedin, Twitter, and Instagram, 60%, 76%, 49%, and 32% of users had access to the above social networks via desktop (*Devices Used for Social Media in the U.S. 2019*, n.d.). This fact convinced us that we need to pay more attention to Facebook and Linkedin. While data was collected from participants using cell phones, tablet and desktop monitors, data presented here are only from subjects (n=59) that participated using desktop monitors.

Table 1. Device usage of social networks in the US as of 2019.

Social media / Device	Instagram	Facebook	Linkedin	Twitter
Desktop	32%	60%	76%	49%
Mobile	83%	76%	54%	75%

II.2.5. Participant Experience and View Questionnaire

The online survey designed for this experiment was created using Qualtrics (www.qualtrics.com). To make it less complicated for participants and make sure that fewer of them leave the survey incomplete, an instruction video was designed and put on the first page of the survey. If they were willing to take the survey, they had to conform to the consent after watching the instruction video. Since the focus of this study was on office space and office employees' view satisfaction, a 3D rendered office space was shown along with a note saying "*Imaging this is your office and you are sitting at your desk looking through the window*". To make it more digestible, three examples were available (figure 6). To create the virtual office space, Revit 2020 was used to perform 3D modelling of a very simple office based on typical floor layouts of office space. The office is confined with walls from 3 sides and a large window glass that opens to an outside area. For rendering, a viewpoint was selected to represent an occupant's position in the space at 1.20 m from the floor. The material, light, shadow, and furniture of the 3D model were set in Revit 2020 to make the interior more realistic. Investigators chose not to include much furniture or temporary artifacts within the space, in an attempt to limit visual obstruction and minimize biases toward subjects' responses.

Figure 6. Three available examples of different view with the rendered 3D model office space. Participant were asked to imagine that they are watching the views through the office window. Note that there are only examples and full screen version of each view was presented in the survey.

The questionnaire included one item asking "*Rank your desired view from the most preferred to the least preferred [(1) is the least preferred and (3) is the most preferred]*" and a video set on each page. There were 12 sets of videos in total in accompany with the rank order question. Repeated-measures were designed to gain multiple individual measurements of each subject. By tapping on the play button, 3 videos (*High, Low, and Middle*) were being played in one window of the screen simultaneously. The videos were arranged in a vertical linear format in a way that views 1, 2, and 3 were located respectively from the top to the bottom of the screen (Figure 7). Participants could watch each video set multiple times and there was no restriction on it.

Figure 7. The format of visual representation of videos recorded from views. Three levels of dynamism were presented in a random order in a linear vertical format.

To eliminate the order effect or any errors due to the order of the videos, a matrix of branch logic allowed for random group assignment. The branch logic was designed based on a permutation of three levels of dynamism (*High*, *Low*, and *Middle*) without replacement. It consisted of 12 columns indicating 12 scenes and 6 rows indicating different permutations of videos. This resulted in 72 different arrangements that participants could only see 12 of them by chance.

II.3. Analysis Methods

All anonymous data were collected and R Script Version 4.0.3 (*Download R-4.0.3 for Windows. The R-Project for Statistical Computing.*, n.d.) was used to conduct data cleaning and organization. 2-way ANOVA was conducted to compare the effect of dynamism in each view within 23 scenes. Because the residuals of the response variable were not normally distributed, a post-hoc by Kruskal-Wallis test was conducted to test the validity of the two-way ANOVA. To test the significance of the impact of the independent variable on view rankings, paired t-Tests (confidence interval = 0.95) were used between different scene conditions within each view to investigate the research hypotheses. Since the data did not meet the normality assumption for t-test, Mann-Whitney U test was adopted to test the significant differences among conditions in this experiment.

II.4. Results

The result section is presented in three parts. First, the preference ranking of participants' responses collected in the online survey are reported in a descriptive statistics table. Second, the results from pixel measurements by Adobe Photoshop and Python for both experimental factors (scene content and dynamism) are presented. Third, statistical approaches and significance tests for each hypothesis are described in a detailed format.

II.4.1. Preference Rankings

Table 2 indicates all 12 views presented in the experiment with the mean value and standard deviation given by subjects' preference rank order for each level of dynamism. For the sake of brevity, several abbreviations are used. Views are presented based on their scene number according to figure 2 that categorized views based on percent natural area. V refers to “view(s)” following the view number in figure 5 and H, L, and M refer to “high”, “low”, and “medium” level of scene dynamism within each of 1 views. For example, V2.H represents “the scene in view 2 with high level of dynamism”. The lower the view number is, the smaller the percent nature is. For instance, view 1 is mostly occupied with built environment elements in an urban area, whereas view12 is 100% natural content.

Participants could rank the scenes in each view either 1, 2, or 3 in a way that 1 is the least preferred and 3 is the most preferred scene. A rank in the middle (2) indicates a neutral preference relative to the other two scenes. Note that the more the mean value is closer to 3, the more the view was most preferred over other scenes in that views. as one would expect given this method, the overall mean value of preference rankings of all 36 scenes in the experiments was 2.0 (*SD = 0.81674, Measurements = 1944*). Mean values, standard deviation and number of observations of each view for all 3 levels of scene dynamism have been summarized in table 2.

To test the significant difference among the mean value of subjects’ responses under different levels of dynamism (*High, Medium and Low*), paired-wise t-Tests (alpha= 0.05) were conducted to evaluate the effect of both dynamism and scene content. Although t-Test is still robust against non-normality (Kim & Park, 2019; Lumley et al., 2002), we also used paired-wise Mann-Whitney U Test, which had been used by other researchers in view research studies (R. S. Ulrich, 1984), to confirm the results of paired-wise t-Tests. The results from the Mann-Whitney U test were perfectly compatible with t-Tests results.

Table 2. Descriptive statistics of subjective responses on view rankings for all 12 views and 36 scene dynamism. The table is ordered based on percent natural area from the lowest to the highest. Within each view, the scene with the highest mean value is shown in bold text.

View, ranked by % nature	ID	Scene Dynamism	N (participants)	Mean	SD
		High	54	2	0.95
	View 1	**Middle**	54	**2.33**	0.67
		Low	54	1.66	0.67
		High	54	1.11	0.32
	View 2	Middle	54	2.22	0.42
		Low	54	**2.66**	0.67
		High	54	1.12	0.33
	View 3	Middle	54	2.5	0.50
		Low	54	2.38	0.70

Table 2. (continued).

View, ranked by % nature	ID	Scene Dynamism	N (participants)	Mean	SD
		High	54	1.44	0.84
	View	Middle	54	2	0.67
	4	**Low**	54	**2.55**	0.50
		High	54	1.22	0.42
	View	**Middle**	54	**2.77**	0.42
	5	Low	54	2	0.67
		**High**	54	**2.44**	0.69
	View	Middle	54	1.88	0.88
	6	Low	54	1.66	0.67
		High	54	1.66	0.82
	View	Middle	54	2	0.47
	7	Low	54	2.33	0.95

Table 2. (continued).

View, ranked by % nature	ID	Scene Dynamism	N (participants)	Mean	SD
		High	54	1.77	0.70
	View	Middle	54	1.88	1.00
	8	**Low**	54	**2.33**	0.47
		High	54	2.33	0.47
	View	**Middle**	54	**2.55**	0.31
	9	Low	54	1.11	0.69
		**High**	60	**2.7**	0.64
	View	Middle	60	2.1	0.54
	10	Low	60	1.2	0.40
		High	48	2.12	0.79
	View	Middle	48	2.5	0.71
	11	Low	48	1.37	0.49

Table 2. (continued).

View, ranked by % nature	ID	Scene Dynamism	N (participants)	Mean	SD
	View 12	High	60	2.4	0.81
		Middle	60	1.7	0.91
		Low	60	1.9	0.54

II.4.2. Scene Dynamism Comparative Analysis

To identify the statistical similarity or difference of subjects' satisfaction rankings within each view with 3 levels of scene dynamism, One-Way ANOVA test were applied to determine whether the mean values of high, low and medium dynamism were significantly different or not. While the ANOVA test revealed a significant effect of dynamism on rankings' mean value of satisfaction ($p<0.01$), the residuals were not normally distributed. Although ANOVA test is still robust against non-normality according to our sample size, a post-hoc analysis was conducted using non-parametric Kruskal-Wallis test, to study the difference of the rankings satisfaction with each of three scene dynamism levels per view. Table 3 summarizes the outcome of multiple non-parametric Kruskal-Wallis tests in detail. Note that the mean value of each level of scene dynamism can be compared to other levels within the same view but they cannot be compared to other views. The reason is that the survey format only allowed participants to compare different levels of scene dynamism within each view, and asked participants to rank order then rather than evaluate them on a continuous response scale. This test revealed the effect of dynamism as the independent variable on satisfaction with view as the response variable was significant (*$p<0.01$*) to all 12 views (Hypothesis 1 confirmed) in this experiment.

Table 3. Results derived from Kruskal Wallis tests between three scenes dynamism (high, middle and low) in each view. Note that, same as non-parametric test, one-way ANOVA test reported significant differences for all 12 views.

ID	Sample	Sample	Mean	STDEV	p-value	<0.05
View 1	High	54	2	0.95	0.0001	Sig.
	Medium	54	2.33	0.67		
	Low	54	1.66	0.67		
View 2	High	54	1.11	0.32	0.0000	Sig.
	Medium	54	2.11	0.42		
	Low	54	2.66	0.67		
View 3	High	54	1.12	0.33	0.0000	Sig.
	Medium	54	2.5	0.50		
	Low	54	2.38	0.70		
View 4	High	54	1.44	0.84	0.0000	Sig.
	Medium	54	2	0.67		
	Low	54	2.55	0.50		
View 5	High	54	1.22	0.42	0.0000	Sig.
	Medium	54	2.77	0.42		
	Low	54	2	0.67		
View 6	High	54	2.44	0.69	0.0000	Sig.
	Medium	54	1.88	0.88		
	Low	54	1.66	0.67		
View 7	High	54	1.66	0.82	0.0001	Sig.
	Medium	54	2	0.47		
	Low	54	2.33	0.95		
View 8	High	54	1.77	0.70	0.0000	Sig.
	Medium	54	1.88	1.00		
	Low	54	2.33	0.47		

Table 3. (continued)

ID	Sample	Sample	Mean	STDEV	p-value	<0.05
View 9	High	54	2.33	0.47	0.0000	Sig.
	Medium	54	2.55	0.31		
	Low	54	1.11	0.69		
View 10	High	60	2.7	0.64	0.0000	Sig.
	Medium	60	2.1	0.54		
	Low	60	1.	0.40		
View 11	High	48	2.12	0.79	0.0000	Sig.
	Medium	48	2.5	0.71		
	Low	48	1.37	0.49		
View 12	High	60	2.4	0.81	0.0000	Sig.
	Medium	60	1.7	0.91		
	Low	60	1.9	0.54		

Since the impact of dynamism varies in different views, we decided to look at each view individually. The first 4 rows in table 3 are devoted to typical urban views with relatively low percent natural content, ranging from 23% to 37%. By examining the preference ranked mean values of high, low and middle dynamism of view 2 *(V2.H: M=1.11, SD=0.32)*, view 3 *(V3.H: M=1.12, SD=0.33)* and view 4 *(V4.H: M=1.44, SD=0.84)*, it was discovered V3.H, V2H and V4.H were significantly less preferred ($p<0.01$) than the other two medium and low level of dynamism within each view. On View 1, that is the most urban view in this study with the least area of natural elements (23%), the greatest mean value among three levels of scene motion was the medium dynamic one *(V1.M: M=2.33, SD=0.67)* and the least mean value belonged to the low dynamic view *(V1.L: M=1.66, SD=0.67)*. Moving forward to view 5 and 7 that depict urban areas with city activity (same as V1, V2, V3, V4), views with high level of dynamism gained the least mean value, which explains that high level of dynamism (*V5.H: M=1.22, SD=0.42,* *V7.H: M=1.66, SD=0.82)* was preferred the least among three levels of activities in these two views (Hypothesis 2 confirmed). On V6 which mostly show human activity in an urban area that has approximately same area of nature and human fabricated environment accompanied by water, high level of dynamism (*V6.H: M=2.44, SD=0.69)* was preferred the most over other two levels of activity. Views with over 65% of natural areas are V8, V9, V10, V11 and V12 at the bottom of table 3. In V8 that shows human activity in an urban area accompanied by water with no trace of traffic flow (same as V6), low level of scene dynamism H (*V8.L: M=2.33, SD=0.47)* significantly ($p<0.01$) was preferred over other three levels of scene dynamism within the view. In V9, that mostly represents human activities and pedestrians with no signs of cars and traffic flow (same as V6 and V8), while the mean value of V9.H (*V9.H: M=2.33, SD=0.47)* and V9.M (*V9.M: M=2.55, SD=0.69)* are so close to each other, V9.M was significantly ($p<0.01$) preferred over other two levels of scene motion.

V10, V11 and V12 are 100% natural views that were employed in this study to identify the impact of dynamism on view satisfaction within natural views. In V10 and V12, as it was supposed at the beginning of the article, high level of scene motion was significantly preferred ($p<0.01$) in V10.H (*V10.H: M=2.7, SD=0.64)* V12.H (*V12.H: M=2.4, SD=0.80*) (Hypothesis 4 confirmed). In V11, while the mean values of middle (*V1.M: M=2.5, SD=0.71*) and high (*V11.H: M=2.1, SD=0.78*) level of scene dynamism are so close, the middle one was significantly ($p<0.01$) selected as the most preferred view. According to table 3, the least mean value among the three levels of scene dynamism in V10 and V11, is the low dynamic view (*V10.L: M=1.20, SD=0.40, V11.L: M=1.37,* *SD=0.49*). In V12, the mean value of the subjects' response for low and medium level of scene dynamism are fairly close (*V12.L: M=1.90, SD=0.54, V12.M: M=1.70, SD=0.90*). In this section pair-wise non-parametric Mann-Whitney U tests were conducted to study all possible comparisons between levels of scene dynamism in each view. To show the effect of dynamism on mean values of subjects' ranking, we managed to show distribution of the data in each view on density plots with mean value axis (figure 8 & 9). By looking at the density plots, the difference among mean values of subjects' responses can be easily identified. The non-parametric Mann-Whitney U test recognized significant or non-significant differences among three levels of scene dynamism in each view. There will be 3 comparisons for each view as follows: High-Low, High-Medium and Medium-Low.

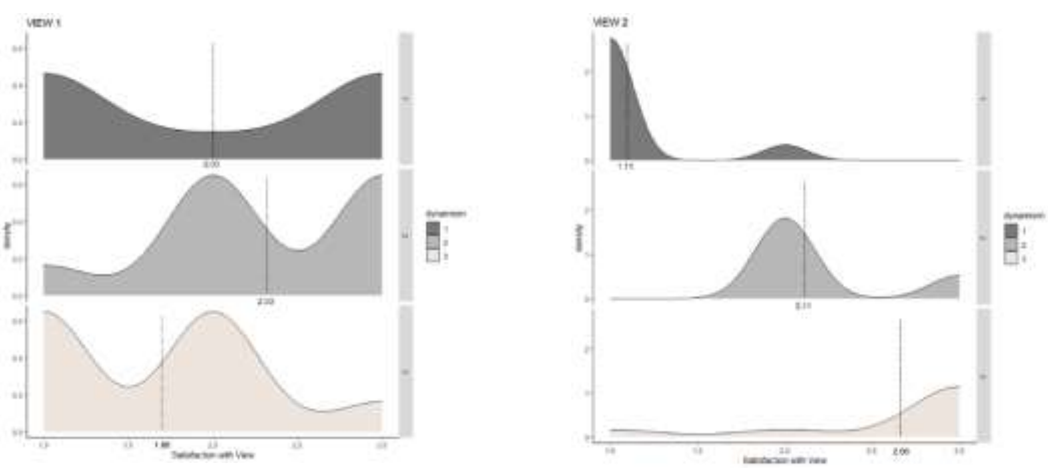


Figure 8. Density plots showing the distribution of the response variable in each scene dynamism within each view along with the dotted line that represents the mean value of subjective rankings. 1, 2 and 3 represents high, middle and low level of scene dynamism respectively.

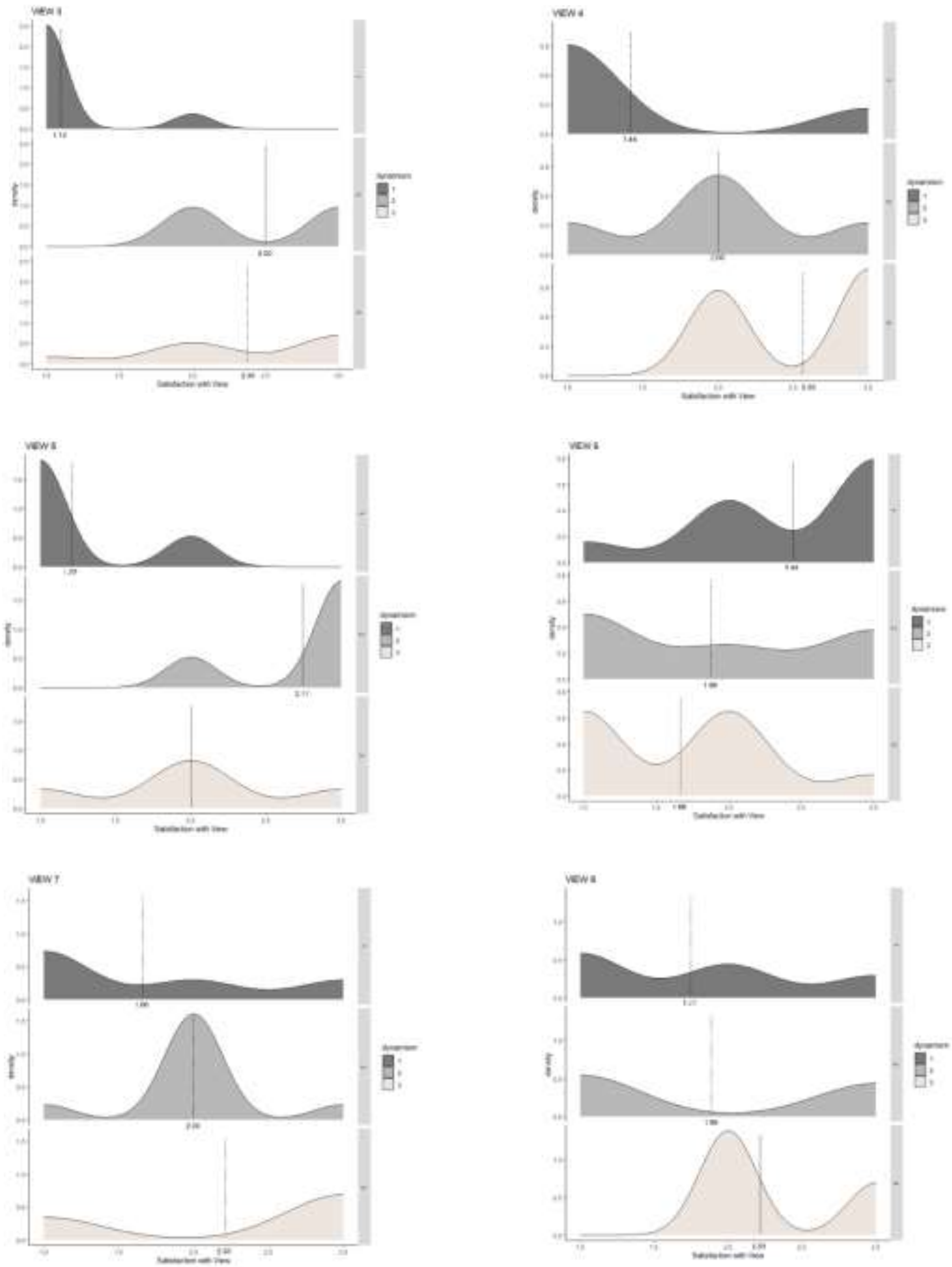


Figure 9. Density plots showing the distribution of the response variable in each scene dynamism within each view along with the dotted line that represents the mean value of subjective rankings. 1, 2 and 3 represents high, middle and low level of scene dynamism respectively.

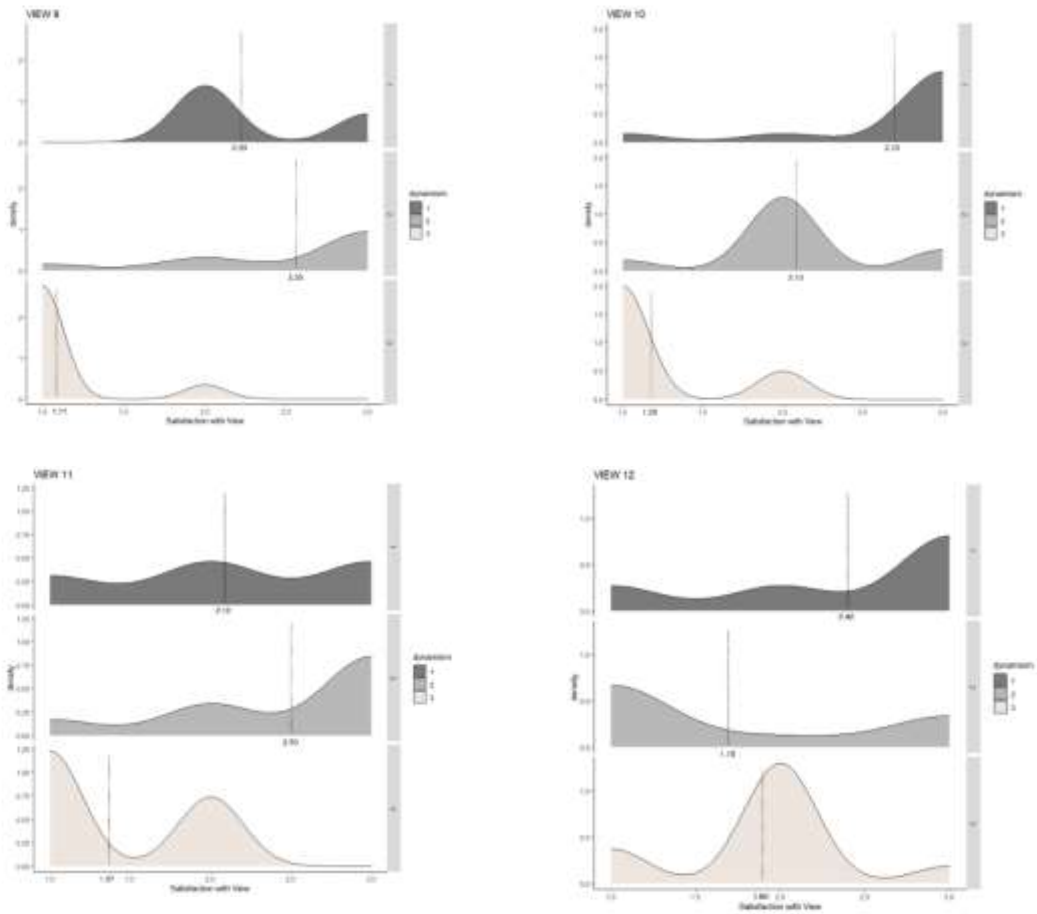


Figure 10. Density plots showing the distribution of the response variable in each scene dynamism within each view along with the dotted line that represents the mean value of subjective rankings. 1, 2 and 3 represents high, middle and low level of scene dynamism respectively.

Table 4 shows the results of 36 pairwise non-parametric Mann-Whitney tests for all possible comparisons between scene dynamism in each view. Initially, it was mentioned that V1.L obtained the least mean value (table 2). Low-Medium (*V1.L: M=1.66, SD=0.67, V1-M=2.33, SD=0.67)* was the only significant ($p<0.01$) comparison that was observed between levels of dynamism in V1 (table 4).

Although two significant differences (*$p<0.01$*) was found between high-low (*V3.H: M=1.12, SD=0.33, V3.L: M=2.37, SD=0.70)* and medium-high *(V3.H: M=2.5, SD=0.50,* *V3.H: M=1.12, SD=0.33),* no significant difference (*p>0.05*) was observed between low and medium level of dynamism in V3. All pairwise comparisons found to be significantly different (*p<0.01*) in V2, V4 and V5 (typical urban views with different percentage of natural areas) with the least mean value for the view with high level of scene motion (table 4). In V6 that depicts urban area with human activity and pedestrians as described before (with no sign of traffic flow), because of the marginal difference in mean values, Low-Med (*V6.M: M=1.88, SD=0.88, V6.L: M=1.66, SD=0.67)* was the only insignificant comparison that was observed among three levels of scene dynamism. V7, similar to other urban views with traffic flow, cars and street, comparisons between High-Low (*V7.H: M=1.66, SD=0.82, V7.M: M=2.33, SD=0.95)* and High-Med (*V7.H: M=1.66, SD=0.82, V7.L: M=2.00, SD=0.47)* were found to be significantly different (*p<0.01*). The only insignificant comparison (*p<0.01*) in V8, was observed between high and middle (*V8.H: M=1.77, SD=0.70, V8.M: M=1.88, SD=1.00)* because of the minor difference in the mean values. Similar to V8, Mann-Whitney non-parametric test showed comparisons to be significantly different (*p<0.01*) in V8 and V9 (table 4) when High-low (*V9.H: M=2.33, SD=0.47, V9.L: M=1.11, SD=0.31)* and low-medium (*V9.H: M=2.33, SD=0.47, V9.M: M=2.55, SD=0.69)* scene dynamism of these two views that that both represents urban area with pedestrians. According to table 2, V9 that is the last view with human activity in urban areas without any trace of traffic (similar to V6 and V8). In V10, V11, and V12, results from the significance test in table 4 show statistically significant different (*p<0.01*) mean values when high level of scene dynamism (*V10.H: M=2.70, SD=0.64, V11.H: M=2.12, SD=0.78, V12.H: M=2.40, SD=0.60)* was compared to the view with low level of dynamism (*V10.L: M=1.20, SD=0.40, V11.L: M=1.37, SD=0.49, V12.L: M=1.90, SD=0.54)* in all 100%-natural views (V10, V11 and V12).

Table 4. Pairwise Mann-Whitney U Test between all three comparisons (high-low, high-middle and low-middle) within scene dynamism of each view. View are ordered based percent nature area from the lowest to the highest (same as table 2).

ID	Dynamism	Sample	Mean	STDEV	U	p-value	<0.01*
View 1	High	54	2	0.95	951	0.0643	Not.
	Low	54	1.66	0.67			
	High	54	2	0.95	534	0.0643	Not.
	Medium	54	2.33	0.67			
	Low	54	1.66	0.67	294	0.0000	Sig.
	Medium	54	2.33	0.67			
View 2	High	54	1.11	0.32	39	0.0000	Sig.
	Low	54	2.66	0.67			
	High	54	1.11	0.32	0	0.0000	Sig.
	Medium	54	2.22	0.42			
	Low	54	2.66	0.67	1029	0.0068	Sig.
	Medium	54	2.22	0.42			
View 3	High	54	1.12	0.33	1101	0.0000	Sig.
	Low	54	2.37	0.70			
	High	54	1.12	0.33	1176	0.0000	Sig.
	Medium	54	2.5	0.50			
	Low	54	2.37	0.70	660	0.4229	Not.
	Medium	54	2.5	0.50			
View 4	High	54	1.44	0.84	1335	0.0000	Sig.
	Low	54	2.55	0.50			
	High	54	1.44	0.84	975	0.0000	Sig.
	Medium	54	2	0.67			
	Low	54	2.55	0.50	330	0.0000	Sig.
	Medium	54	2	0.67			

Table 4. (continued)

ID	Dynamism	Sample	Mean	STDEV	U	p-value	<0.01*
View 5	High	54	1.22	0.42	258	0.0000	Sig.
	Low	54	2	0.67			
	High	54	1.22	0.42	0	0.0000	Sig.
	Medium	54	2.77	0.42			
	Low	54	2	0.67	258	0.0000	Sig.
	Medium	54	2.77	0.42			
View 6	High	54	2.44	0.69	1227	0.0000	Sig.
	Low	54	1.66	0.67			
	High	54	2.44	0.69	1044	0.0074	Sig.
	Medium	54	1.88	0.88			
	Low	54	1.66	0.67	606	0.2219	Not.
	Medium	54	1.88	0.88			
View 7	High	54	1.66	0.82	1044	0.0058	Sig.
	Low	54	2.33	0.95			
	High	54	1.66	0.82	990	0.0145	Sig.
	Medium	54	2	0.47			
	Low	54	2.33	0.95	549	0.0769	Not.
	Medium	54	2	0.47			
View 8	High	54	1.77	0.70	330	0.0000	Sig.
	Low	54	2.33	0.47			
	High	54	1.77	0.70	609	0.2323	Not.
	Medium	54	1.88	1.00			
	Low	54	2.33	0.47	1041	0.0074	Sig.
	Medium	54	1.88	1.00			
View 9	High	54	2.33	0.47	0	0.0000	Sig.
	Low	54	1.11	0.32			
	High	54	2.33	0.47	882	0.1887	Not.
	Medium	54	2.55	0.70			
	Low	54	1.11	0.32	1428	0.0000	Sig.
	Medium	54	2.55	0.70			

Table 4. (continued)

ID	Dynamism	Sample	Mean	STDEV	U	p-value	<0.01*
View 10	High	60	2.7	0.64	1773	0.0000	Sig.
	Low	60	1.2	0.40			
	High	60	2.7	0.64	1356	0.0005	Sig.
	Medium	60	2.1	0.54			
	Low	60	1.2	0.40	165	0.0000	Sig.
	Medium	60	2.1	0.54			
View 11	High	48	2.12	0.79	222	0.0000	Sig.
	Low	48	1.37	0.50			
	High	48	2.12	0.70	753	0.0799	Not.
	Medium	48	2.5	0.71			
	Low	48	1.37	0.50	1083	0.0000	Sig.
	Medium	48	2.5	0.71			
View 12	High	60	2.4	0.80	1335	0.0006	Sig.
	Low	60	1.9	0.54			
	High	60	2.4	0.80	1299	0.0030	Sig.
	Medium	60	1.7	0.90			
	Low	60	1.9	0.54	1062	0.2484	Not.
	Medium	60	1.7	0.90			

II.5. Discussion

In this study, our first hypothesis regarding the view satisfaction being impacted by view dynamism was supported by the results in table 3 showing that the mean values of three levels of high, medium and low dynamism for all 12 views are significantly different (*$p<0.01$*) from each other. Taking a closer look at results of the pair-wise comparisons handed by the non-parametric Mann-Whitney test in table 4 revealed that not all the mean values impacted by dynamism in the same way. This made us provide the density plots to make it visually undemanding for observing where the true impact originates from. A major finding of this study was related to a common trend among views from urban areas with traffic flow of different level of dynamism (V2, V3, V4, V5 and V7) indicating that high level of dynamism in these types of views was preferred the least over low and medium dynamic levels. Another piece of evidence for this finding showed significant difference ($p<0.01$) when high level of dynamism was compared to low dynamic views in all V2, V3, V4, V5 and V7. 5 out of 6 of the urban views reported the least mean satisfaction value for the view with high level of dynamism.

This illustrates that urban views with low or medium level of dynamism were preferred over high dynamic urban views that represent traffic jam and congested streets. V1 that has the greatest pixel area covered by built environment reported different results compared to other urban views with traffic flow.

V1.L has the least sum of dynamic pixels (*sum of contour area < 80,000 & Mean of Contours = 617*) compared to other urban views in this experiment. The pixel measurement explains that V1.L is way static than other urban views with a marginal level of scene motion. When looking at video recorded from V1.L, hardly if ever marginal movements can be detected. This condition might depict a ghost town for participants that contributed to the least preferred view among three levels of dynamism in this specific view. According to sum of contours in figure 11, a great difference was found between sum of contours when low was compared to high and medium level of dynamism.

High
Sum of Contours = 16,708,035
Mean = 1,865

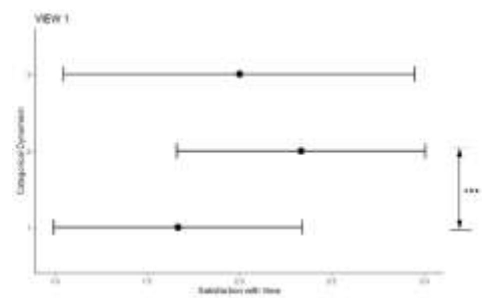
Medium
Sum of Contours = 7,166,304
Mean = 1,227

Low
Sum of Contours = 789,381
Mean = 617

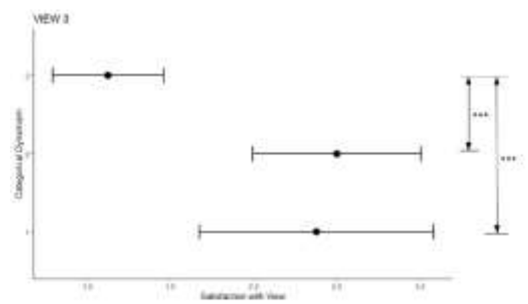
Figure 11. Some of contours and mean value of measured contours by Python for V1 indicates that the V1.L is almost static with a very low sum and mean of contours.

In V1, V3 and V5 the most preferred view among three levels of scene motion became the medium dynamic one (*V1.M: M=2.33, SD=0.67, V3.M: M=2.5, SD=0.50, V5.M: M=2.7, SD=0.42)*. This finding attests the result in V1 concluding that urban views with either no dynamism in traffic flow or high level of scene dynamism ensued from vehicular traffic are less preferred by occupants. The distinction between V1-V3-V5 and V2-V4-V7 is the static low scene dynamism with approximately no noticeable urban activity in the first group. As indicated in figure 12 & 13, the mean value of all measured contours by Python in V1.L, V3.L and V5.L are smaller than the same measurement of low scene dynamic views in V2.L, V4.L and V7.L. This might explains that V1.L, V3.L and V5.L depict a very static and motionless urban view that might look like a ghost town indicating that it may not be a safe place.

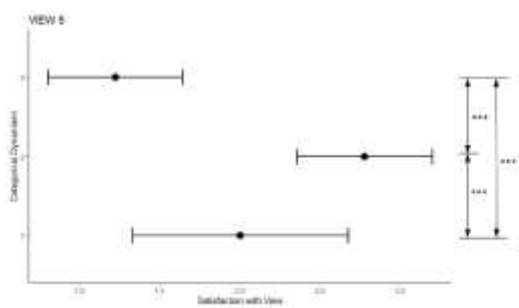
V6, V8 and V9 are three urban views which only depict human activity without traffic flow and cars. Since, the view with high level of activity for V6 was recorded during sunset, the video was rendered with a different colour and lighting condition compared to low and medium (*V6.L: M=1.66, SD=0.67, V6.M: M=1.88, SD=0.88)* level of scene dynamism in this view. This made two distinctions between high dynamic view and other two medium and low scene dynamism in V6 (Figure 14 & 15). One of the differences is the warmer colour specially on the front building and the other one is the sparkles on the water that added to both dynamism and attractiveness of the view. Figure 8 shows that the view with medium level of scene dynamism measured by Python has lower human activity than view with greater sum of contour and mean of contour.



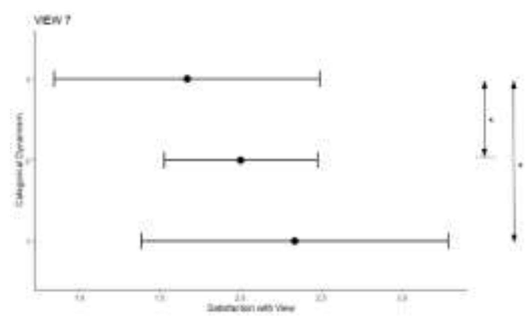
Medium = 2.33
Low dynamism contour mean value =617



Medium = 2.33
Low dynamism contour mean value =1233

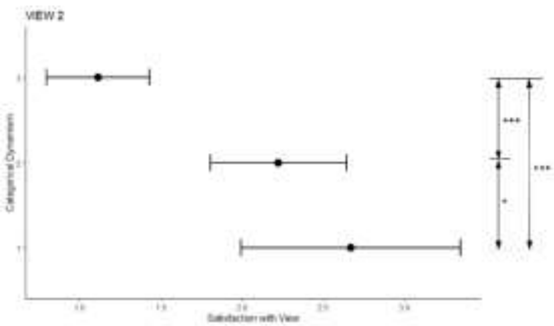


Medium = 2.77
Low dynamism contour mean value =1157

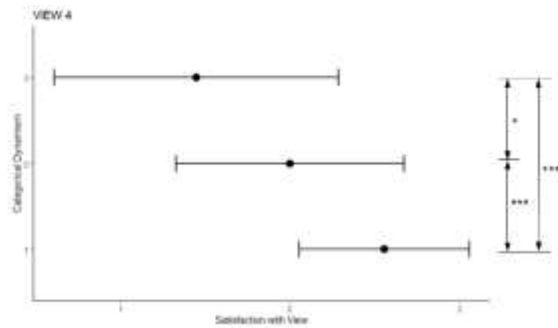


Low = 2.33
Low dynamism contour mean value =1254

Figure 12.Horizontal error bars showing both the mean value of subjective responses of scene dynamism in each view and significant pairwise comparisons. 1, 2, and 3 in each figure denote low, medium and high scene dynamism respectively.



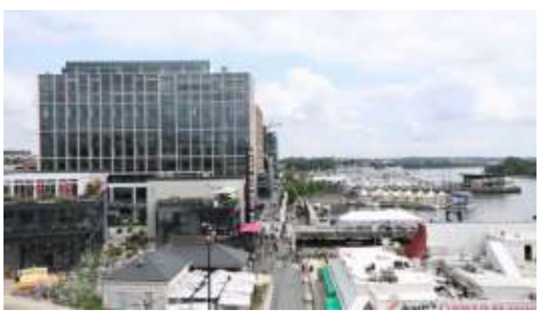
Low = 2.66
Low dynamism contour mean value =1533



Low = 2.55
Low dynamism contour mean value =3802

Figure 13.Horizontal error bars showing both the mean value of subjective responses of scene dynamism in each view and significant pairwise comparisons. 1, 2, and 3 in each figure denote low, medium and high scene dynamism respectively.

V6-A



Sum of contours = 1,935,999

Mean of contours = 591

V6-B

Sum of contours = 6,073,085

Mean of contours = 795

Figure 14. Difference in colour and lighting condition in View 6. Right is the High level of scene dynamism and left is the medium and low. V8-C and V8-D represent the medium and low level of scene dynamism in View 8.

V8-C

Sum of contours = 35,335,277

Mean of contours = 1616

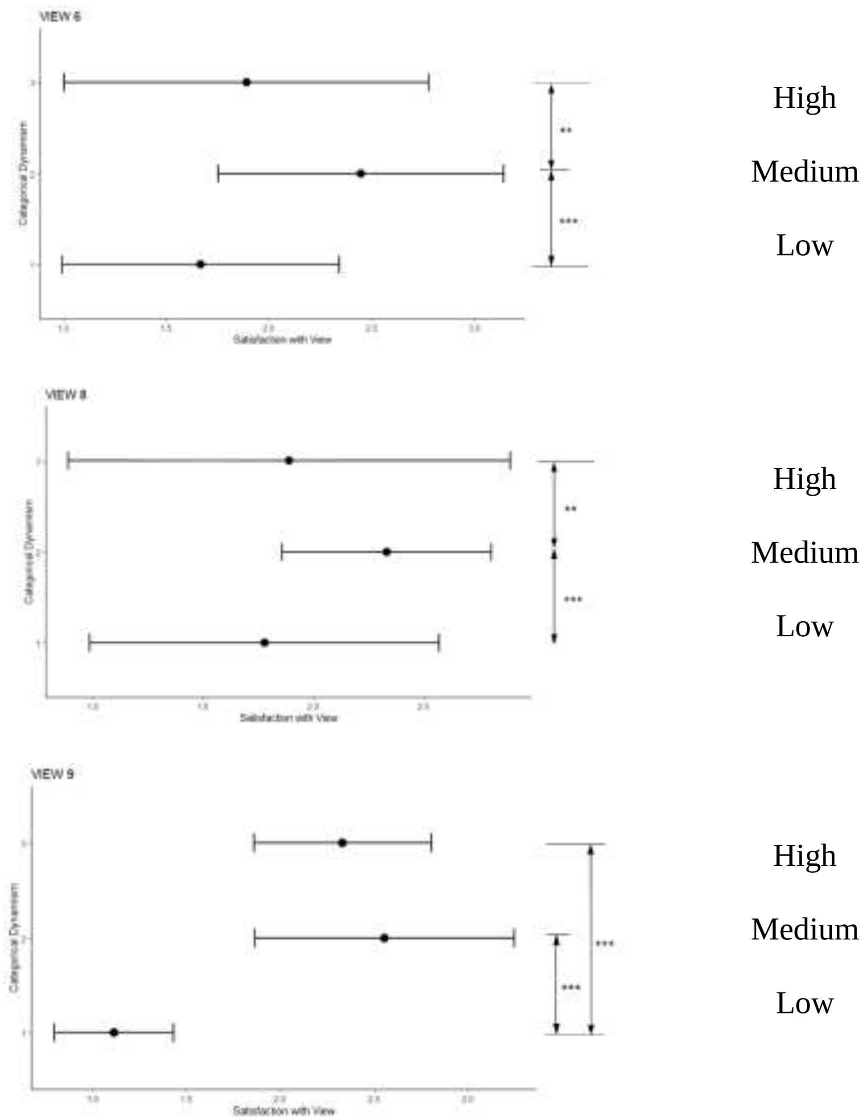
V8-D

Sum of contours = 69,877,639

Mean of contours = 1690

Figure 15. Difference in colour and lighting condition in View 6. Right is the High level of scene dynamism and left is the medium and low. V8-C and V8-D represent the medium and low level of scene dynamism in View 8.

This discrepancy in V6 indicates that Python could not distinguish dynamism ensued from human activity and sparkles on water. In this case, if we establish the results from V6 based on observed human activity, view with medium level of human activity (figure 14-B) is preferred over the high dynamic view showing people flocking in the urban area (figure 14-A). Same as V6, we observed same discrepancy in V8 because of the existence of water in the view and sunshine on its surfaces that led to having greater number for both sum of contours and mean value of the contour area in the view with almost no human activity.



***(p<0.01)**
****(p<0.001)**
*****(p<0.0001)**

Figure 16. Bar plots showing the mean value and p-value of pair-wise non-parametric Mann Whitney test between levels of dynamism for view 6, 8 and 9 showing pedestrians and no vehicular traffic.

Since a considerable area of the view is occupied with water, sparkles caused by sunlight added greatly to the number of dynamic pixels (*sum of contour area < 60,000,000 & Mean of Contours = 1690).* To this end, V8.H (*V8.H: M=1.77, SD=0.70)* that has no human activity gained the least mean value of subjective preference rankings and V8.L

(*V8.L: M=2.33, SD=0.47)* that was identified as a low dynamic view with a medium level of human and natural activity was preferred the most. Without considering the error in measuring the dynamism caused by sparkles of water, it is understood that medium level of human activity is preferred the most in urban views with only human activity and no sign of traffic (hypothesis 3 confirmed). Results from Mann-Whitney test on V9 show same preference as observed in V8 and V6.

The fact that our data collection, scene selection and video recording were accomplished during COVID-19 Pandemic in 2020, might impacted our research study. Although we did our best to record videos in a way that they become easily distinguishable by their three levels of scene dynamism in each view, some of the levels might be close but slightly different from each other.

For instance, V1 in which no significant difference (table 4) *($p<0.01$, $U=534$)* was found between high and medium level of scene dynamism (*V1.H: M=2.0, SD=0.95, V1.M: M=2.11, SD=0.67)* because medium and high level of scene dynamism were almost identical. To prove that, Python script reported close mean of contours for these two levels (*V1.H: 1868, V1.M: 1227*) for high and medium level of scene dynamism in V1. This condition might be an explanation for insignificant differences found in V3 and V7 when medium and low level of scene dynamism were compared to each other (table 4). As a result of existing water in V6 and V8 the discrepancy explained above happened but python worked very well for V9 that did not have water in it. Figure 16 indicates a same trend for preference ranking for V6, V8 and V9 by having the medium level of scene motion as the most preferred one and low as the least preferred view among three levels of dynamism. In 3 out of 3 urban views with human activity and without vehicular traffic, medium level of scene motion was selected as the most preferred view showing that having a moderate dynamism in preferred for office views. Initially it was presumed that high level of scene dynamism will be preferred the most in urban views without any vehicular traffic (hypothesis 3 was not supported).

V10, V11 and V9 that are 100% natural views as described in figure 4 & 5 with different level of scene dynamism. By interpreting the result of Mann-Whitney U test in table 4 and looking as density plots in figure 8 and 9, it is revealed that 2 out of 3 100%-natural views gained the greatest mean value of subjective rankings for their high level of dynamism. In V10 (*V10.H: M=2.1, SD=0.54)* and V12 (*V12.H: M=2.4, SD=0.80)*, as it was assumed (hypothesis 4 confirmed), views with high level of dynamism was selected as the most preferred one.

Although no significant difference (*p<0.01, U=753*) was observed between high and medium level of scene motion in V1, it was the only view among 100%-natural views that its medium level of dynamism was selected as the most preferred view (*V11.M: M=2.5, SD=0.71)*.

CHAPTER III

III.1. Conclusion and Discussion

This research arises an important set of issues for designer and daylight researchers. With respect to the major findings of this research, dynamism was found to be a good predictor for view satisfaction with different content. This study adopted a new methodology and contributed to the body of knowledge in terms of the following: (i) it proposes a new predictor variable that had not investigated before in research studies on environmental preference, scene satisfaction, and view satisfaction. Considering dynamism as an independent variable along with scene content might give different results compared to findings of experiments that only considered scene content. (ii) it proposes a new method that was designed to test the level of scene motion by pixel measurements that has not been used before for this specific purpose. The method can be used even by non-professional to assess view quality of different view contents.

III.2. Future Studies and Limitation

For further studies in future, having a wide spectrum of dynamism in different scene contents would be a worthwhile attempt to see how satisfaction changes in a wider spectrum when other levels other than high, low and medium are considered. This expansion of the dynamism spectrum happening in different scene contents may indicate that for further levels of scene dynamism in different scene content satisfaction shows a different prediction of the view quality. This expansion will help us to examine the precision and tactfulness of the proposed method with a broader database and metrics used in this study. The future metric may be prone to eliminate the error of the current study for V6 and V8 in which water sparkles added to dynamism value measure by Python where Python could not differentiate between dynamism ensued from water sparkles and human activity. The refinement of the quantitative measure for dynamism may identify the source of dynamism such as water, trees, cars and people to find a new relationship between human perceptions of dynamism and view satisfaction. Although it has been investigated that participants can disregard cofounding variables when assessing the view (Matusiak & Klockner, 2016), the future project in this scope should come up with a method in which confounding variables such as weather condition are to be eliminated.

We used office and work setting as a stimuli and asked participants as the office occupants to imagine that they are ranking the view through their office window. Considering other options such as bedroom, classrooms and/or nursing homes etc. may discover new findings for the relationship between view satisfaction as the dependent variable and dynamism as the independent variable. Since cultural perception of value surrounding view quality and content may differ substantially across the globe, this aspect of the study offers a robust response with higher confidence and replicability.

III.3. Key Findings

This study examined human subjects' satisfaction with view under 3 different levels of scene dynamism (high, middle and low) measured by python in 12 recorded views with different scene contents. A sample of 60 human subjects, who were asked to rank views from the most preferred (3) to the least preferred (1), examined a repeated-measures design on an online survey to investigate the relationship between view dynamism and satisfaction with view. The following conclusions are reported to determine which level of scene motion is preferred the most among different scene contents.

1. Scene dynamism found to be a good predictor for view satisfaction. Changes in the scene dynamism in views with different content impact subjective responses on view satisfaction.
2. In urban views with vehicular traffic, high level of scene dynamism was selected as the least preferred view among three levels of dynamism. High level of scene dynamism in urban views showing vehicular traffic flow were significantly less preferred over low dynamic views in 5 out of 6 urban scenes.
3. In urban views without any vehicular traffic representation, the medium level of scene motion is the most preferred view. This finding show that empty urban views depict ghost towns negatively impact office occupants' satisfaction.
4. Natural views with high and medium level of scene motion were preferred over low level of view dynamism. All comparisons between high and low level of dynamism found to be significantly different in 100% natural views.

REFERENCES CITED

Abboushi, B., Elzeyadi, I., Wymelenberg, K. V. D., Taylor, R., Sereno, M., & Jacobsen, G. (2020). Assessing the Visual Comfort, Visual Interest of Sunlight Patterns, and View Quality under Different Window Conditions in an Open-Plan Office. *LEUKOS*, *0*(0), 1–17. https://doi.org/10.1080/15502724.2020.1785309

Al Horr, Y., Arif, M., Kaushik, A., Mazroei, A., Katafygiotou, M., & Elsarrag, E. (2016). Occupant productivity and office indoor environment quality: A review of the literature. *Building and Environment*, *105*, 369–389. https://doi.org/10.1016/j.buildenv.2016.06.001

Al-Akl, N. M., Karaan, E. N., Al-Zein, M. S., & Assaad, S. (2018). The landscape of urban cemeteries in Beirut: Perceptions and preferences. *Urban Forestry & Urban Greening*, *33*, 66–74. https://doi.org/10.1016/j.ufug.2018.04.011

American Time Use Survey Charts Page. (n.d.). Retrieved September 15, 2020, from https://www.bls.gov/tus/charts.htm

An, M., Colarelli, S. M., O'Brien, K., & Boyajian, M. E. (2016). Why We Need More Nature at Work: Effects of Natural Elements and Sunlight on Employee Mental Health and Work Attitudes. *PloS One*, *11*(5), e0155614-. https://doi.org/10.1371/journal.pone.0155614

Benfield, J. A., Rainbolt, G. N., Bell, P. A., & Donovan, G. H. (2015). Classrooms With Nature Views: Evidence of Differing Student Perceptions and Behaviors. *Environment and Behavior*, *47*(2), 140–157. https://doi.org/10.1177/0013916513499583

Boubekri, M., & Haghighat, F. (1993). Windows and Environmental Satisfaction: A Survey Study of an Office Building. *Indoor and Built Environment*, *2*(3), 164–172. https://doi.org/10.1177/1420326X9300200305

Bringslimark, T., Hartig, T., & Grindal Patil, G. (2011). Adaptation to Windowlessness: Do Office Workers Compensate for a Lack of Visual Access to the Outdoors? *Environment and Behavior*, *43*(4), 469–487. https://doi.org/10.1177/0013916510368351

Brown, T. C., & Daniel, T. C. (1991). Landscape Aesthetics of Riparian Environments: Relationship of Flow Quantity to Scenic Quality Along a Wild and Scenic River. *Water Resources Research*, *27*(8), 1787–1795. https://doi.org/10.1029/91WR00975

Butler, D. L., & Biner, P. M. (1989). Effects of Setting on Window Preferences and Factors Associated with Those Preferences. *Environment and Behavior*, *21*(1), 17–31. https://doi.org/10.1177/0013916589211002

Cole, D. N., & Hall, T. E. (2010). Experiencing the Restorative Components of Wilderness Environments: Does Congestion Interfere and Does Length of Exposure Matter? *Environment and Behavior*, *42*(6), 806–823. https://doi.org/10.1177/0013916509347248

Collins, Belinda L. (2016). Review of the psychological reaction to windows: *Lighting Research & Technology*. https://doi.org/10.1177/14771535760080020601

Collins, Belinda Lowenhaupt. (1975). *Windows and people: A literature survey : psychological reaction to environments with and without windows*. USDeptof Commerce, National Bureau of Standards : For sale by the Suptof Docs, USGovtPrintOff.

Devices used for social media in the U.S. 2019. (n.d.). Statista. Retrieved January 30, 2021, from https://www.statista.com/statistics/184318/daily-social-media-activities-of-us-adults-device/

Di Dio, C., Ardizzi, M., Massaro, D., Di Cesare, G., Gilli, G., Marchetti, A., & Gallese, V. (2016). Human, Nature, Dynamism: The Effects of Content and Movement Perception on Brain Activations during the Aesthetic Judgment of Representational Paintings. *Frontiers in Human Neuroscience*, *9*. https://doi.org/10.3389/fnhum.2015.00705

Download Python. (n.d.). Python.Org. Retrieved May 4, 2021, from https://www.python.org/downloads/

Download R-3.6.2 for Windows. The R-project for statistical computing. (n.d.). Retrieved May 5, 2021, from https://cran.r-project.org/bin/windows/base/old/3.6.2/

Finnegan, M. C., & Solomon, L. Z. (1981). Work Attitudes in Windowed vs. Windowless Environments. *The Journal of Social Psychology*, *115*(2), 291–292. https://doi.org/10.1080/00224545.1981.9711674

Gibson, J. J. J. J. (1979). *The ecological approach to visual perception*. Houghton Mifflin.

Glen P. Nimnicht. (1966). Windows and School Design. *Phi Delta Kappan*, *47*(6), 305–307.

Hartig, T., Böök, A., Garvill, J., Olsson, T., & Gärling, T. (1996). Environmental influences on psychological restoration. *Scandinavian Journal of Psychology*, *37*(4), 378–393. https://doi.org/10.1111/j.1467-9450.1996.tb00670.x

Heerwagen, J. H., & Orians, G. H. (1986). Adaptations to Windowlessness: A Study of the Use of Visual Decor in Windowed and Windowless Offices. *Environment and Behavior*, *18*(5), 623–639. https://doi.org/10.1177/0013916586185003

Heft, H., & Nasar, J. L. (2000). Evaluating Environmental Scenes Using Dynamic Versus Static Displays. *Environment and Behavior*, *32*(3), 301–322. https://doi.org/10.1177/00139160021972540

Hellinga, H., & Hordijk, T. (2014). The D&V analysis method: A method for the analysis of daylight access and view quality. *Building and Environment*, *79*, 101–114. https://doi.org/10.1016/j.buildenv.2014.04.032

Herzog, T. R., & Gale, T. A. (1996). Preference for Urban Buildings as a Function of Age and Nature Context. *Environment and Behavior*, *28*(1), 44–72. https://doi.org/10.1177/0013916596281003

Herzog, T. R., & Shier, R. L. (2000). Complexity, Age, and Building Preference. *Environment and Behavior*, *32*(4), 557–575. https://doi.org/10.1177/00139160021972667

Hetherington, J., Daniel, T. C., & Brown, T. C. (1993). Is motion more important than it sounds?: The medium of presentation in environment perception research. *Journal of Environmental Psychology*, *13*(4), 283–291. https://doi.org/10.1016/s0272-4944(05)80251-8

Hull, R. B., & Stewart, W. P. (1992). Validity of photo-based scenic beauty judgments. *Journal of Environmental Psychology*, *12*(2), 101–114. https://doi.org/10.1016/s0272-4944(05)80063-5

Kaplan, R. (1989). *The experience of nature: A psychological perspective*. Cambridge University Press.

Kaplan, R. (1993). The role of nature in the context of the workplace. *Landscape and Urban Planning*, *26*(1–4), 193–201. https://doi.org/10.1016/0169-2046(93)90016-7

Kaplan, R. (2001). The Nature of the View from Home: Psychological Benefits. *Environment and Behavior*, *33*(4), 507–542. https://doi.org/10.1177/00139160121973115

Kaplan, R., Kaplan, S., & Brown, T. (1989). Environmental Preference: A Comparison of Four Domains of Predictors. *Environment and Behavior*, *21*(5), 509–530. https://doi.org/10.1177/0013916589215001

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, *15*(3), 169–182. https://doi.org/10.1016/0272-4944(95)90001-2

Kaplan, S., Kaplan, R., & Wendt, J. S. (1972). Rated preference and complexity for natural and urban visual material. *Perception & Psychophysics*, *12*(4), 354–356. https://doi.org/10.3758/BF03207221

Keighley, E. C. (1973a). Visual requirements and reduced fenestration in offices—A study of multiple apertures and window area. *Building Science*, *8*(4), 321–331. https://doi.org/10.1016/0007-3628(73)90017-0

Keighley, E. C. (1973b). Visual requirements and reduced fenestration in office buildings—A study of window shape. *Building Science*, *8*(4), 311–320. https://doi.org/10.1016/0007-3628(73)90016-9

KFIR, I. Z., & MUNEMOTO, J. (2003). EVALUATION OF THE VIEW FROM THE DWELLING UNITS ON MAN MADE ISLANDS IN OSAKA BAY: Photos analysis of the preferred view using binary recursive partitioning in relation to satisfaction with the views. *Nihon Kenchiku Gakkai Keikakukei Ronbunshū*, *68*(563), 195–203. https://doi.org/10.3130/aija.68.195_1

Kim, T. K., & Park, J. H. (2019). More about the basic assumptions of t-test: Normality and sample size. *Korean Journal of Anesthesiology*, *72*(4), 331–335. https://doi.org/10.4097/kja.d.18.00292

Leather, P., Pyrgas, M., Beale, D., & Lawrence, C. (1998). Windows in the Workplace: Sunlight, View, and Occupational Stress. *Environment and Behavior*, *30*(6), 739–762. https://doi.org/10.1177/001391659803000601

Lumley, T., Diehr, P., Emerson, S., & Chen, L. (2002). The importance of the normality assumption in large public health data sets. *Annual Review of Public Health*, *23*, 151–169. https://doi.org/10.1146/annurev.publhealth.23.100901.140546

Markus, T. A. (1967). The function of windows—A reappraisal. *Building Science*, *2*(2), 97–121. https://doi.org/10.1016/0007-3628(67)90012-6

Matusiak, B. S., & Klockner, C. A. (2016). How we evaluate the view out through the window. *Architectural Science Review*, *59*(3), 203–211. https://doi.org/10.1080/00038628.2015.1032879

OpenCV. (n.d.). OpenCV. Retrieved May 8, 2021, from https://opencv.org/

Raanaas, R. K., Patil, G. G., & Hartig, T. (2012). Health benefits of a view of nature through the window: A quasi-experimental study of patients in a residential rehabilitation center. *Clinical Rehabilitation*, *26*(1), 21–32. https://doi.org/10.1177/0269215511412800

Rockcastle, S., & Andersen, M. (2014). Measuring the dynamics of contrast & daylight variability in architecture: A proof-of-concept methodology. *Building and Environment*, *81*, 320–333. https://doi.org/10.1016/j.buildenv.2014.06.012

Rudd, A., & Bergey, D. (2014). *Ventilation System Effectiveness and Tested Indoor Air Quality Impacts* (DOE/GO-102014-4362). National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/1126286

Ruys, T. (1970). *Windowless offices.* University of Washington.

Sgouramani, H., Moutoussis, K., & Vatakis, A. (2019). Move Still: The Effects of Implied and Real Motion on the Duration Estimates of Dance Steps. *Perception*, *48*(7), 616–628. https://doi.org/10.1177/0301006619854914

Shafer, E. L., & Brush, R. O. (1977). How to measure preferences for photographs of natural landscapes. *Landscape Planning*, *4*, 237–256. https://doi.org/10.1016/0304-3924(77)90027-2

Sommer, R. (1974). *Tight spaces: Hard architecture and how to humanize it*. Prentice-Hall, Inc.

Spehar, B., & Taylor, R. P. (2013). *Fractals in art and nature: Why do we like them? 8651,* 865118. https://doi.org/10.1117/12.2012076

Stewart, T. R., Middleton, P., Downton, M., & Ely, D. (1984). Judgments of photographs vs. Field observations in studies of perception and judgment of the visual environment. *Journal of Environmental Psychology*, *4*(4), 283–302. https://doi.org/10.1016/s0272-4944(84)80001-8

Taylor, R. P. (2006). Reduction of Physiological Stress Using Fractal Art and Architecture. *Leonardo*, *39*(3), 245–251. https://doi.org/10.1162/leon.2006.39.3.245

Taylor, R., Spehar, B., Hagerhall, C., & Van Donkelaar, P. (2011). Perceptual and Physiological Responses to Jackson Pollock's Fractals. *Frontiers in Human Neuroscience, 5*. https://doi.org/10.3389/fnhum.2011.00060

Trøstrup, C. H., Christiansen, A. B., Stølen, K. S., Nielsen, P. K., & Stelter, R. (2019). The effect of nature exposure on the mental health of patients: A systematic review. *Quality of Life Research*, *28*(7), 1695–1703. https://doi.org/10.1007/s11136-019-02125-9

Tuaycharoen, N., & Tregenza, P. (2005). Discomfort glare from interesting images. *Lighting Research & Technology*, *37*(4), 329–338. https://doi.org/10.1191/1365782805li147oa

Turan, I., Chegut, A., Fink, D., & Reinhart, C. (2021). *Development of View Analysis Metrics and Their Financial Impacts on Office Rents* (SSRN Scholarly Paper ID 3784759). Social Science Research Network. https://doi.org/10.2139/ssrn.3784759

Ulrich, R. S. (1984). View through a window may influence recovery from surgery. *Science*, *224*(4647), 420–421. https://doi.org/10.1126/science.6143402

Ulrich, Roger S. (1981). Natural Versus Urban Scenes: Some Psychophysiological Effects. *Environment and Behavior*, *13*(5), 523–556. https://doi.org/10.1177/0013916581135001

Ulrich, Roger S., Simons, R. F., Losito, B. D., Fiorito, E., Miles, M. A., & Zelson, M. (1991). Stress recovery during exposure to natural and urban environments. *Journal of Environmental Psychology*, *11*(3), 201–230. https://doi.org/10.1016/S0272-4944(05)80184-7

U.S.: Number of full-time workers in August 2019. (n.d.). Statista. Retrieved September 15, 2020, from https://www.statista.com/statistics/192361/unadjusted-monthly-number-of-full-time-employees-in-the-us/

Van Den Wymelenberg, K., Inanici, M., & Johnson, P. (2010). The Effect of Luminance Distribution Patterns on Occupant Preference in a Daylit Office Environment. *LEUKOS*, *7*(2), 103–122. https://doi.org/10.1582/LEUKOS.2010.07.02003

Velarde, M. D., Fry, G., & Tveit, M. (2007). Health effects of viewing landscapes – Landscape types in environmental psychology. *Urban Forestry & Urban Greening*, *6*(4), 199–212. https://doi.org/10.1016/j.ufug.2007.07.001

Ward Thompson, C., Roe, J., Aspinall, P., Mitchell, R., Clow, A., & Miller, D. (2012). More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning*, *105*(3), 221–229. https://doi.org/10.1016/j.landurbplan.2011.12.015

Wells, B. W. P. (1965). Subjective responses to the lighting installation in a modern office building and their design implications. *Building Science*, *1*(1), 57–68. https://doi.org/10.1016/0007-3628(65)90006-X

Wilson, L. M. (1972). Intensive care delirium. The effect of outside deprivation in a windowless unit. *Archives of Internal Medicine*, *130*(2), 225–226. https://doi.org/10.1001/archinte.130.2.225