CASE STUDY

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Biometric responses to green and complete street elements in Devens, Massachusetts

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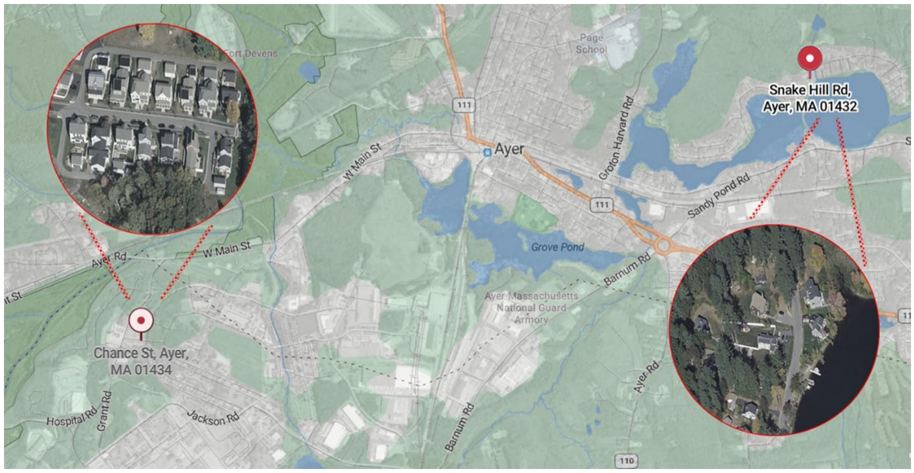
Abstract
Understanding human responses to the built environment is vital for effective urban design and sustainable transportation planning. This study presents a methodology that employs eye-tracking technology and facial expression analysis to compare conscious and unconscious reactions to street designs featuring differing levels of Green and Complete Street (GCS) elements. Conducted in Devens, Massachusetts, the research evaluates the impacts of current and prospective design modifications on human well-being. The study employed still images and videos of urban streetscapes, altered to reflect no, low, and high GCS levels. Unconscious reactions were recorded via remote eye-tracking and emotion recognition software, while conscious responses were gathered using an emoji-based self-report survey. High-GCS environments elicited stronger visual attention and more positive emotions, especially toward green infrastructure. The results highlight the importance of incorporating pedestrian-friendly, green elements into urban design.

Keywords Green and complete street elements (GCS), Walkability, Urban experience, Emotional responses

1 Introduction

The renewed interest in green and complete street design has gained momentum in light of COVID-19's dramatic impact on people's activities and their use of private and public spaces [1–3]. During the lockdown phase of the pandemic, neighborhoods were filled with people staying home, working remotely, and attending school virtually. Bristowe and Heckert's [1] review of Green Infrastructure use during the pandemic found a notable increase in the utilization and appreciation of neighborhood Green Infrastructure, emphasizing its health benefits, such as stress relief. In recent years, cities worldwide have embraced urban design modifications to promote active mobility, such as cycling and walking, fostering human health and well-being [4]. Indeed, COVID-19 has highlighted the significance of urban and street design research in understanding how people engage with their surrounding built environment.

This study contributes to this evolving discourse by examining how individuals react to and engage with neighborhoods and streetscapes, particularly in Devens, Massachusetts (Map 1). Devens, a former military base located 50 miles west of Boston, is managed



Map 1 Locus map showing the location of the examined roads.

by the Devens Enterprise Commission (DEC), which serves as the regulatory and permitting authority. The DEC has remained committed to sustainable redevelopment, ensuring people remain at the center of neighborhood and street design. Overseeing infrastructure planning, design, permitting, and construction, the DEC has prioritized the principles outlined in the Devens Reuse Plan [5, 6], which envisions an integrated, sustainable community comprising both commercial and residential spaces. In 2021, building upon its 2017 Complete Streets Policy, the DEC further reinforced its commitment to holistic, people-centered development by integrating Green Infrastructure and Complete Streets into a unified Green and Complete Streets (GCS) policy [7].

In this study, we seek to examine street design alternatives in alignment with DEC's GCS Policy, utilizing biometric data and eye-tracking technology to investigate conscious and unconscious responses of human from different background, to varying levels of GCS elements. By integrating data from eye-tracking glasses—capturing unconscious reactions—with self-reported questionnaire responses reflecting conscious perceptions, this study aims to evaluate how current and potential street design modifications impact human well-being.

Three key research questions guide this investigation:

(1) How do GCS elements impact viewers' unconscious attention and emotional responses?
(2) Are the responses from eye-tracking glasses consistent with participants' self-reported emotional assessments of GCS elements?
(3) How does a person's background or identity relate to these responses?

The next section of the paper provides a literature review on Green and Complete Streets, introducing readers to the study area. This follows an overview of biometric data applications and eye-tracking technologies in urban design research. These methodologies are then outlined in detail, describing the processes used to analyze both conscious and unconscious human responses to the built environment. Finally, the results are presented, offering insights into how this study contributes to the broader field of urban development and street design. The findings will be critically analyzed to address the research questions, followed by a discussion of the study's limitations and potential avenues for future research.

2 Literature review

2.1 Green and complete streets

With increased time at home during the COVID-19 pandemic, there has been a demonstrated need for more pedestrian and cycling-friendly environments [8]—something that complete street design has been looking at for many years (see [9], for a review). Complete streets typically include safe and accessible places for a range of transportation and mobility options, including cyclists, pedestrians, and a roadway design that accommodates vehicular uses, such as cars, trucks, multiple vehicles, and transit [10, 11]. Safety and accessibility for all road users are emphasized, rather than the more traditional auto-centric approach to street design, which has dominated development for the past eight decades since WWII [12].

Researchers have shown that complete street design elements have conscious and unconscious impacts on increasing physical activity [13] and promoting walkability [14]. In 2016, Wang, Chau, and Leung reviewed numerous studies to report on which physically built environment attributes influence and inspire walking and cycling. They note that the road traffic network and green view and landscape deserve more attention in street design [15]. Once implemented, complete streets can encourage a mode shift towards walking and cycling, reducing congestion, fuel usage, and decreasing carbon emissions [16].

The literature suggests that high settlement density and urban stressors (such as noise, fear of crime, and crowding) can impose psychological demands that people find excessive [17]. One outcome of mental fatigue may be increased outbursts of anger and even violence [18]. Contact with nature appears to help mitigate mental fatigue, which in turn may reduce aggression and violence [19]. Research in environmental psychology suggests that people's desire for nature, to be surrounded or to have any contact with nature, serves as an important adaptive function known as psychological restoration [17]. Contact with natural environments is an effective way of obtaining restoration from stress and mental fatigue compared to an ordinary built environment.

Green streets typically focus on how to utilize best practices in design and construction to incorporate environmentally responsible methods for stormwater management (A Case Study of Lancaster, PA, 2014), placement of street trees and vegetation [20], and the careful selection of materials used, including adopting use of recycled materials when possible [21]. The benefits of incorporating green infrastructure directly into the street right-of-way have been shown to reduce the urban heat island effect, stormwater run-off, traffic speed, and urban noise, and assist in improving quality of life [22].

In a systemic review of the hierarchy of walking needs, Paydar and Fard [3] outline how natural elements are shown to have a notable impact on stress reduction and improved mental health of pedestrians. Higher levels of green space in neighbourhoods have been associated with healthier cortisol levels [23]. This need often leads to exploiting all horizontal surfaces in cities, even roofs, to create greener, low-carbon cities with cleaner air and healthier residents [24]. Urban life and urban stressors are factors identified as motivating people to look for areas with more green space [18].

The concept of GCS is still emerging [25], integrating the previously separate concepts of complete streets and green streets into one paradigm that aims to accomplish the goals of both [7]. These designs integrate stormwater infrastructure, shade trees, and landscaping to mimic natural hydrology more closely into safe, accessible, connected roadways and path networks while promoting an infrastructure that promotes improved public health and safety.

Green and Complete Street design aims to create safe and accessible pathways for all users while protecting the natural environment and enhancing the social environment [21]. In the present study, the DEC and Tufts field teams continue to collaborate to study these ideals further by using eye tracking and biometric technologies.

2.2 Eye tracking and emotion recognition

Eye-tracking and facial expression analysis technologies capture both unconscious and conscious eye movements and micro-expressions, providing insights into human perception and behaviour [26, 27]. The increasing interest in GCS research has led to adopting biometric tools in urban planning and marketing, introducing new terminology such as fixations and preattentive processing to evaluate built environments [28].

Eye-tracking technology measures gaze fixation and how individuals process images, track gaze paths, and focus on specific elements within an environment [29]. Studies have analyzed saccade amplitudes, blink rates, and fixation points to explore landscape perception [30, 31]. Fixation count, time to first fixation (TTFF), and gaze dispersion reveal which built environment characteristics attract attention, such as façades and windows [14]. Advancements in biometric research have also enabled the detection of subtle emotional responses triggered by urban stimuli. Facial recognition tools utilize statistical models, facial databases, and machine learning, providing insights into unconscious experiences(iMotions, 2016). However, there is ongoing debate regarding the consistency of facial expressions in conveying emotions, which remains beyond the scope of this paper [32].

To address limitations in previous research, this study incorporates video analysis alongside traditional photographic methods. Gaber and Gaber [33] highlight the shortcomings of two-dimensional images in capturing spatial depth, which can significantly influence human experience. By incorporating video clips, this research aims to provide a more comprehensive assessment of how individuals engage with built environments [34, 35]. This literature review establishes the foundation for the subsequent methodology section, detailing the research design, data collection processes, and analytical techniques used to assess conscious and unconscious responses to GCS elements.

3 Methodology

This study evaluated design proposals featuring low versus high Green and Complete Street (GCS) elements for a segment of Goddard Street in Devens and Snake Hill Road in Ayer.[1] This new residential street is part of a former military neighborhood and brownfield site that has undergone remediation, planning, and permitting as part of the 130-unit new urbanist-style [36] residential development, Emerson Green. Specifically, the study aimed to assess whether a measurable relationship exists between low and high GCS elements and subjects' unconscious or subjective responses to presented images. Results were analyzed by comparing unconscious biometric responses (captured through eye-tracking and facial expression analysis software) and subjective survey answers to images under each design condition. Different design conditions were

[1] Ayer is closely tied to Devens through geography, infrastructure, shared services, and historical development centered around the former Fort Devens military base.

presented to minimize response biases associated with specific conditions. Through this analysis, the study quantitatively measured human responses to GCS elements, establishing a theoretical foundation for each research question and making assumptions about possible participant responses to the examined stimuli.

4 Research area

Devens is a 4,400-acre former military base transformed into an intentional, sustainable residential and commercial community. As the permitting and regulatory authority, the Devens Enterprise Commission (DEC) oversees this expansive project and facilitates sustainable redevelopment initiatives. DEC's efforts aim to maximize efficiency, reduce waste, and permanently protect over 1400 acres of open space, benefiting approximately 120 organizations and 9000 employees in Devens [37].

The redevelopment of Devens has included projects such as Emerson Green, a 130-unit new-urbanist-style residential development integrating mixed-income housing types. During the first phase (2016–2017), seventeen single and two-family homes were constructed along a newly designed portion of Chance Street. To evaluate the impact of design modifications on human perception, this study employed eye-tracking emulation software (3M's Visual Attention Software, VAS). This software generates "heatmaps" that highlight areas of high visual attention and preattentive visual sequence diagrams using images from Chance Street as stimuli [26].

The project progressed through multiple phases of analysis and design, with a focus on reimagining the existing neighborhood and transforming its streets to promote the health of its inhabitants. The green and complete elements and policies that we, as the design team, adhered to during the design process—while also evaluating their significance through this specific research—are explained in the following section.

5 Research design

The study utilized the online version of iMotions software, where selected stimuli were uploaded, allowing all participants to complete the study using a link and their computer at any time. The study design followed a pre-computed format within iMotions, presenting all stimuli sequentially to participants. Based on research questions, assumptions, and methodology, the study investigated:

(1) *How do green and complete street elements impact a viewer's unconscious and emotional responses?*

Eye fixations and time spent on a focal point are associated with viewer preferences [27]. Streetscape elements such as visually compelling paving and shrubbery that frame pedestrian paths attract visual attention [14, 26]. Prior research has shown that street edges attract the most visual engagement [38]. Similarly, Rosas et al. [39] found that textured surfaces (e.g., rocks) drew more attention than smooth patterns. This study employed iMotions 9.3.01 software to analyze gaze points, fixation, and saccades, hypothesizing that participants would exhibit a significant unconscious response to images featuring high GCS elements compared to low GCS elements.

Additionally, the study predicted differences in emotional responses via facial mapping between high and low GCS images. Specifically, participants were hypothesized to exhibit positive emotional responses to images with high GCS elements. Previous research by Jevtic et al. [4] indicated that flower colors strongly influence well-being, with yellow flowers eliciting greater relaxation than red or white flowers. Similarly, Simpson, Thwaites, and Freeth [40] observed that street edges, through interstitial spaces such as ledges, porches, and stairs, enhance perceptions of security in public streets.

(2) *Are the responses from eye-tracking glasses consistent with the participants' self-reported emotional assessment of GCS elements?*

Biometric data captured participants' unconscious responses to stimuli, while self-report surveys assessed conscious preferences for low versus high GCS images. By analyzing survey preference responses, the study aimed to explore the relationship between biometric data and individuals' perceptions of urban spaces and their emotional reactions.

Researchers often utilize self-report surveys and present participants with images with a preference question. Many use a seven-point scale; for example, Kim et al. [41] asked participants to rate their level of preference (very displeasing to very pleasing); Luigi et al. [42] asked participants to rate the "environmental quality of this place" (Negatively to Positively) as well as rating the visual environment with a scale of adjectives (Not Pleasant/Pleasant, Chaotic/Calm, Boring/Vivacious). Noland et al. [27] used a larger scale, asking participants to rate images shown on the screen with the continuum defined as −10 is "worst," and + 10 is "best," with no other descriptors given. In an additional study, Hollander and Sussman [26] aimed to identify which image details were focused on that made them feel more or less pleasant.

For this study, participants rated images using a seven-point emoji-anchored scale to ensure neutrality in language and vocabulary. Emoji-based scales have demonstrated psychometric properties comparable to lexicon-based scales [43]. The analysis integrated qualitative expert assessments of the images with quantitative data to identify elements leading to high and low rankings. Heatmaps generated by iMotions were analyzed to test whether fixations correlated with participants reported emotional responses, hypothesizing that high GCS images would receive "smiling emoji" ratings more frequently.

(3) *How does a person's background/identity relate to those responses?*

Complete Street designs can improve public health by providing safe and accessible places for more active modes of transportation and recreation, which can increase physical activity [13]. They also contribute to equity and be an economic driver, as people without cars or who cannot drive will be more able to get around safely [44]. Hospitalization, air quality, obesity, mental health, and safety are some urban risk factors that could be transformed through complete street design to determine residents' health and reactions [45]. This study examined how a participant's background—such as growing up in an urban, suburban, or rural setting—affected their reactions to low versus high GCS images.

5.1 Photo and video inventory

The study was submitted and approved by the ethical committee of our Institutional Review Board. All stimuli consisted of images and videos taken from Chance Street and Snake Hill Road in Ayer, where we spent several days capturing photographs and videos. Variables such as the presence or absence of sidewalks, variations in pavement and sidewalk materials, and greenery were manipulated.

All images were framed from the eye-level vantage point of a pedestrian standing in the foreground of the scene. Images were all captured at a minimum of 300dpi resolution in landscape orientation (1920 × 1080 pixels, Bit depth 32). The study collected 250 images from three site visits, selecting six images from Chance Street, representing low GCS, edited also for the high GCS, and nine images from Snake Hill Road in neighbouring Ayer, representing no GCS.

Images (n = 6, original images) were digitally altered in Photoshop (n = 6, edited images) to create high GCS conditions by adding horticultural elements, modifying pavement materials, and adjusting colours for consistency. For example, horticultural elements such as trees or flowers were added; sections of the street and/or sidewalk were deleted and/or replaced with alternative materials; and colours were edited to create consistent variables such as sky/grass colour across all images (see Fig. 1 for sample). Each variable (pavement and sidewalk materials, greenery, etc.) was changed based on the extensive professional urban design expertise of the Devens Green and Complete Streets Team to comply with their requirements and their Green and Complete Street policy. This process resulted in a complete set of twenty-one still image stimuli for all subjects to include in the study slideshow presentation (6 original, 6 edited, and 9 not edited with no GCS). Six video stimuli were also included, recorded on Apple and Android phones from a pedestrian perspective (4 s, 1920 × 1080 resolution, 30.16 frames/second). The videos were created by zooming in on the examined still pictures to examined correlations between static and dynamic visual responses.

5.2 Survey questions

An online survey through the Qualtrics platform, collected demographic data such as gender, education, employment status and conscious responses to images with no/low/high GCS elements (for the full questionnaire see Appendix 1). After consenting and completing a calibration sequence, participants were exposed to twenty-one images and 6 videos in random order (images: 5 s; videos: 4 s). Following each stimulus, participants responded to a question: "How does this image make you feel?" on a 7-point emoji scale (sad to happy). Each stimulus appeared separately in the screen so responses from the participants could be given without interference (Fig. 2). These survey images were presented randomly during the study with no time limit for display; the subject advanced to the next slide by manually clicking Next.

5.3 Study implementation

The study aimed for a diverse participant pool using iMotions Online, accessible via desktop or laptop computers with cameras. While cost-effective, online studies present challenges such as high attrition rates and data quality concerns [46]. Visual impairment,

Fig.1 Examples of Research Stimuli. Images examples: (left) Original image from Ayer (no GCS), (middle) Original image of Chance Street image (low GCS) and (right) Altered duplicate Chance Street image (high GCS).

Fig. 2 Example of Image with subjective survey response question.

lighting, and participant adherence to instructions affect data quality. Detailed instructions and pre- and post-calibration slides (n = 13) were included to mitigate these issues. Participants performed head-positioning and lighting checks before exposure to study stimuli following those slides.

Following iMotions' experimental setup recommendations, instructions, head-positioning checks, and calibration slides were incorporated ("Definitive Guide for Facial Expression Analysis," https://imotions.com/guides/). Participants re-consented after the debrief and were permitted to use images in publications. Regardless of consent status, all participants completing the intervention received a $10 e-gift card.

Between January 19 and February 8, 2022, 93 participants were recruited via social media and completed the study through an embedded iMotions link. The target sample size was 100, anticipating incomplete responses and invalid data. After consent and pre-calibration, study images and videos were presented once per participant in a randomized order (image exposure: 5 s; video exposure: 4 s) to capture unconscious biometric responses. Survey image slides measured conscious responses with no exposure time limit. Research objective was to capture pre-attentive responses to the stimuli, typically occurring within the first 3–5 s of exposure. For image stimuli, data were collected over a full 5-s period. However, due to limitations related to data storage, memory capacity, and the computational resources required for video editing, the duration of video stimuli was reduced by 20%, resulting in a 4-s exposure period.

Metric standards for inclusion were 5.0 eye-tracking accuracy, 60% eye-tracking quality, and 60% facial recognition quality (iMotions R Notebooks, 2022). The standards established by the software programmers ensure the accuracy of the recordings by filtering out irrelevant data—such as movements caused by mascara-coated eyelashes rather than actual pupil motion—that could otherwise lead to malfunctions or false readings. Following these guidelines, biometric recordings from 39 participants qualified for analysis. Data was processed using iMotions' algorithms and securely stored on a Dell computer at the [university name withheld to preserve anonymity] University.

The study was conducted in three phases: design, calibration, recording, and data analysis. During the design phase, the iMotions Online platform and Qualtrics were utilized to develop the study's template, while the research team simultaneously gathered and modified images and videos to serve as the experimental stimuli. In the second phase, participants were recruited through open calls, and the recording sessions were conducted by guiding participants through the study protocol, the consent forms and Qualtrics questions, the calibration process, the image/videos observation, and the emoji's questions. All recordings were automatically saved on the iMotions platform, later downloaded and reuploaded into iMotions 9.3 offline to enable detailed analysis. The research team defined polygons around specific street-related variables within the software, designating them as Areas of Interest (AOIs), allowing the software to generate metrics for the overall image and the targeted built environment characteristics under investigation. In the final phase, the exported data, including heatmaps, gaze paths, and metric-rich Excel files, were systematically saved and subjected to statistical analysis to assess their significance.

6 Findings

The study participants were predominantly female (N = 26, 66%), followed by male participants (N = 11, 28%) and non-binary/third-gender participants (N = 2, 5%). The majority were between 18 and 34 (N = 35, 89%), with a smaller representation from the 35–54 age group (N = 4, 10%). Employment status was evenly split between employed individuals (N = 18, 46%) and students (N = 17, 43%), while two respondents reported being unemployed (5%) and two preferred not to answer (5%). In terms of education, 69% of participants (N = 27) had a bachelor's degree or higher, and 25% (N = 10) had some college experience. In comparison, one participant had an associate degree (2.5%) or less than a high school education (2.5%).

Regarding neighborhood background, the majority of participants identified their origin as suburban (N = 23, 59%), with 28% from urban areas and 13% (N = 5) from rural settings. However, none of the participants currently resided in rural neighborhoods, with most living in urban areas (N = 29, 74%), while a smaller proportion remained in suburban settings (N = 10, 26%) (Fig. 3).

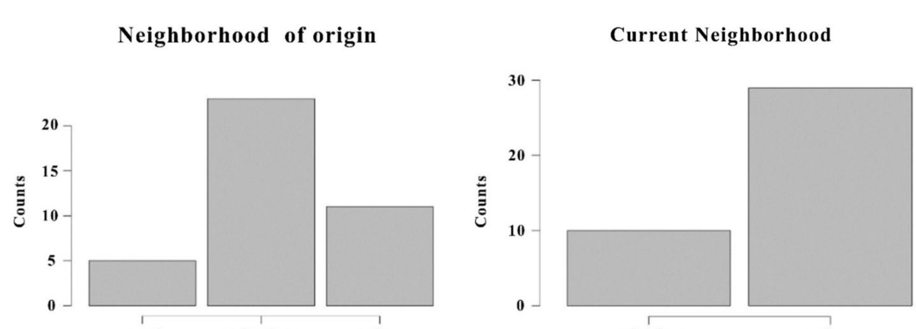


Fig. 3 Graph analysis of neighbourhood identification.

6.1 Attention patterns in response to green and complete street (GCS) elements

Through eye-tracking analysis, the experiment evaluated participants' attention to Green and Complete Street (GCS) elements, measuring unconscious attention and emotional responses in high, low, and no GCS conditions across image and video stimuli.[2] Heatmap[3] analyses revealed that natural materials such as trees, bricks, stones, and grass consistently attracted more attention than asphalt or built infrastructure. In high GCS images, sidewalks and adjacent green areas drew attention comparable to haptic elements such as front porches in lower GCS images.

In high GCS images, attention was significantly reduced for street surfaces. In contrast, images of low or no GCS conditions elicited increased attention toward asphalt, as indicated by heatmap red spots (Fig. 4). This attention shifts to asphalt, despite participants' familiarity with low-GCS environments, suggests a possible connection between the materiality of streets and perceived security or discomfort (Fig. 5). Further research is needed to verify this hypothesis.

6.2 Eye-tracking metrics: fixation count, dispersion, and time to first fixation (TTFF)

General eye-tracking metrics, including fixation count, time to first fixation (TTFF), and dispersion, revealed notable differences between high, low, and no GCS conditions. When analyzing full images, fixation counts were comparable across conditions. However, differences became pronounced when isolating streets and sidewalks as areas of interest (AOI). Streets in low and no GCS images received lower fixation counts, while sidewalks in high GCS images had significantly higher fixation counts. Video analysis indicated a progressive increase in attention toward green elements as the video operator moved forward (Table 1).

Fixation duration and dispersion[4] were also examined to assess attention retention on specific elements. Participants spent longer observing sidewalks in high GCS images

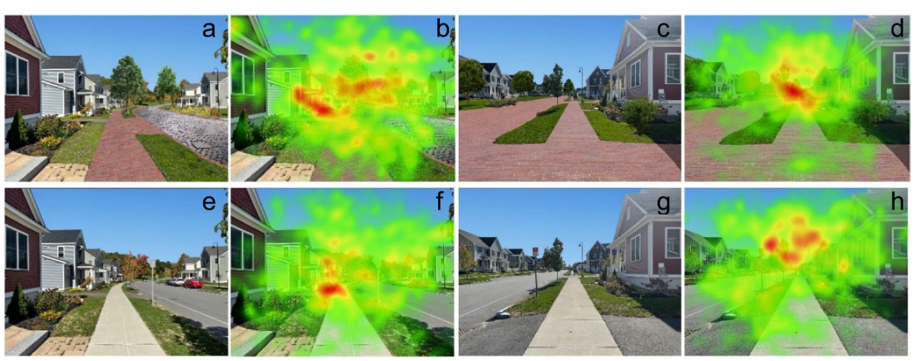


Fig. 4 Original and heatmap images of high and low GCS. Top row: high GCS images **(a)** and **(c)** are original images, **(b)** and **(d)** show heatmaps from eye-tracking. Lower row: low GCS images, **(e)** and **(g)** are original images and **(f) and (h)** show heatmaps from eye-tracking.

[2] All low and high GCS stimuli were compared in pairs of images (A1-A7) and pairs of videos (B1-B3), while videos and images of No GCS were analyzed separately as a third category in our results (C1-C9). This separation allowed for the collection of aggregate metrics for each category, ensuring clarity in comparisons.

[3] Heatmaps were exported after analysing the aggregation of recordings in iMotions 9.3.1 software. They coloured the areas of stimuli that attracted more attention from participants. Green areas show the areas with less attention, while the gradient to red shows the participants' more significant points in terms of attention, interest, and observation time. Areas that stayed uncoloured meant no significant gaze moves, and attention was recorded for those parts.

[4] Dispersion shows the spatial distance between points using temporal and spatial information at the same time. The higher the number is, the more attractive the observed element is.

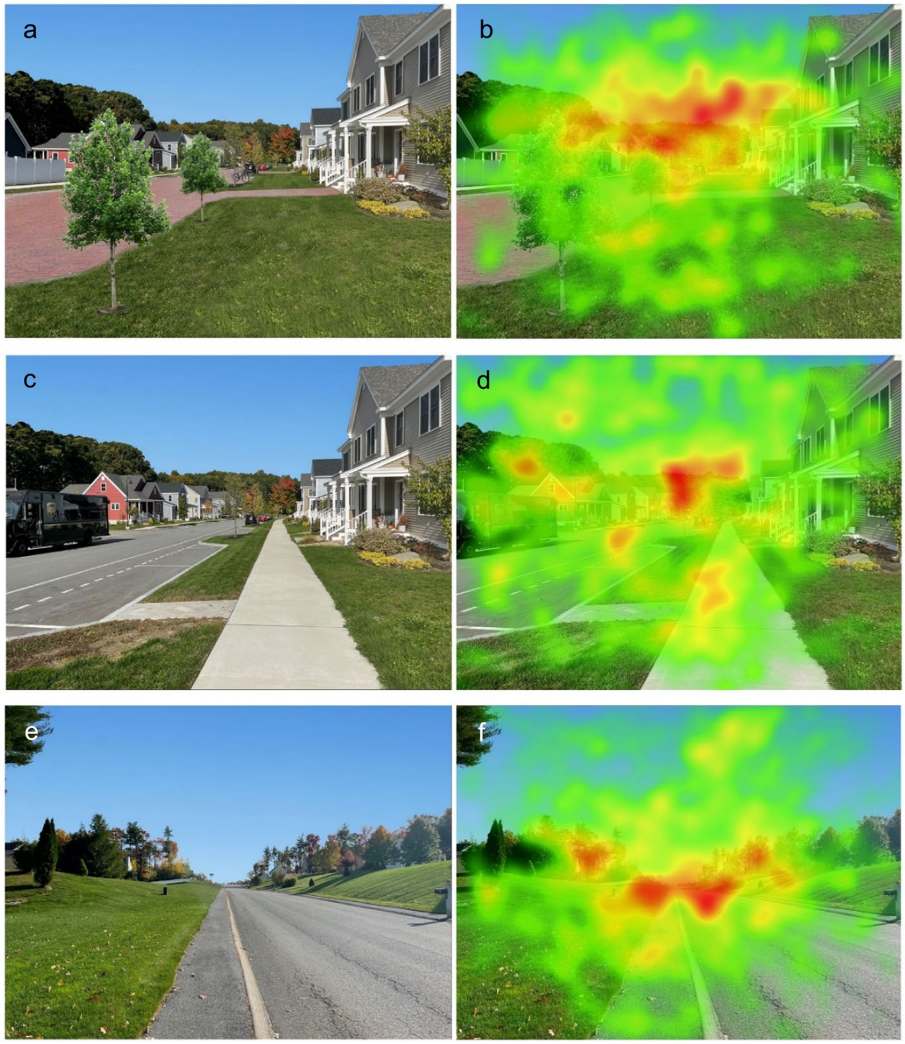


Fig. 5 Comparison of original images and their heatmaps for high, low and no GCS. Compare the elements attracts participants' attention in the two first images to the third, where asphalt is the dominant element. **(a)** Original image of high GCS, **(b)** Heatmap image of image (**a**), **(c)** Original image of low GCS, **(d)** Heatmap image of image (**c**), **(e)** Original image of no GCS, **(f)** Heatmap image of image (**e**).

than in low GCS conditions, contributing to higher dispersion values. In contrast, no GCS images, such as Ayer's Snake Hill Road, exhibited lower dispersion, reflecting reduced participant engagement. Comparing fixation duration with dispersion metrics confirmed that sidewalks remained central to participants' observational patterns, supporting our hypothesis regarding their importance in spatial navigation (Table 2).

TTFF measurements were analyzed to examine gaze behavior differences. Results showed that initial fixations were directed toward elements other than streets or sidewalks, as indicated by smaller TTFF values for full AOI analysis compared to street or sidewalk-specific analyses. Greenery and natural elements in high GCS images attracted the highest first fixations within the first 2–3 s of stimulus exposure. In contrast, in low GCS images, fixations first targeted the street before shifting to GCS elements. Materiality also influenced TTFF, with streets that blended into the environment receiving earlier fixations than those with starkly contrasting textures. Notably, in both high and low

Table 1 Fixation count metric per category (A, B, C).

	FULL AOI		STREET AOI		SIDEWALK AOI	
	LOW GCE	HIGH GCE	LOW GCE	HIGH GCE	LOW GCE	HIGH GCE
A1	3.9	4.5	1.4	1.6	3.2	4
A3	4.4	4.3	1.4	1.4	1.6	1.9
A4	4.8	4.5	4.1	1.8	2.6	0
A5	4.5	4.2	1.5	1.5	1.7	2.3
A6	4.3	4.7	1.1	1.9	1.3	3.2
A7	4.9	4.3	1.9	1.4	2.2	1
B1	5.1	5.4	1.6	2.1	2.6	2.3
B2	5.1	7.1	1.6	1.3	2.6	2.5
B3	5.1	8.6	1.6	2.8	2.6	2.4
	NO GCE		NO GCE		NO GCE	
C1	5.9		3.4		2.1	
C2	5.2		2.4		2.8	
C3	4.5		2.1		1.6	
C4	4.9		2.7		1.9	
C5	4.2		1.5		3.8	
C6	3.9		2		2.3	
C7	4.7		2.8		2	
C8	4.2		1.9		2.8	
C9	4.6		2.8		2.3	

Every line represents sets of images while columns represent the changes in AOI examined frame. The numbers are metrics given by iMotions 9.3. software analysis. The higher the number of this metric, the more stressed the respondent appeared, showing the participants' unfamiliarity with greener sidewalks

Table 2 Duration and Dispersion (standard deviation) collected data per category showing the importance of every stimulus.

	FULL AOI					FULL AOI	
	Low GCE		High GCE			NO GCE	
	DURATION (ms)	DISPERSION	DURATION (ms)	DISPERSION		DURATION (ms)	DISPERSION
A1	1063.1	2.1	777.3	1.8	C1	742.1	1.8
A3	832.7	2	838.1	2.1	C2	762.5	1.7
A4	823	2	945.9	1.9	C3	854.5	1.8
A5	828.7	2.1	722.3	1.8	C4	712.2	1.8
A6	1035.2	2	923.2	1.8	C5	902.3	2.1
A7	598	1.7	857.7	1.9	C6	989.2	2.2
B1	793	1.8	1082.2	1.9	C7	818.6	1.9
B2	793	1.8	812	1.8	C8	877.2	2.1
B3	793	1.8	753.5	1.7	C9	601.6	1.6
STREET AOI					STREET AOI		
A1	1198.1	2.5	1221.5	2.1	C1	1036.2	2.2
A3	607.5	2.1	433.6	1.6	C2	830	1.5
A4	888.9	2.4	1178.8	1.7	C3	1374.2	2.6
A5	1192.5	3.6	617.7	1.9	C4	1095	2.3
A6	1391.3	3	1035.2	2.4	C5	1219.9	2.7
A7	939.1	2	1032.1	2.5	C6	1194.8	2.6
B1	600.2	1.4	2362.3	2.7	C7	785.4	2.1
B2	600.2	1.4	1290	2.2	C8	1102.2	2.6
B3	600.2	1.4	813.8	2.3	C9	746.8	2.1
SIDEWALK AOI					SIDEWALK AOI		
A1	1506.3	4.8	1612	6.3	C1	1405.6	2.2
A3	952.2	1.6	1004.3	2.6	C2	844.4	2.2
A4	1533.8	4.2	2168.7	5.4	C3	761.4	2.3
A5	1094.7	2.3	1088.1	2.3	C4	803.4	2.3
A6	1048.1	2.5	3248.2	4.7	C5	2667.5	5.5
A7	689.4	2.2	4032.8	7	C6	2559.8	6.5
B1	1589.2	2.3	1765.6	2.1	C7	2693.8	6
B2	1589.2	2.3	1086.3	2.9	C8	2136.4	4.8
B3	1589.2	2.3	1014.9	2	C9	1251.8	3.4

This table gives a scale of dispersion. The higher this number, the bigger the dispersion

GCS images, nearly 70% of initial street fixations were followed by sidewalk fixations, while this percentage dropped to approximately 52% in no GCS conditions (Table 3).

6.3 Emotional responses to GCS environments

Emotional responses were analyzed to determine whether the built environment influenced participants' feelings over time. For the purposes of this study, and in alignment with prior literature, we presented only selected sample images at this stage. This approach was intended to help participants relax after previous exposure to both static and dynamic visual stimuli, minimizing the risk of overstimulation and allowing them to better focus on the image evaluation task. The images were carefully chosen to represent all three predefined categories. No significant emotional expressions were recorded in images where streets lacked sidewalks or were composed of asphalt. Conversely, high GCS images elicited expressions of joy, surprise, and, in some cases, fear or anger. Temporal analysis of emotional expressions indicated that stimuli featuring red colors, rough textures (e.g., artificially added elements in photoshopped images), and white flowers were associated with negative emotions,[5] whereas natural elements such as trees and greenery correlated with joy and happiness. These findings align with previous studies [3, 4].

Patterns of emotional expression also evolved over the duration of stimulus observation. Negative emotions were often preceded by attention to dark areas, undefined spaces, or parking zones. In contrast, positive emotions followed exposure to characteristics in the environment such as the sky, white architectural elements, green spaces, and pedestrian-friendly infrastructure. These findings suggest an implicit, unconscious response to GCS design features.

A comparison of emoji survey responses and biometric emotional recordings revealed discrepancies between conscious and unconscious emotional reactions. Participants frequently failed to consciously attribute emotional significance to the stimuli. While biometric data indicated clear affective responses to different GCS conditions, when asked to evaluate images using an emoji-anchored seven-point scale, more than 50% of participants selected a positive emoji, while approximately 15% provided no response (Fig. 6 is giving the average emoji's values with a trend line).

Table 3 Length of first fixation, in milliseconds, of all the examined images (full: examined the whole image, street: focus only on street areas, sidewalk: focus only on sidewalks).

Pair	A1	A3	A4	A5	A6	A7	B1	B2	B3
LOW GCE FULL	699.7	340.3	452.7	448.3	594.4	751	667.8	667.8	667.8
HIGH GCE FULL	420.1	477.8	388.2	603.2	414.8	612.4	647.6	536.3	536.3
LOW GCE STREET	1422	1913.1	1357	2260.1	1654	1545.7	2968.4	2968.4	2968.4
HIGH GCE STREET	1562.4	993.1	1442.6	1654	1246.6	1684.4	2129.1	5862.7	5862.7
LOW GCE SIDEWALK	862.7	1150.5	1470.5	573.8	1453.7	1706.9	782.1	782.1	782.1
HIGH GCE SIDEWALK	1222.5	1976.1	1346.3	751.1	938.2	314.5	2962.2	5348.8	5348.8
	C1	C2	C3	C4	C5	C6	C7	C8	C9
NO GCE FULL	355.6	770.6	424.1	474.5	525.5	576.6	491.8	491	526
NO GCE STREET	1310.9	2662.8	798.5	886.6	1355.5	809	1104.2	1038.8	680.1
NO GCE SIDEWALK	1996.3	815.2	1962.8	806.7	120	1945.2	321	117	1760.3

[5] Emotional responses were recorded using iMotions software, which analyzed participants' facial expressions to generate metrics on the expression of specific emotions. The software provided detailed data on whether or not particular emotions were expressed.

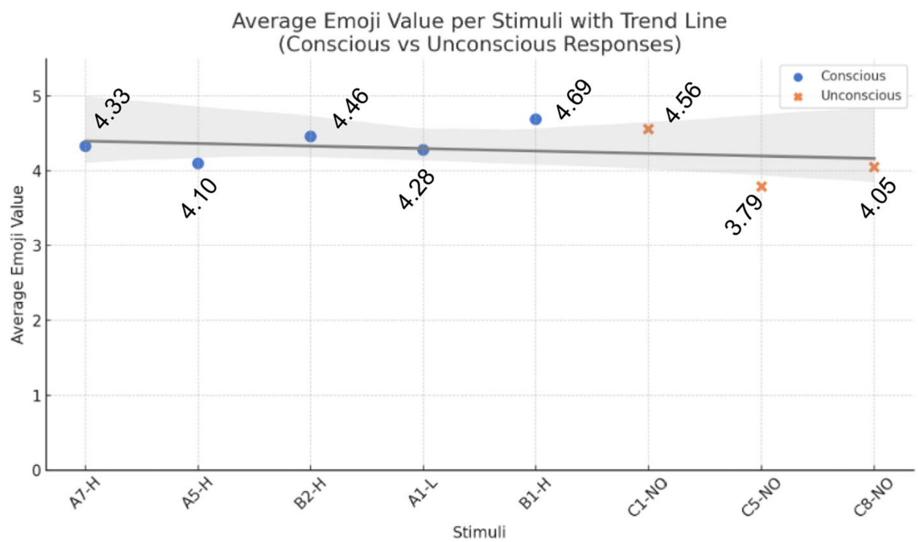


Fig. 6 Average Emoji Value per Stimuli with Trend Line comparing conscious and unconscious responses.

6.4 Statistical comparisons of conscious emotional responses

Using Welch's t-test for unequal sample sizes, we compared mean response differences in participants' self-reported emotional reactions to GCS elements. High GCS images were rated significantly higher (M = 5.24, SD = 1.09) than no GCS images (M = 4.63, SD = 2.36; t(106) = 2.78, p = 0.0064) on the emoji-anchored scale. A similar trend was observed when comparing low and no GCS conditions (Low GCS M = 5.24, SD = 1.24; No GCS M = 4.63, SD = 2.36; t(99) = 2.86, p = 0.0051). However, no statistically significant difference was found between high and low GCS conditions as whole groups, nor for individual high vs. low image stimuli (For full Welch's t-test results, see Appendix 2).

These results highlight the gap between conscious and unconscious responses to GCS elements. While biometric data demonstrated strong affective reactions to greener environments, self-reported evaluations were more neutral. This suggests that participants may lack conscious awareness of how the built environment affects their mood, supporting the idea that increased exposure, and training could improve recognition of such effects [47, 48].

6.5 Influence of neighbourhood type on emotional response

Further analysis examined whether participants' neighborhood of origin or current neighborhood influenced conscious emotional responses to GCS images. Welch's t-test revealed significant mean differences in the following comparisons: suburban vs. urban origins for high GCS images, rural vs. urban origins for no GCS images, and suburban vs. urban origins overall. Participants from urban backgrounds consistently reported higher positive responses across all GCS conditions, although low GCS images did not reach statistical significance.

When analyzing responses based on current neighborhood type, urban residents again provided higher ratings across all GCS categories (low, high, and no GCS),[6] with statistical significance observed only for low GCS images. Given that none of the stimuli

[6] All low and high GSE stimuli were compared in pairs of images (A1-A7) and pairs of videos (B1-B3), while videos and images of No GSE were analyzed separately as a third category in our results (C1-C9). This separation allowed for the collection of aggregate metrics for each category, ensuring clarity in comparisons.

depicted urban environments, future studies should examine urban-specific GCS conditions to further explore these differences.

The findings demonstrate that participants unconsciously reacted to GCS elements, particularly in their attention patterns and emotional responses. Attention was drawn toward natural and pedestrian-friendly elements, while fixation metrics confirmed the importance of sidewalks in navigation. Emotional responses varied significantly across GCS conditions, with biometric data showing stronger affective reactions than conscious survey responses. Statistical analyses further revealed that urban residents exhibited more positive conscious reactions to GCS stimuli, reinforcing the importance of prior environmental exposure in shaping perceptions of the built environment.

7 Discussion and conclusion

This study used eye-tracking and environmental modelling through images and videos to examine the relationship between green and complete street elements (GCS) and participants' conscious and unconscious reactions. To ensure a controlled approach, we modified the original pictures, transforming their built environment characteristics to assess reactions at different GCS levels. Through tracking technologies, we recorded participants' responses, analyzing images and decomposing them into separate spatial elements and objects.

The results confirmed our expectations, demonstrating that (a) Higher GCS streets generated stronger and more distinct responses, (b) Sidewalks and their built environment characteristics significantly influenced participants' visual experience, (c) Emotional reactions were more easily elicited from images with high GCS, and (d) Physical elements such as trees, grass, flowers, and the sky were strongly linked to participants' first fixation and gaze patterns. These findings support our initial hypotheses and align with previous research [16, 23]. Despite these meaningful insights, this study had limitations that should be addressed in future research. One of the most significant limitations was the loss of approximately 60% of the initial recordings, which may have introduced bias. Additionally, variations in participants' observation angles, despite the images and videos being recorded from an eye-level perspective, or the possibility that emojis are not a neutral language, could have influenced the results. Future studies should refine methodological controls to mitigate these limitations and enhance reliability.

Multiple analyses were conducted in response to the study's three primary research questions—examining the relationship between conscious and unconscious responses to different levels of GCS stimuli, the consistency of these responses, and their connection to participants' backgrounds. The results indicated that participants' unconscious attention and emotional responses were drawn to natural elements, such as the sky, white and yellow flowers, and green spaces, followed by sidewalks, front porches, and other built environment characteristics that relate to human motion and peripersonal space. Sidewalks emerged as a focal point of attention, frequently evoking emotional responses, predominantly positive ones. However, the materiality of sidewalks played a critical role in influencing gaze paths and observation patterns. While the study primarily focused on the interaction between GCS and participant behaviour, materiality emerged as a key variable warranting further exploration, particularly in relation to visually compelling paving.

A notable finding was the inconsistency between participants' unconscious reactions and conscious emoji-based evaluations of the observed stimuli. When participants were asked to rate their emotional response to images consciously, they provided answers seemingly influenced by prior visual experience rather than their actual unconscious reactions. This suggests that prior experiences shaped an allocentric representation of the images, preventing participants from fully expressing their genuine, instinctive reactions. This hypothesis is supported by the work of Avraamides and Kelly [48] on spatial memory systems.

While the study collected data on participants' neighborhood types and living environments, no strong correlation was observed between these factors and unconscious responses. However, new questions arose regarding participants' sense of safety, as suggested by Simpson et al. [50]. Participants' attention was frequently drawn to the edges of sidewalks, transitions between materials, and spatial boundaries. The consistent focus on sidewalks reinforces previous research, suggesting that people are naturally drawn to edges [14]. While raising further sub-questions, these findings reinforce the importance of GCS elements in designing more walkable and sustainable urban environments.

Beyond individual perceptions, the results underscore the broader implications of GCS for community health and environmental sustainability. Green and complete street design elements have been widely recognized for their positive impact on public health, particularly in light of contemporary challenges such as COVID-19. Biometric studies confirm that unconscious brain processes are crucial in shaping experience. At the same time, eye-tracking analysis provides urban planners valuable tools to design environments that align with human behaviour and well-being. While this study primarily focused on walking and biking infrastructure, it is essential to consider the potential impact of GCS on driving behaviour. Although not a primary focus of this research, future studies should assess whether GCS elements influence driver attention and safety, offering a more comprehensive understanding of their effects across all modes of transportation.

Additionally, this study highlighted the significance of edging, materiality, and GCS elements in promoting walkability. These findings align with previous research [45] and introduce a new perspective on peripersonal space[7] [50, 51], suggesting that participants unconsciously extend their sense of space into the public realm when exposed to high GCS environments. Edited versions of the stimuli, incorporating high GCS elements, appeared to facilitate an unconscious appropriation of public space, particularly sidewalks. However, the absence of a consistent and systematic observational pattern, attributable to disruptions such as material discontinuities (as evidenced by attention heatmaps), interruptions or complete lack of the horizon line (often due to vegetative elements such as trees), dark areas, and other negative spatial features, appears to have contributed to a disjunction between conscious and unconscious perceptual responses. It is posited that these spatial and visual inconsistencies hindered the development of a coherent visual engagement strategy. Future research should explore these factors in greater depth, particularly in relation to participants' urban or suburban environments and their long-term impact on spatial perception, mental health, and well-being. Additionally, a more extensive analysis of the results based on gender or other demographic

[7] Peripersonal space refers to the space surrounding the body where we can reach or be reached by external entities, including objects or other individuals.

variables, currently limited by the sample size, could offer valuable new insights and expand the scope of the study. Finally, a systematic exploration of how motion within the video stimuli affects perception represents a promising direction for the team's future research. Ultimately, this study not only reaffirmed the importance of GCS elements in urban design and their benefits for public health but also highlighted the necessity of bridging the gap between conscious and unconscious user reactions. By integrating these insights into urban planning and design processes, cities can create more livable, human-centered spaces that promote well-being and a healthier way of living.

Appendix 1: Devens study survey

Urban design and biometrics

Hello and thank you again for participating in this research project, which is being conducted by Tufts University's Department of Urban and Environmental Policy & Planning (Tufts UEP).

This study is funded by a grant from Devens Enterprise Commission.

You are welcome to stop your participation in this study at any time. Only completed surveys will be used for analysis. Rest assured that any identifying video and screenshots captured by this intervention will remain strictly confidential, and screenshots and videos will only be shared in presentations or reports with your express consent. All eye tracking and facial analysis data will be anonymously aggregated.

If you have any questions please contact [lead authors name] at the research team: [email of the author].

Please click the arrow to begin.

Q2 How would you best describe your gender?

- Male (1)
- Female (2)
- Non-binary/third gender (3)
- Prefer not to answer (4)

Q3 Which category below includes your age?

- 18–24 (2)
- 25–34 (3)
- 35–44 (4)
- 45–54 (5)
- 55–64 (6)
- 65–74 (7)
- 75 or older (8)
- Prefer not to answer (9)

Q4 What is the highest level of school you have completed or the highest degree you have received?

- Less than a high school diploma (1)
- High school degree or equivalent (e.g. GED) (2)
- Some college, no degree (3)
- Associate degree (e.g. AA, AS) (4)

- Bachelor's degee (e.g. BA, BS) (5)
- Graduate degree or above (e.g. MA, MS,PhD) (6)
- Prefer not to answer (7)

Q5 Which of the following categories best describes your employment status?

- Employed, working 1–39 h per week (1)
- Employed, working 40 h or more per week (2)
- Not employed and currently looking for work (3)
- Not employed and not currently looking for work (4)
- Student (5)
- Retired (6)
- Unable to work due to disability (7)
- Providing care to others (unpaid) (8)
- Prefer not to answer (9)

Q6 In the following pages, you will be presented various images of urban design and asked to rate certain qualities. There is no time limit on how long you wish to look at an image.

After answering the questions below each image, click the arrow to move to the next image. You may use the back arrow to revisit a previous image if you wish.

Q7

How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Positively (7)

Q8 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q9

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q10

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q11

How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Positively (7)

Q12 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

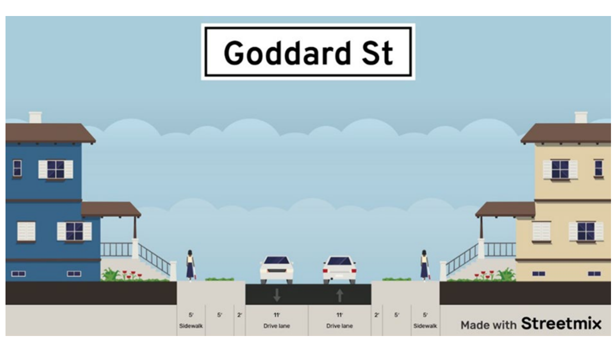
Q13

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q14

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q15



How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q16 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

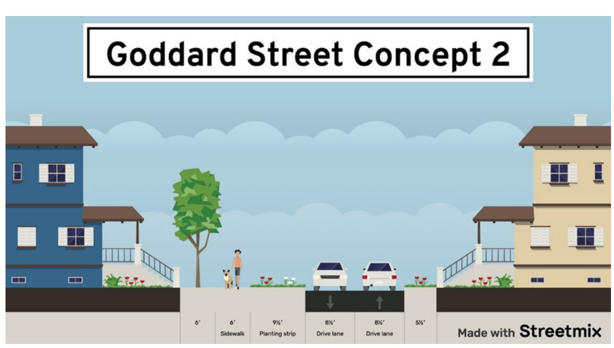
Q17

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q18

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q19



How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q20 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

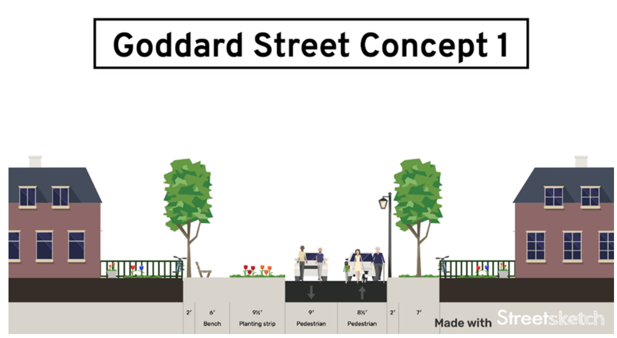
Q21

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q22

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q23



How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q24 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q25

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q26

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q27

How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q28 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

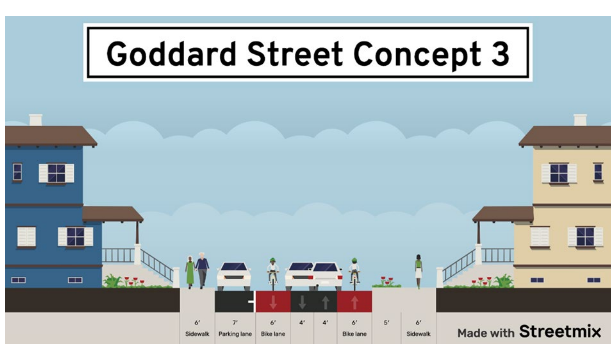
Q29

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q30

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q31



How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q32 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q33

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q34

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q35

How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q36 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q37

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q38

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q39

How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)

- (5)
- (6)
- Pleasantly (7)

Q40 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q41

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q42

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q43

How would rate the environmental quality of this place?

- Negatively (1)

- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasantly (7)

Q44 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q45

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q46

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q47

How would rate the environmental quality of this place?

- Negatively (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasantly (7)

Q48 **How would you rate this site in reference to the following adjectives?**

- Not Pleasant (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Pleasant (7)

Q49

- Chaotic (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Calm (7)

Q50

- Boring (1)
- (2)
- (3)
- (4)
- (5)
- (6)
- Vivacious (7)

Q51 Thank you for your participation. Please close this window and return to the Qualtrics survey.

Appendix 2

Using the Welch's t-test due to unequal sample sizes, we compared response mean differences for each green element group category as a whole (responses for high, low, no green image stimuli) to see whether presence of green elements changed participants' subjective reaction/mood. We also compared response mean differences for individual image stimuli for high vs low green elements. If $P(T \leq t)$ two-tail is less than 0.05, we would reject the null hypothesis and conclude that the mean difference between the two groups is statistically significantly different at the level $\alpha = 0.05$. Through the t-tests, we found statistical significance in mean response differences for high/low green elements vs those that had no green elements. However, we found no statistical significance for comparing the mean differences for high vs low green elements as whole groups and also no significance for the comparisons based on individual high vs low image stimuli.

t-Test: Two-Sample Assuming Unequal Variances

	HI	*LO*
Mean	5.239583	5.242647
Variance	1.089364	1.236983
Observations	96	136
Hypothesized M	0	
df	212	
t Stat	-0.02143	
P(T<=t) one-tai	0.491462	
t Critical one-ta	1.652073	
P(T<=t) two-tai	0.982925	
t Critical two-ta	1.971217	
NOT SIGNIFICANT		

	HI	*NO*
Mean	5.239583	4.636364
Variance	1.089364	2.358042
Observatio	96	66
Hypothesiz	0	
df	106	
t Stat	2.780214	
P(T<=t) one	0.003215	
t Critical or	1.659356	
P(T<=t) twc	0.006429	
t Critical tw	1.982597	
SIGNIFICANT		

	LO	*NO*
Mean	5.242647	4.636364
Variance	1.236983	2.358042
Observatio	136	66
Hypothesiz	0	
df	99	
t Stat	2.863673	
P(T<=t) one	0.002556	
t Critical or	1.660391	
P(T<=t) twc	0.005112	
t Critical tw	1.984217	
SIGNIFICANT		

Comparing Individual Stimuli Images

t-Test: Two-Sample Assuming Unequal Variances

	HI Image 8	*LO Image 8280*
Mean	5.121212	5.21875
Variance	1.234848	1.079637
Observations	33	32
Hypothesized M	0	
df	63	
t Stat	-0.36565	
P(T<=t) one-tai	0.357927	
t Critical one-ta	1.669402	
P(T<=t) two-tai	0.715854	
t Critical two-ta	1.998341	

	HI Image 8	*LO Image 8280*
Mean	5.16129	5.138889
Variance	1.206452	1.323016
Observatio	31	36
Hypothesiz	0	
df	64	
t Stat	0.081436	
P(T<=t) one	0.467674	
t Critical or	1.669013	
P(T<=t) twc	0.935349	
t Critical tw	1.99773	

	HI Image 817	*Image 817*
Mean	5.4375	5.382353
Variance	0.834677	1.031194
Observatio	32	34
Hypothesiz	0	
df	64	
t Stat	0.232184	
P(T<=t) one	0.408568	
t Critical or	1.669013	
P(T<=t) twc	0.817136	
t Critical tw	1.99773	

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Author contributions
Dr. M. Christofi: methodology, software, data analysis and interpretation, statistical analysis, visualisation and presentation of the results, writing. Dr. J.B.Hollander: conceptualisation, processing, provided theoretical grounding for the study's framework, writing, review and editing, methodology, funding acquisition, supervision. A. Sussman: conceptualisation, methodology, data collection, review and editing. L. Carlson-Hill: data collection, manuscript drafting, visualisation and presentation of the results, writing. B. Suedmeyer and N. Angus: methodology, writing, review and editing. All authors participated in critical revisions of the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

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Data availability
The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy and ethical considerations, biometric and survey data cannot be publicly shared but may be provided in anonymized form for research purposes. Eye-tracking and facial reaction data collection and analysis were conducted using the iMotions online platform and iMotions 9.3 application (https://imotions.com/). Emoji-based survey responses and biometric data were collected through Qualtrics XM (https://www.qualtrics.com/), while statistical analyses, including Welch's t-test, were performed to assess differences in participants' responses. Any data requests must comply with the ethical guidelines approved by Tufts University Ethics Committee and the informed consent agreements signed by participants.

Declarations

Ethics approval and consent to participate
This study involving human participants was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. The Tufts University Ethics Committee reviewed and approved the research protocol, with approval reference number STUDY# 00003079. All participants provided informed consent before the study, including

consent for collecting and analyzing biometric and survey data. Participants were informed about the purpose of the study, their right to withdraw at any time and the confidentiality of their responses. Data collection and handling procedures ensured compliance with ethical guidelines to protect participants' privacy and well-being. Written informed consent to participate was obtained from all individual participants included in the study. The experimental protocol was reviewed and approved by the Tufts University Ethics Committee.

Consent for publication
Written informed consent to publish was obtained from all participants and all the authors.

Competing interests
The authors declare no competing interests.

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