Building Better Than We Know: Maintenance, Eye Movements, and Social Trust

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Abstract

Objective: To determine if remediating images of poorly maintained residential properties increases social trust and identify which aspects of the built environment participants attend to when making social decisions.
Methods: Using a within-subject design and a multilevel approach to analysis, participant's eye movements and attitudinal states were recorded as they were presented with a series of static images of residential properties. These residential properties were chosen from areas which are categorised as being among the most deprived according to the English Index of Multiple Deprivation. The images then had the salient aspects of physical disorder corrected using digital imaging software. The resulting experimental stimuli were presented in both 'original/unmaintained' and 'manipulated/maintained' conditions to each participant along with a question regarding social trust.
Results: Images of residential properties in the maintained condition were associated with higher social trust scores (likelihood ratio test χ^2 (1) = 548.13, p < .001). Images of residential properties in the unmaintained condition were associated with longer dwell durations (likelihood ratio test χ^2 (1) = 329.46, p < .001).
Conclusions: These findings suggest that the visual component of maintenance interventions may contribute to their effectiveness by shaping initial social trust perceptions.

Keywords

Community Perception; Social Trust; Active Inference; Life History; Eye Movements

1. Building Better Than We Know: Maintenance, Eye Movements, and Social Trust

We shape our buildings; thereafter they shape us.

-Winston Churchill, *House of Commons Rebuilding, 1943*

In 2011, O'Brien and Wilson introduced the construct of *Community Perception* to describe a psychological process through which individuals rapidly assess the social quality of unfamiliar neighbourhoods using environmental cues. Adopting an explicitly evolutionary approach, they proposed that in group-living ultra-social species that must navigate both familiar and unfamiliar social and physical environments, the ability to quickly infer the types of social encounters that might occur would be adaptive. Their characterisation of community perception as an evolved cognitive mechanism motivated the present research, which seeks to identify the specific perceptual and attentional processes underlying this phenomenon. Building on O'Brien and Wilson's primary work, this study represents a novel approach to incorporate physiological measurement, specifically eye-tracking methodology, to test their construct of community perception and elucidate its proximate mechanisms.

Community perception sits at the intersection of environmental psychology, urban sociology, and evolutionary science. Understanding how physical environments shape social judgments has profound implications for urban policy and public health. Wilson and Kelling’s (1982) broken windows theory argued that visible signs of disorder signal social breakdown and predict neighbourhood decline. Subsequent

work, notably Sampson et al. (1997), clarified that these effects operate primarily through collective efficacy, the shared capacity of residents to maintain order, rather than direct causation. Together, these findings establish that environmental features function as meaningful social signals. O'Brien and Wilson's (2011) evolutionary framework extends this perspective by proposing that sensitivity to such cues reflects adaptive cognitive mechanisms shaped by natural selection. This Darwinian approach has inspired a growing body of research examining urban environments through a biosocial lens (Nettle et al., 2014; Nettle, 2015; Corcoran et al., 2017, 2018, 2019).

The empirical support for community perception has grown substantially since O'Brien and Wilson's initial demonstration. In their original study, O'Brien and Wilson (2011) found that participants could generate accurate assessments of unfamiliar neighbourhoods' social quality using only photographs of the built environment, and modulated their social behaviour in a prisoner's dilemma game accordingly. This result indicated an adaptive social response to potentially threatening social contexts. In a follow-up study, O'Brien et al. (2014) found evidence for 'local adaptations' in community perception, showing that individuals' sensitivity to different cues of disorder was calibrated to their developmental environments. Parallel work by Nettle and colleagues in the UK's Tyneside Neighbourhoods Project has provided converging evidence (2015): For instance, Nettle et al. (2014) demonstrated that brief exposure to a neighbourhood's built environment significantly altered visitors' self-reported social trust and paranoia, with effects mirroring levels recorded among residents of those neighbourhoods.

1.1 Social Trust and Environmental Disorder

Central to community perception is social trust, specifically, judgements about the trustworthiness of residents living in observed neighbourhoods. Social trust represents a fundamental component of social capital, influencing willingness to cooperate with neighbours, engage in collective action, and invest in community life (Putnam, 2000; Sampson, 2012). Neighbourhood physical disorder, including broken windows, graffiti, litter, and poorly maintained properties, has been consistently linked to reduced social trust (Ross et al., 2001; Sampson & Raudenbush, 1999). Taylor (2001) found that residents of physically deteriorated neighbourhoods reported lower trust in neighbours and greater fear of crime, effects that persisted even after controlling for actual crime rates and demographic composition.

The relationship between physical disorder and social trust is likely mediated by multiple pathways. Building on collective efficacy theory (Sampson & Raudenbush, 1999), visible signs of disorder such as poorly maintained public spaces signal insufficient local capacity or willingness to uphold shared norms. These cues may undermine perceptions of cooperation and informal social control, eroding trust among residents. Recent analysis of the UK Household Longitudinal Study provides physiological support for this interpretation: individuals living in poorly maintained environments exhibit significantly elevated levels of C-reactive protein (CRP), a biomarker of chronic stress and systemic inflammation, even after adjusting for demographic, socioeconomic, and health behaviour covariates (McAleavey et al., 2025). This association suggests that environmental maintenance operates as a salient indicator of social quality, where the absence of upkeep communicates diminished potential for prosocial engagement. Given humans' status as obligate

social primates, such signals may activate stress-related pathways, with implications for both social cohesion and health.

1.2 Evolutionary Framework: Ultimate and Proximate Explanations

When O'Brien and Wilson (2011) introduced community perception, they explicitly grounded their approach in an evolutionary perspective organised around Tinbergen's (1963) distinction between ultimate and proximate explanations.

Ultimate explanations address why a trait evolved, its adaptive function and the selective pressures that shaped it, whilst proximate explanations address how a trait operates through immediate mechanisms and developmental processes. In the context of community perception, the ultimate explanation concerns why humans evolved sensitivity to environmental cues signalling social cohesion and safety, presumably because such sensitivity improved survival and reproductive success in ancestral environments. The proximate explanation addresses the cognitive, perceptual, and neural mechanisms through which environmental features currently influence social judgements.

Whilst O'Brien and Wilson (2011) and Nettle and colleagues (Nettle, 2015; Nettle et al., 2014) have provided compelling evidence for neighbourhood effects on psychology and behaviour, neither research programme has detailed the proximate-level cognitive and perceptual processes that mediate these effects. As Nettle (2015, p. 110) observed, no objective, quantifiable, physiological data have been collected regarding which cues are attended to during community perception, despite this being "eminently amenable to experimental investigation using approaches such as eye tracking." The present study addresses this gap by employing eye-tracking

methodology to identify which environmental features capture attention and how attentional allocation relates to social trust judgements.

1.3 Life History Theory and Individual Differences

Life history theory provides a framework for understanding individual differences in community perception. This theory posits that organisms allocate finite energetic resources among competing demands, growth, maintenance, and reproduction, forming coordinated strategies along a fast-slow continuum (Stearns, 1992). Fast strategies, typically adaptive in unpredictable or harsh environments, are characterised by accelerated development, earlier reproduction, more offspring with less parental investment per offspring, and prioritisation of immediate reproduction over long-term survival. Slow strategies, adaptive in stable environments with high resource availability, feature delayed maturation, later reproduction, fewer offspring with greater parental investment, and prioritisation of somatic maintenance and skill development (Del Giudice et al., 2015).

In humans, these strategies manifest as coordinated suites of cognitive, emotional, and behavioural traits (Ellis et al., 2009). Individuals adopting faster strategies exhibit greater present orientation, risk-taking, and vigilance to environmental threats, whilst those with slower strategies show future orientation, risk aversion, and greater trust in social institutions (Griskevicius et al., 2011). Critically, developmental experiences shape life history strategies, with exposure to environmental harshness and unpredictability calibrating individuals toward faster strategies (Belsky et al., 2012). This calibration may extend to perceptual processes: individuals from harsher environments might allocate attention differently when assessing neighbourhoods,

potentially showing enhanced sensitivity to cues of disorder that signal threat or reduced cooperation.

Recent research has challenged deficit-oriented perspectives on developmental adversity, demonstrating that stress exposure can enhance cognitive abilities relevant to harsh environments (Ellis et al., 2017; Frankenhuis & de Weerth, 2013). Individuals from disadvantaged backgrounds sometimes show superior performance on tasks involving learning about dangerous situations or remembering threatening social information, suggesting specialised adaptations rather than general impairment. In the context of community perception, faster life history strategies might facilitate rapid detection of disorder cues, enabling swift assessment of neighbourhood safety and social cohesion.

1.4 Active Inference and Predictive Processing

A complementary process theory addressing proximate mechanisms is active inference, a predictive processing framework proposing that perception involves minimising prediction errors between sensory input and internal models (Friston, 2010, Heins et al., 2020; Mirza et al., 2016; Mirza et al., 2019; Pezzulo et al., 2022; Veissière et al., 2020). Rather than passively receiving information, perceivers actively generate predictions about sensory data based on prior experience, with attention directed toward prediction errors, discrepancies between expected and observed features. In well-maintained environments, which conform to expectations of orderly neighbourhoods, prediction errors are minimal, and attention disperses broadly. In disordered environments, salient features (broken windows, overgrown gardens, peeling paint) violate expectations, generating prediction errors that capture attention and trigger model updating.

This framework predicts that unmaintained properties should elicit longer viewing times on disordered features as perceivers attempt to resolve prediction errors and update beliefs about neighbourhood quality. Furthermore, if attention to disorder mediates trust judgements, then greater attentional allocation to disordered features should predict lower social trust ratings. Active inference thus provides testable predictions about both attentional patterns and their relationship to social evaluations.

1.5 Present Study

This study investigates the proximate mechanisms underlying O'Brien and Wilson's (2011) community perception construct using eye-tracking methodology. We advance four hypotheses.

First, replicating O'Brien and Wilson's core finding, we predict that participants will rate residents of poorly maintained built environments as meriting lower social trust than residents of well-maintained properties (H1).

Second, addressing the gap identified by Nettle regarding physiological measurement, we test active inference predictions that disorder cues generate attention-capturing prediction errors. Specifically, we hypothesize that gaze sequences will be broadly similar across conditions, but participants will fixate on disorder cues earlier and dwell longer in unmaintained properties (H2).

Third, extending O'Brien et al.'s (2014) work on local adaptations, we examine whether life history strategy moderates responses. We predict that lower Mini-K scores will be associated with lower overall social trust (H3), reflecting faster strategies' heightened vigilance.

Finally, drawing on research showing enhanced threat detection in harsh-environment-adapted individuals (Ellis et al., 2017; Frankenhuis & de Weerth, 2013), we predict that lower Mini-K scores will be associated with more efficient visual foraging, attending to disorder cues more rapidly (H4).

By integrating social trust ratings with eye-tracking data and individual differences, this study provides the first comprehensive investigation of key proximate mechanisms underlying community perception.

2. Material and Methods

2.1 Participants

In total 97 participants (74 females and 23 males) residing in the UK completed the study in a laboratory setting. Participants were recruited through the University of Essex's Psychology Department participant pool. Participants received either a payment of 7 GBP or course credit for participation. All participants gave informed written consent, and the study received ethical approval from the University of Essex's ethics committee (DM1902). The age of the participants ranged between 18 and 68, with mean 23.72 years and standard deviation 9.77 years. All participants reported normal or corrected to normal visual acuity.

2.1.1 Sample Size and Power

A formal power analysis was not conducted prior to this study due to the complexity of the planned multilevel model (MLM) design and the absence of reliable prior estimates for key parameters such as effect sizes, intraclass correlation coefficients

(ICCs), and variance components. Instead, the study aimed to maximise statistical sensitivity by recruiting a sample size consistent with similar published work and by employing a within-subjects design to enhance statistical power, ensuring that the sample size exceeded the minimum required to conduct the planned analysis at both the participant (Level 2, L2) the trial (Level 1, L1) levels (Mehmetoglu & Jakobsen, 2017, p. 206; Snijders & Bosker, 2011, p. 177). The final sample of 97 participants exceeded those in comparable eye-tracking studies of environmental perception: Hollander et al. (2020) included 63 participants, and Rosas et al. (2023) reported seven studies with between 49 and 62 participants. Our within-subjects design, where each participant viewed all 20 properties in both maintained and unmaintained conditions, provided 3,880 observations for our multilevel models, offering substantial statistical power for detecting both L1 and L2 effects.

2.2 Materials

2.2.1 Experimental stimuli and fillers

To generate the experimental stimuli 10 residential neighbourhoods were identified from the first 10 areas (using the statistical geography of Lower Layer Super Output Areas) which fall within the first decile of the first percentile of the list of 32,844 English neighbourhoods in the Index of Multiple Deprivation, the UK government's preferred measure of deprivation (2015). Focal properties were then nominated from within these locations by a built environment professional during virtual site visits, via Google Street View (Google, n.d.), using a single criterion: *please identify all properties in serious need of maintenance.* Multiple studies have found that virtual audits using Google Street View are as accurate as in-person observational field audits in assessing multiple aspects of neighbourhood characteristics, including

disorder in the built environment (Bader et al., 2017; Mooney et al., 2017; Rundle et al., 2011). The source images used for the 20 experimental stimuli were then captured by the experimenter.

The unmaintained versions of the experimental stimuli were simply the cropped and colour corrected renderings of the aforementioned captured source images. The maintained versions of the stimuli had the salient aspects of physical disorder from the three categories of cues identified by O'Brien and colleagues' (2014) study on local adaptations of community perception - sanitation, vegetation, and the pavement - digitally remediated using Adobe Photoshop (see Figure 1 for an example, and the Open Science Framework Environmental Psychology Study https://osf.io/p5uh2/ for the complete stimuli set including URLs, locations, and capture dates). Additionally, there were 15 filler stimuli which were chosen to match the experimental stimuli's urban characteristics (i.e., the same architectural style, period, and massing).

The number of 20 experimental stimuli was arrived at in light of the work of Orquin and Holmqvist (2018). When using naturalistic stimuli in eye tracking studies, Orquin and Holmqvist calculated that once the threshold of 16 different stimuli is passed, the potential bias the individual image level differences introduce into analysis is significantly attenuated (2018).

Figure 1

Example of Experimental Stimuli in the Two Conditions

(Figure_1)

Note. (A) Experimental stimulus as captured, simply cropped to an optimal display size and colour-corrected (the unmaintained condition); (B) Image with the digital remediation process completed (the maintained condition).

2.3 Measures

2.3.1 Covariate measures

The covariates comprised demographic measures for age, sex, ethnicity, and region of birth. We created a measure of the micro-level developmental residential environment; “How would you describe the neighbourhood/area in which you grew up?” (*Urban*; *Suburban*; *Semi-rural*; *Rural*). The motive for the inclusion of the participant’s developmental residential environment was to see if the associations O’Brien et al. (2014) found in their local adaptations study apply to the paradigm we employ in the present study, too.

We also administered the Mini-K scale, a psychometric measure of life history schedule (Figueredo et al., 2017), and the General Health Questionnaire (GHQ) 12 scale; a screening tool designed to detect current state mental disturbances and disorders (Goldberg and Williams, 1988). The Mini-K is a 20-item self-report measure that assess constructs including insight, planning, and future orientation; interpersonal relationships and family support; and social contact and relationships (e.g., "while growing up, I had a close and warm relationship with my biological mother" and "I often make plans in advance"). Participants respond on a 7-point Likert scale from "disagree strongly" to "agree strongly". Higher scores indicate slower life history strategies characterised by future orientation, stable relationships, and greater parental investment. The GHQ 12 is a 12-item screening instrument for psychiatric morbidity. Items assess symptoms including concentration difficulties, sleep disturbance, perceived usefulness, decision-making capacity, stress perception, and confidence (e.g., "Have you recently lost much sleep over worry?" and "Have you recently felt constantly under strain?"). Participants respond on a 4-

point scale, which was scored using the GHQ method (0-0-1-1) to produce a score ranging from 0-12. Following standard practice, scores of 4 or more were classified as "caseness" indicating probable psychiatric morbidity. The GHQ 12 was included to allow for exploratory analysis of the data to see if clinically significant levels of minor mental disturbances were affecting eye movements and social trust. Previous eye tracking experiments have shown that depressed people selectively attend to "negative" stimuli for longer periods of time, while fixating on pleasant stimuli less frequently (Corcoran et al., 2019; Eizenman et al, 2003; Kellough et al., 2008).

And, finally, for those who identified as still being members on their parents' households, we administered three measures of socioeconomic position: number of parents in household, parental education level, and parental household income. For those who identified as living independently of their parents, their own household income and educational level were also measured.

2.3.2 Outcome measures

The outcome measures comprised a physiological measure of attention (eye movements and fixations) and a single item 7-point social trust scale, "The residents of this street can be trusted" (1=*Not at all* to 7= *A great deal*). This social trust scale was adapted from an item from the Project on Human Development in Chicago Neighbourhoods study (Earls et al., 1994).

For psychophysiological analysis, areas of interest (AOI) were defined as regions containing visible physical disorder in the unmaintained condition. The size and number of degraded areas varied across images to reflect authentic variation in property condition. This approach preserves ecological validity by reflecting real-

world variation in property conditions. Our multilevel analytical approach controls for any differences between scenes and accounts for nesting of AOIs within images. Data Viewer 3.1 (SR Research, Canada) was used to create reports. The eye movement characteristics selected for analysis provide information about how early and how much each AOI was attended: First Fixation Index (a measure of the priority given to an AOI within a viewing session; with the number 1 indicating that it was selected on the first fixation); and Total Dwell Time (also known as total gaze duration, measured in ms, which quantifies how much time in total is spent fixating this AOI). Again, following the advice outlined in Orquin and Holmqvist (2018), we restricted the measures to the minimum required to operationalise the constructs of theoretical interest. Table 1 reports all of the types of data collected.

Table 1 *All of the Outcome and Covariate Measures*

2.4 Procedure

Figure 2

Flowchart of Experimental Procedure

(Figure_2)

On arrival in the laboratory participants read and completed consent forms and were asked to confirm that they had normal or corrected to normal vision (Figure 2). Then participants completed the survey containing the covariate measures on a desktop computer (administered online through Qualtrics; see Open Science Framework, Environment Psychology Study, Covariate Measures Qualtrics https://osf.io/p5uh2/).

Participants were then seated, with a chin-rest ensuring that their eyes were [approximately] 60 cm from the screen on which the stimuli were displayed. A 9-point

calibration and validation was then completed to ensure that all recordings had a mean spatial error of better than 0.5°. Stimuli were presented on a 19-inch colour monitor. At this distance, the image frame subtended approximately 38° × 30° of visual angle. The experiments took place in a dimly illuminated, sound-attenuated room. Stimulus generation, presentation and data collection were controlled by Experiment Builder software (SR Research, Canada) and run on a desktop computer (control PC). Monocular eye position was recorded using a desktop mounted Eyelink 1000 eye tracker (SR Research, Canada) sampling eye positions at 1000Hz. Saccades and fixations were defined according to Eyelink's acceleration and velocity thresholds. At the start of the testing period, participants were given the instruction (via an on-screen text message): "You are to imagine yourself walking along a street where you would expect to encounter the houses depicted in the following images". Following every trial, they responded to the single item 7-point social trust scale. To record their social trust ratings of the stimuli, an IBM numeric keypad was connected via USB to the control PC. Each trial began with a fixation cross presented at the centre of a blank screen; the start of the 15 s trial being triggered by the participant's fixation on this point (permitting a self-paced break between each trial).

A 15-second viewing duration was selected based on established precedent in eye-tracking research on environmental perception. Previous eye-tracking studies examining responses to built environments have employed similar viewing durations, with Hollander et al. (2020) using 15 seconds per trial, and Rosas et al. (2023) reporting on seven studies using 12-second trials. This duration avoids both ceiling effects (where all areas of interest would be exhaustively examined) and floor effects (where insufficient exploration would occur), whilst minimising participant fatigue across the 60 trials.

Two practise trials, constituting a practise block, with an option for the participant to ask the experimenter for clarifications regarding the procedure, preceded the two experimental blocks of 30 trials.

The experimental stimuli were presented in unmaintained and maintained conditions to each participant for 15 s each; counterbalanced over two experimental blocks and assigned in a random order to each participant. Each experimental block of 30 trials comprised 10 unmaintained stimuli, 10 maintained stimuli, and 10 filler stimuli.

Of the filler stimuli, 10 only appeared once over the course of the two experimental blocks, with the remaining five being repeated (unmodified) across both blocks (to echo the presentation of the experimental stimuli). Thus, each data collection session comprised of 60 trials, divided into two 30 trial experimental blocks, presenting a stimulus and the social trust scale, with a self-paced break at the midpoint to further address potential participant fatigue.

The inclusion of the filler trials was to mitigate the potential of participants discerning the nature of the manipulation, and to serve as controls during the analysis stage (see Results). A scripted debrief conducted by the experimenter followed each session (see Open Science Framework, Environmental Psychology Study, Appendix A https://osf.io/p5uh2/), allowing for the identification of any participants who had discerned the manipulation, and if so, to what extent.

Further, to be able to analyse whether some factor regarding the sequence of the presentation of the stimuli was affecting participant's eye movements or social trust ratings, 49 of the participants were run with experimental stimuli 1 – 10 in the unmaintained condition in the first experimental block, and 48 were run with experimental stimuli 11 – 20 in the unmaintained condition in the first experimental

block. Participants were randomly assigned to one of these two conditions. This design allowed us to first assess, and if necessary, mitigate, potential bias introduced by sequence effects during data collection at the analysis stage.

2.5 Statistical Analysis

All descriptive and inferential statistics were conducted using Stata 14 (2015). We employed multilevel modelling to account for the nested structure of the data, with observations nested within participants. This approach appropriately models within-subject dependencies and allows simultaneous examination of image-level (maintenance condition – L1) and participant-level (e.g. life history schedule – L2) effects.

3. Results

3.1 Analysis Strategy

In terms of experimental design, it should be emphasized that for analytical purposes, following Holmqvist and Andersson (2017), we made the AOI the experimental item, instead of the stimulus images; thus, maintenance as a category, constituted of distributed AOIs of varying size and number but with homogeneous semantics, is the unit of analysis (Holmqvist and Andersson, 2017).

3.1.1 Eye movements workflow

AOI and interest period (IP) data were first processed, and variable reports generated, using DataViewer 3.1 software (SR Research, Canada). The resulting files then went through further data management and cleaning using Microsoft Excel (2019).

3.1.2 Survey workflow

Covariate data were recorded online using Qualtrics (n.d.); these were then exported for initial cleaning and management to Microsoft Excel (2019). Subsequently, these data were combined with the eye movement data and social trust scale ratings in Stata 14 (2015). Given the data structure, all analysis was planned to be conducted using an MLM approach.

The socioeconomic position (SEP) variable was derived from summing the scores of the three relevant measures: number of parents in childhood household, childhood household income, and parents' educational level, and assigning each participant to one of three levels (scores 2/3 = *low*, 4 = *medium*, 5/6 = *high*). In the cases where participants had established their own households, the highest levels in the respective measures across the two households was used to calculate the score. Ethnicity, region of birth, and developmental residential environment were rendered in broad categories due to small cell sizes for some groups. Following established practice (Goldberg & Williams, 1988; James et al., 2013) we used a score of 4 as the cut-off point for the GHQ 12 Caseness variable. Descriptive statistics for the outcomes and covariates appear in Table 2.

Table 2 *Descriptive Summaries for Outcomes and Covariates*

3.1.3 Analysis checks

A *t*-test was conducted to assess whether there was any bias introduced to the social trust ratings of stimuli by sequence effects; first viewing ratings of the selected fillers (M = 4.39, SD = 1.46) and second viewing ratings (M = 4.22, SD = 1.43). The test was not significant, t (580) = -1.47, p = .143.

3.1.4 Potential exclusion

Five of the 97 participants discerned the manipulation (as assessed by the experimenter's debrief). No significant differences were found in the distributions of either their social trust ratings or eye movements data, when compared to the rest of the sample. Thus, we retained their data for our main analysis (for comparison, see Open Science Framework, Environmental Psychology Study, Appendix B https://osf.io/p5uh2/files/758nu for the inferential analyses that follow in this Results section computed after the participants who discerned the manipulation were excluded). All participants met satisfactory parameters for the calibration and validation of the eye tracker, so no participants were excluded on these grounds, either.

3.2 Social Trust Score

Table 3 presents multilevel regression results where the social trust score is the outcome: this is the assessment of H_1 and H_3.

In a null model predicting the social trust score, the interclass correlation indicated (ICC) 33.4 percent of the variation lay between participants (log likelihood -5734.9). Significant higher-level variation remains in both the fully adjusted model (34.3 percent) and the most successful model (36.8 percent).

The first hypothesis (H_1) is supported; as model 1 in Table 3 shows, images of residential properties with higher levels of remedial maintenance completed (the maintained condition) are associated with higher social trust scores (log likelihood -5460.9; likelihood ratio test χ^2 (1) = 548.13, $p < .001$).

The introduction of the maintenance variable as a random slope in model 2 also significantly improves model fit. The negative direction of the correlation (-.20) signals that, for participants with lower levels of overall social trust, the level

maintenance has a greater impact on their decision-making regarding trustworthiness (χ^2 (2) = 11.71, p = .003).

Table 3 *Multilevel Regression Analysis for Models Estimating Social Trust Score as a Function of Maintenance, Mini-K Score, and Covariates*

The addition of the life history measure (Mini-K score) in model 3, which is also significant, improves model fit still further (log likelihood -5452.2). It signals that a participant at the *fastest* (-3) end of this scale would have a trust score 1.68 units lower (Mini-K coefficient 0.28 x 6 - the range of the Mini-K scale), on average, than a participant with the *slowest* (3+) schedule for the typical property, χ^2 (1) = 5.59, p = .018.

Thus, H_3 is supported. A participant's reaction to the stimuli is significantly related to their Mini-K score in the predicted direction.

These relationships remain significant after controlling for socio-demographic characteristics (model 4). In the instance of the life history measure, its effect is greater and more significant after the inclusion of the participant-level controls (0.28, $p < 0.05$ vs. 0.38, $p < 0.01$). These results show that property maintenance informs decision making regarding the trustworthiness of unknown residents, and that a participant's life history schedule is a further determinant in the process (Figure 3 panel A).

In the fully adjusted model, only nationality, with non-EU residents being significantly less trusting, reaches significance. A signal of a macro-level developmental effect. The micro-level developmental environment (whether the participant grew up in an urban; suburban; semi-rural/rural, context) had no significant impact on participants' attitudinal state.

It is worth noting that although the log likelihood of the fully adjusted model is an improvement on the previous model (log likelihood -5446.6 vs. log likelihood -5452.2), it does not constitute an overall improvement in model fit – the log ratio test between model 3 and the fully adjusted was χ^2 (11) = 11.20, p = .427. The Akaike information criterion (AIC) also indicates a decrement of fit (AIC 10918.5 vs. AIC 10929.3).

Figure 3

Maintenance Effects on Social Trust and Visual Attention: Individual Differences in Life History Strategy.

(Figure_3)

Note. N = 97 participants. Panels A–C show individual participant trajectories colour-coded by Mini-K life history score (fast/red to slow/blue) and mean trajectory (black dashed line). Multilevel regression analyses were conducted on square-root transformed dwell duration and first fixation data to meet normality assumptions; untransformed values are displayed for interpretability. β values shown in panels reflect coefficients from transformed-scale analyses. The maintenance effect is consistent across life history strategies. ***p < .001.

3.3 Dwell Duration

Dwell duration on the areas of the images where maintenance was identified as being required was positively skewed and so a square root transformation was performed for multilevel regression analysis.

Table 4 presents the results where the transformed dwell duration is the outcome: this is the assessment of prediction H_2.

In a null model predicting dwell duration, the interclass correlation indicated 4.8 percent of the variation lay between participants (log likelihood -16429.9). Significant higher-level variation remains in both the fully adjusted model (7.8 percent) and the most successful model (9.0 percent).

Table 4 *Multilevel Regression Analysis for Models Estimating Dwell Duration as a Function of Maintenance, Mini-K Score, Mental Health, and Covariates*

H_2 is supported (Figure 3 panel B); images of residential properties with lower levels of remedial maintenance completed (the unmaintained condition) are associated with longer dwell durations on the areas of disordered materials (log likelihood 16265.2; likelihood ratio test χ^2 (1) = 329.46, p < .001).

The introduction of the maintenance variable as a random slope in model 2 also significantly improves model fit (log likelihood -16256.1). The negative direction of the correlation (-1.56) signals that for participants with shorter durations of overall dwell time in the areas of interest, the level of maintenance has a greater impact on their decision to dwell longer in the unmaintained condition (χ^2 (2) = 18.12, p = 0.001). Participants who typically have shorter dwell durations at the areas of interest in the maintained condition gaze significantly longer at the disordered materials in the unmaintained condition.

The addition of the life history measure (Mini-K score) did not improve the model fit (model 3) Table 4 (log likelihood -16255.8; χ^2 (2) = 0.61, p = .437). Thus, the H_4 is not supported.

However, an exploratory analysis introducing the GHQ 12 caseness variable (model 4) did significantly improve the model fit, log likelihood -16251.9; χ^2 (1) = 8.30, p = .004.

These relationships remain significant after controlling for socio-demographic covariates. The results signal that maintenance acts to inform the phenotypic trait of dwell duration – a behaviour associated with participants paying greater attention to information salient to a task, and that a participant's mental wellbeing is also

significantly associated with dwell duration, with those meeting the clinical cut-off for concern regarding mental ill health attending to the areas of interest for less time than their healthy counterparts.

In common with the social trust score results, in the fully adjusted model, only nationality, with non-EU residents being significantly less likely to dwell on the areas of interest, reaches significance. A macro-level developmental effect. And, in another similarity with the social trust score results, the micro-level developmental environment had no significant impact on participants' behaviour.

Again, it is worth noting that although the log likelihood of the fully adjusted model is an improvement on the previous model (log likelihood -16251.9 vs. -16245.6 log likelihood), it does not constitute an overall improvement in model fit – the log ratio test between model 4 and the fully adjusted model was χ^2 (10) = 12.76, p = .238. The AIC also indicates a slight decrement of fit.

3.4 First Fixation Index

First fixation index is a measure of the temporal sequence of fixations in a viewing session. As part of H_2 we predicted that participants would be quicker to attend to the cues of disorder in the unmaintained condition than the corresponding areas in the maintained condition.

As with dwell duration, the first fixation index results were positively skewed and so a square root transformation was performed for multilevel regression analysis.

In a null model predicting index of first fixation, the interclass correlation indicated 2.5% of the variation lay between participants (log likelihood -6819.9). This does not meet the conventional threshold to warrant conducting MLM analysis (see

Mehmetoglu & Jakobsen, 2016). Thus, a single-level approach to analysis was adopted.

In this revised analytical strategy, an exploratory *t*-test was first conducted to assess whether the areas of interest in the unmaintained condition (M = 2.283, SD = 1.236) were visited earlier in the viewing session than the corresponding areas of interest in the maintained condition (M = 2.542, SD = 1.552); an image-level assessment of difference. The test was significant, although the effect size was small, t (3878) = -5.734, $p < .001$, d = -.18. This finding supports prediction H_2, participants will be quicker to identify and attend to salient information regarding their task.

Following this, and in order to test H_4, a single-level regression was performed with a robust estimation of standard error, to account for the clustering in the data structure (Table 5). Whilst the level of maintenance remained significant, the effect size was, again, small (Figure 3 panel C). Neither the Mini-K or GHQ 12 Caseness measure were significant in subsequent model specifications. Thus, H_4 is not supported. When a model with the socio-demographic covariates was run, sex, with male participants being quicker to the areas of interest, and socioeconomic position, with participants in the low SEP category being slower to the area of interest, both returned significant results. But with such low effect sizes, the drawing of any inferences would be unwarranted.

Table 5 *Robust Linear Regression Analysis for Models Estimating First Fixation Index (Transformed) as a Function of Maintenance, Mini-K Score, Mental Health, and Covariates; Accounting for Clustering*

3.5 Exploratory Analysis: Social Trust Score and Dwell Duration

Table 6 presents multilevel regression results where the social trust score is once again the outcome, only this is time we test an exploratory hypothesis; does dwell duration itself associate negatively with social trust?

Table 6 *Multilevel Regression Analysis for Models Estimating Social Trust Score as a Function of Dwell Duration, Maintenance and Mini-K Score*

As with our previous analysis of the social trust score, the null model returns an interclass correlation indicating that 33.4 percent of the variation lay between participants (log likelihood -5734.9). Significant higher-level variation remains in the fully adjusted model (37.2 percent).

Our exploratory hypothesis is supported; as model 1 signals, for every one unit increase in dwell duration there is a statistically significant decrease in the social trust score (log likelihood -5683.3; likelihood ratio test χ^2 (1) = 103.27, p < .001).

Unsurprisingly, given our previous results, the size of this effect is attenuated when we introduce the maintenance condition variable, first as a random intercept (model 2), and then as a random coefficient (model 3); once again, the negative direction of the correlation, which is now marginally increased (-.22), signals that, for participants with lower levels of overall social trust, the level of maintenance has a greater positive impact on their decision-making regarding social trustworthiness.

This pattern is followed when we introduce the life history measure (Mini-K) into the model; substantively the same results as our first planned analysis, but with a marginal improvement of model fit when compared to model 4 from Table 3 (log likelihood -5452.2 vs. log likelihood -5444.2; χ^2 (1) = 16.08, p < .001). Not only do we gaze for longer at the areas we either find, or expect, to be rich in information about maintenance, the longer we gaze at these areas in a given image of a residential location, the less trustworthy we report people resident there to be.

4. Discussion

Community perception was proposed more than a decade ago by two evolutionary social scientists, building on the cognate constructs of collective efficacy and neighbourhood effects from sociology, criminology, social epidemiology, and public health (Galster, 2012; O'Brien & Wilson, 2011; Sampson et al., 1997). The current study confirms, using a different methodology, the findings of O'Brien and Wilson (2011), and the work they inspired by Nettle and colleagues (2014); social trust is significantly affected by residential maintenance.

The present study also reports the first eye tracking evidence in support of the findings of O'Brien and Wilson's (2014) self-report study that found that cues that afford an assessment of ambient levels of maintenance, a class of cue that Friston and colleagues have recently categorized as "epistemic resources" (Veissière et al., 2020), are selectively attended to when engaged on the task of assessing the social value of imagined residents.

The study also finds evidence consistent with the active inference framework approach to perception, with participants "foraging" for longer at disordered areas of the built environment and attending more rapidly to the epistemic resources therein

(Mirza et al., 2019; Veissière et al., 2020; Clark 2015). In addition, we find a negative association between the duration a participant spends visually foraging, and social trust; the longer we gaze at disordered areas, the less we trust (Table 6). These results indicate that attentional allocation to disordered areas directly relates to social trust judgements, suggesting that visual processing depth affects social evaluations.

The present study also builds upon the community perception literature further to demonstrate that, as predicted, an individual's life history strategy affects cognitive processes relating to social trust. However, it does not find evidence of the predicted association between perceptual processing and this construct. And, although we find an association between which global region a participant grew up in and the measures of social trust and dwell duration, it is noteworthy that we find no associations between the particular residential environments experienced during development and the outcomes.

Finally, the findings of our first exploratory analysis, which examined whether mental health status, as measured by the GHQ 12 scale, affected eye movements, were significant but inconsistent with previous eye tracking studies that found increased negative attentional bias in depressed people (Eizenman et al, 2003; Kellough et al., 2008). This result could be explained by the fact that poor residential maintenance, in and of itself, is not always considered a negative stimulus.

4.1 "Avenues of Intervention"

Unusually for a social researcher ostensibly working in the field of ethnography, but in common with O'Brien and Wilson, Nettle has speculated about possible "avenues of intervention" that might make a significant difference to the lives of the residents in communities like Neighbourhood B in the Tyneside Neighbourhoods Project; an area

which falls within the first percentile of the most deprived English neighbourhoods according to the Index of Multiple Deprivation (2015, p. 25). Nettle observed that simply addressing the ambient maintenance of a neighbourhood might lead to significant gains in the perception of the quality of the social environment (2015, p.113).

With the present study, the motivation behind the selection of residential properties from areas identified as the most deprived by the English Index of Multiple Deprivation (2015), was led by such an intervention-focused agenda. We speculated that the margins between the malign social environment prevalent in such neighbourhoods and a benign social environment might be bridged through a systematic, easily replicable, maintenance-led intervention. The present study demonstrates that people naturally attend to these disorderly features in images of urban environments, and that, whilst holding all other visual aspects of the scene constant, participant's attitudes to the trustworthiness of imagined residents were positively impacted by the digital remediation of their residential neighbourhood; hence making these features viable targets for future initiatives seeking to increase social trust.

As one of us has outlined elsewhere (McAleavey, 2023) in both surprising and encouraging work recently conducted by Charles Branas and colleagues in the US, actual remedial interventions to poorly maintained residential properties and vacant lots in deprived neighbourhoods have been proven to reduce gun crime by 29% (the primary motivation for the group's federally funded interventions), nuisance crime by 30%, increase the rate at which people report sharing the same values as their neighbours by 39%, and decrease instances of self-reported depression by 46% (Branas et al., 2018). Branas has labelled such interventions as "win win win

science” on account of the multiple benefits that accrue from the relatively inexpensive remediation of the residential built environment (Branas, 2018). Whilst Branas and colleagues theoretically ground their work within the collective efficacy and broken windows theory frameworks (Kondo et al., 2015; MacDonald et al., 2019; MacDonald et al., 2022; Wilson and Kelling, 1982; Sampson et al., 1997), they are yet to identify a clear causal pathway to account for the multiple social benefits that result from their interventions. Our findings contribute by isolating the perceptual component of maintenance interventions. By demonstrating that visual cues alone affect social trust judgements, we provide evidence for one mechanism through which real-world interventions might operate. However, lasting community-level effects require actual physical improvements that genuinely enhance neighbourhood quality and safety, not merely improved visual appearances (McAleavey et al. 2025, MacDonald et al., 2019).

4.2 Limitations

There are at least five potential limitations concerning the results of this study. Clearly being invited into a well-resourced and carefully maintained laboratory to undertake an experiment where you gaze at static photographs on a monitor is significantly different from the experience of being a pedestrian visitor to a residential street in a deprived, and unfamiliar, part of town. Foulsham and Kingstone (2017) found that there are differences between where people look when they are actually a pedestrian in the environment compared to looking at a picture of the same scene. That said, Wilkins and colleagues have found that photographs function as good surrogates for the natural scenes themselves whilst studying visual discomfort triggered by urban scenes employing a near infrared spectroscopy paradigm (Le et al., 2016).

In future work on community perception, mobile eye tracking equipment could be used to record eye movements in real-time and in situ. Nevertheless, the present study does demonstrate that, at the very least, disordered features of a mediated residential built environment are a priority for people when considering the question of social trust.

The urban topography of the UK is markedly different to the US context in which O'Brien and Wilson conducted their study (2011). Additionally, the commitment to using neighbourhoods identified as being within the first decile of the first percentile of the list of 32,844 English neighbourhoods in Index of Multiple Deprivation (2015) limited our potential sample to areas which are predominately made up of late nineteenth and early twentieth century terraced housing stock. Consequently, these factors precluded the opportunity of exploring two of the three aspects of O'Brien et al.'s (2014) refined construct of community perception, namely, vegetation and pavement, as distinct categories.

Additionally, although the present study, in line with O'Brien and Wilson's original design (2011), uses stimuli with an isolated view of the focal property, their induction protocol also provided the participants with views along the residential street, in both directions, together with the view directly opposite the focal property, thus giving the participant a sense of the urban context. Given the pragmatic constraints of the eye tracking methodology, we restricted the stimuli sample, and the experimental manipulation, to solely the straight-on view of the focal (experimentally manipulated) residence. This pragmatic decision reduces the ecological validity of the present study in comparison to O'Brien and Wilson's protocol and could have inadvertently primed the participant to focus solely on the presumed resident of the focal residence, rather than the broader social environment, when making their response

to the trust question. Both of these limitations could be addressed with the use of mobile eye tracking protocol outlined above.

Another challenge to the external validity of the present study was the composition of the sample; predominately staff and students at the University of Essex. Further research is required using representative samples from both resident communities and actual visitors to a specific location to see if similar associations remain present.

The sample's sex imbalance (76% female, n = 74) also limits generalisability. While sex showed no significant effects on social trust (Table 3, $\beta = -0.02$, SE = 0.19) or dwell duration (Table 4, $\beta = -1.72$, SE = 1.03), males did fixate on areas of interest significantly earlier than females (Table 5, $\beta = -0.190$, $p < .01$), albeit with a low effect size. Given evidence that sex influences environmental perception and trust (Snedker, 2015; van den Akker et al., 2020), future research would benefit from sex-balanced samples to further examine whether the relationship between maintenance and social trust differs systematically between males and females, as well as extending to non-binary individuals not represented in our sample.

Regarding our use of life history theory in the current study a recent special issue of Evolution and Human Behaviour, several contributors challenged attempts in the evolutionary human sciences to account for inter-individual differences in cognitive, perceptual, physiological, and morphological traits from a life history perspective – arguing that it is essentially a between-group or species-level account of variation (see, for instance, Stearns & Rodrigues, 2020). Further, among those prepared to countenance its use within human populations and between individuals, it was contested whether the tools of the psychometric approach, such as the Mini-K,

function as valid assays of an individual's life history strategy (Sear, 2020). In short, it is an open empirical question whether this perspective will prove a valuable addition to theorising about community perception as proposed in the present manuscript. This study employed the Mini-K scale unaware of its creator's commitment to a largely genetically determined conception of a single life history continuum; with all humans, male and female alike, falling somewhere along a single fast-slow dimension (Black et al., 2017; Figueredo et al., 2017; Sear, 2020). Clearly, given our interest in the harshness and predictability of developmental environments (i.e., Ellis et al., 2017), O'Brien et al.'s (2014), the local adaptations extension of community perception, and Nettle et al.'s (2014) rapid updating of cognitive and psychological processes as a function of exposures to different residential built environments, Figueredo's conception of life history (Black et al., 2017) does not resonate with this study's approach. In future work, we recommend adopting Sear's (2020) advice for a more nuanced approach to both construct measurement and theorising; retaining the fast-slow continuum as a motivating heuristic, not as an exhaustive formal description.

In a final issue regarding validity, it should be noted that a number of top-down models of visual search (e.g., Guided Search 6.0, Wolfe, 2021; Yarbus, 1967) would also be consistent with the findings reported here as support for Friston's active inference framework (Linson et al., 2018; Mirza et al., 2016; Mirza et al., 2019; Veissière et al., 2020). We prefer the active inference approach because we contend it provides a more fundamental proximate account of perception, cognition, and behaviour, and is thus better resourced for both our present purposes and future research attempting to develop a process theory of community perception (Clark, 2015; Smith et al., 2022).

4.3 Conclusion

Residential maintenance matters when people make judgements about the social behaviour of others. Different fields across the social sciences are looking to influence public policy by leveraging such findings to design interventions that promote human flourishing in deprived neighbourhoods. Adopting a biosocial approach, informed by evolutionary theory, we demonstrated a first principles account of aspects of the cognitive processes at play in an instance of community perception. Future work will look to further elucidate the proximate mechanisms that underlie this cognitive process, in the hope that it will lead to still more impactful evidence-based policy proposals.

References

Bader, M. D., Mooney, S. J., Bennett, B., & Rundle, A. G. (2017). The promise, practicalities, and perils of virtually auditing neighborhoods using Google street view. *The ANNALS of the American Academy of Political and Social Science*, *669*(1), 18-40. https://doi.org/10.1177/0002716216681488

Belsky, J., Schlomer, G. L., & Ellis, B. J. (2012). Beyond cumulative risk: Distinguishing harshness and unpredictability as determinants of parenting and early life history strategy. *Developmental Psychology*, *48*(3), 662-673. https://doi.org/10.1037/a0024454

Black, C. J., Figueredo, A. J., & Jacobs, W. J. (2017). Substance, history, and politics: An examination of the conceptual underpinnings of alternative approaches to the life history narrative. *Evolutionary Psychology*, *15*(1), https://doi.org/10.1177/1474704916670402

Branas, C.C. (2018, June 5). Charles Branas: The Disease of Gun Violence. [Video] Icahn School of Medicine. https://youtu.be/LtkVTpeCt_4

Branas, C. C., South, E., Kondo, M. C., Hohl, B. C., Bourgois, P., Wiebe, D. J., & MacDonald, J. M. (2018). Citywide cluster randomized trial to restore blighted vacant land and its effects on violence, crime, and fear. *Proceedings of the National Academy of Sciences*, *115*(12), 2946-2951. https://doi.org/10.1073/pnas.1718503115

Clark, A. (2015). *Surfing uncertainty: Prediction, action, and the embodied mind*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780190217013.001.0001

Conger, R. D., & Donnellan, M. B. (2007). An interactionist perspective on the socioeconomic context of human development. *Annual Review of*

Psychology, *58*, 175-199. https://doi.org/10.1146/annurev.psych.58.110405.085551

Corcoran, R., Mansfield, R., Giokas, T., Hawkins, A., Bamford, L., & Marshall, G. (2017). Places change minds: Exploring the psychology of urbanicity using a brief contemplation method. *SAGE Open, 7*(2), 429. https://doi.org/10.1177/2158244017707004

Corcoran, R., Mansfield, R., de Bezenac, C., Anderson, E., Overbury, K., & Marshall, G. (2018). Perceived neighbourhood affluence, mental health and wellbeing influence judgements of threat and trust on our streets: An urban walking study. *PloS one*, *13*(8). https://doi.org/10.1371/journal.pone.0202412

Corcoran, R., Richardson, A., Marshall, G. & de Bezenac, C. (2019). To dwell or not to dwell? Attentional and emotional responses to residential places, differing in subjective desirability. *Journal of Biourbanism*,*1*(7), 49-65.

Churchill, W. (1943) *House of Commons Rebuilding: 28 October 1943*. Retrieved from http://hansard.millbanksystems.com/commons/1943/oct/28/house-of-commons-rebuilding

Del Giudice, M., Gangestad, S. W., & Kaplan, H. S. (2015). Life history theory and evolutionary psychology. In D. M. Buss (Ed.), *The handbook of evolutionary psychology* (2nd ed., pp. 88-114). John Wiley & Sons. https://doi.org/10.1002/9781119125563.evpsych102

Earls, F. J., Brooks-Gunn. J, Raudenbush, S.W., & Sampson, R.J. (1994) Project on Human Development in Chicago Neighbourhoods: Community Survey, 1994-1995. Instrument. Retrieved from https://www.icpsr.umich.edu/files/PHDCN/community-survey.pdf

Eizenman, M., Yu, L.H., Grupp, L., Eizenman, E., Ellenbogen, M., & Gemar, M. (2003). A naturalistic vision scanning approach to assess selective attention in major depressive disorder. *Psychiatry Research, 118 (2)*, 117–128. https://doi.org/10.1016/S0165-1781(03)00068-4

Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). Fundamental dimensions of environmental risk: The impact of harsh versus unpredictable environments on the evolution and development of life history strategies. *Human Nature*, *20*(2), 204-268. https://doi.org/10.1007/s12110-009-9063-7

Ellis, B. J., Bianchi, J., Griskevicius, V., & Frankenhuis, W. E. (2017). Beyond risk and protective factors: An adaptation-based approach to resilience. *Perspectives on Psychological Science*, *12*(4), 561-587. https://doi.org/10.1177/1745691617693054

Eyelink II [Apparatus and software]. (2004) Mississauga, Ontario, Canada: SR Research

Figueredo, A. J., Garcia, R. A., Menke, J. M., Jacobs, W. J., Gladden, P. R., Bianchi, J., ... & Li, N. P. (2017). The K-SF-42: A new short form of the Arizona Life History Battery. *Evolutionary Psychology*, *15*(1). https://doi.org/10.1177/1474704916676276

Foulsham, T., & Kingstone, A. (2017). Are fixations in static natural scenes a useful predictor of attention in the real world?. *Canadian Journal of Experimental Psychology/Revue Canadienne de Psychologie Expérimentale*, *71*(2), 172 - 181. https://doi.org/10.1037/cep0000125

Frankenhuis, W. E., & de Weerth, C. (2013). Does Early-Life Exposure to Stress Shape or Impair Cognition? *Current Directions in Psychological Science*, *22*(5), 407-412. https://doi.org/10.1177/0963721413484324

Friston, K. J. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*, 127–138. https://doi.org/10.1038/nrn2787

Galster, G. C. (2012). The mechanism (s) of neighbourhood effects: Theory, evidence, and policy implications. In: van Ham, M., Manley, D., Bailey, N., Simpson, L., Maclennan, D. (eds) *Neighbourhood effects research: New perspectives.* Springer, Dordrecht. https://doi.org/10.1007/978-94-007-2309-2_2

Goldberg, D. P., & Williams, P. (1988). A User's Guide to the General Health Questionnaire (NFER-NELSON, Windsor). *Goldberg A User's Guide to the General Health Questionnaire1988*.

Griskevicius, V., Tybur, J. M., Delton, A. W., & Robertson, T. E. (2011). The influence of mortality and socioeconomic status on risk and delayed rewards: A life history theory approach. *Journal of Personality and Social Psychology*, *100*(6), 1015-1026. https://doi.org/10.1037/a0022403

Heins, R. C., Mirza, M. B., Parr, T., Friston, K., Kagan, I., & Pooresmaeili, A. (2020). Deep active inference and scene construction. *Frontiers in Artificial Intelligence*, *3*. https://doi.org/10.3389/frai.2020.509354

Hollander, J. B., Sussman, A., Purdy Levering, A., & Foster-Karim, C. (2020). Using Eye-Tracking to Understand Human Responses to Traditional Neighborhood Designs. *Planning Practice & Research*, *35*(5), 485–509. https://doi.org/10.1080/02697459.2020.1768332

Holmqvist, K., & Andersson, R. (2017). Eye tracking: A comprehensive guide to methods. *paradigms and measures*. Lund, Sweden: Lund Eye-Tracking Research Institute.

James, D., Yates, J., & Ferguson, E. (2013). Can the 12-item General Health Questionnaire be used to identify medical students who might 'struggle' on the medical course? A prospective study on two cohorts. *BMC medical education*, *13*, 48. https://doi.org/10.1186/1472-6920-13-48

Kellough, J. L., Beevers, C. G., Ellis, A. J., & Wells, T. T. (2008). Time course of selective attention in clinically depressed young adults: An eye tracking study. *Behaviour Research and Therapy, 46*(11), 1238–1243. https://doi.org/10.1016/j.brat.2008.07.004

Kondo, M. C., Keene, D., Hohl, B. C., MacDonald, J. M., & Branas, C. C. (2015). A difference-in-differences study of the effects of a new abandoned building remediation strategy on safety. *PloS one*, 10(7). https://doi.org/10.1371/journal.pone.0129582

Le, A. T., Payne, J., Clarke, C., Kelly, M. A., Prudenziati, F., Armsby, E., ... & Wilkins, A. J. (2017). Discomfort from urban scenes: Metabolic consequences. *Landscape and Urban Planning*, *160*, 61-68. https://doi.org/10.1016/j.landurbplan.2016.12.003

Linson, A., Clark, A., Ramamoorthy, S., & Friston, K. (2018). The Active Inference Approach to Ecological Perception: General Information Dynamics for Natural and Artificial Embodied Cognition. *Frontiers in Robotics and AI*, *5*, 21. https://doi.org/10.3389/frobt.2018.00021

MacDonald, J., Branas, C., & Stokes, R. (2019). *Changing places: The science and art of new urban planning*. Princeton University Press.

MacDonald, J., Nguyen, V., Jensen, S. T., & Branas, C. C. (2022). Reducing crime by remediating vacant lots: the moderating effect of nearby land uses. *Journal of Experimental Criminology*, 1-26. https://doi.org/10.1007/s11292-020-09452-9

McAleavey, David M (2023) *Building better than we know: The residential built environment, trust, social behaviour, biology, and health.* Doctoral thesis, University of Essex.

McAleavey, D., O'Gorman, R., & Clair, A. (2025). Why Maintenance Matters: Disorder in the Built Environment and Physical Health. *Human Ethology*, *40*(1), 2–17. https://doi.org/10.22330/001c.133698

Microsoft. (2019). Microsoft Excel [Computer software]. Retrieved from https://www.microsoft.com/en-us/microsoft-365/excel

Mirza, M. B., Adams, R. A., Mathys, C. D., & Friston, K. J. (2016). Scene construction, visual foraging, and active inference. *Frontiers in computational neuroscience*, *10*, 56. https://doi.org/10.3389/fncom.2016.00056

Mirza, M. B., Adams, R. A., Friston, K., & Parr, T. (2019). Introducing a Bayesian model of selective attention based on active inference. *Scientific reports*, *9*(1), 1-22. https://doi.org/10.1038/s41598-019-50138-8

Mooney, S. J., Bader, M. D., Lovasi, G. S., Teitler, J. O., Koenen, K. C., Aiello, A. E., ... & Rundle, A. G. (2017). Street audits to measure neighborhood disorder: virtual or in-person?. *American journal of epidemiology*, *186*(3), 265-273. https://doi.org/10.1093/aje/kwx004

Nettle, D., Pepper, G. V., Jobling, R., & Schroeder, K. B. (2014). Being there: a brief visit to a neighbourhood induces the social attitudes of that neighbourhood. *PeerJ*, 2, e236. http://doi.org/10.7717/peerj.236

Nettle, D. (2015). *Tyneside Neighbourhoods: Deprivation, Social Life and Social Behaviour in One British City*. Cambridge: Open Book Publishers. https://doi.org/10.11647/OBP.0084

Mehmetoglu, M., & Jakobsen, J. V. T. (2016). *Applied statistics using stata: A guide for the social sciences*. Thousand Oaks, CA: SAGE Publications

O'Brien D. T., & Wilson D. S. (2011). Community perception: the ability to assess the safety of unfamiliar neighbourhoods and respond adaptively. *J. Pers. Soc. Psychol*. 100 (4), 606–620. https://doi.org/10.1037/a0022803

O'Brien, D. T., Norton, C. C., Cohen, J., & Wilson, D. S. (2014). Local adaptation in community perception how background impacts judgments of neighborhood safety. *Environment and Behavior*, 46(2), 213-240. https://doi.org/10.1177/0013916512456844

Orquin, J. L., & Holmqvist, K. (2018). Threats to the validity of eye-movement research in psychology. *Behavior Research Methods*, *50*(4), 1645-1656. https://doi.org/10.3758/s13428-017-0998-z

Pezzulo, G., Parr, T., & Friston, K. (2022). The evolution of brain architectures for predictive coding and active inference. *Philosophical Transactions of the Royal Society B*, *377*(1844). https://doi.org/10.1098/rstb.2020.0531

Photoshop (CS) [Computer software] San Jose, CA: Adobe Inc

Putnam, R. D. (2000). *Bowling alone: The collapse and revival of American community*. Simon & Schuster.

Qualtrics. (n.d.). *Qualtrics* (Version 2023.7) [Online platform]. Qualtrics. https://www.qualtrics.com

Rosas, H. J., Sussman, A., Sekely, A. C., & Lavdas, A. A. (2023). Using Eye Tracking to Reveal Responses to the Built Environment and Its Constituents. *Applied Sciences*, *13*(21), 12071. https://doi.org/10.3390/app132112071

Ross, C. E., Mirowsky, J., & Pribesh, S. (2001). Powerlessness and the amplification of threat: Neighborhood disadvantage, disorder, and mistrust. *American Sociological Review*, *66*(4), 568-591. https://doi.org/10.2307/3088923

Rundle, A. G., Bader, M. D., Richards, C. A., Neckerman, K. M., & Teitler, J. O. (2011). Using Google Street View to audit neighborhood environments. *American journal of preventive medicine*, *40*(1), 94-100 https://doi.org/10.1016/j.amepre.2010.09.034.

Sampson, R. J. (2012). *Great American city: Chicago and the enduring neighborhood effect.* Chicago, IL: University of Chicago Press.

Sampson, R. J., & Raudenbush, S. W. (1999). Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American Journal of Sociology*, *105*(3), 603-651. https://doi.org/10.1086/210356

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, *277*(5328), 918-924. https://doi.org/10.1126/science.277.5328.918

Sear, R. (2020). Do human 'life history strategies' exist?. *Evolution and Human Behavior*, *41*(6), 513-526. https://doi.org/10.1016/j.evolhumbehav.2020.09.004

Smith, R., Ramstead, M.J.D. & Kiefer, A. (2022). Active inference models do not contradict folk psychology. *Synthese 200*, 81. https://doi.org/10.1007/s11229-022-03480-w

Smith, T., Noble, M., Noble, S., Wright, G., McLennan, D., & Plunkett, E. (2015). The English indices of deprivation 2015. London: Department for Communities and Local Government, 1-94. https://doi.org/10.1007/s11229-022-03480-w

Snedker, K. A. (2015). Neighborhood conditions and fear of crime: A reconsideration of sex differences. *Crime & Delinquency, 61*(1), 45–70. https://doi.org/10.1177/0011128710389587

Snijders, T. and Bosker, R. (2011) Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling. 2nd Edition, Sage Publications, London.

StataCorp. (2015). Stata Statistical Software: Release 14 [Computer software]. College Station, TX: StataCorp LP.

Stearns, S. C. (1992). *The evolution of life histories*. Oxford: Oxford University Press.

Stearns, S. C. (2000). Life history evolution: successes, limitations, and prospects. *Naturwissenschaften*, *87*(11), 476-486.

Stearns, S. C., & Rodrigues, A. M. (2020). On the use of “life history theory” in evolutionary psychology. *Evolution and Human Behavior*. 41(6), 474-485. https://doi.org/10.1016/j.evolhumbehav.2020.02.001

Taylor, R. B. (2001). *Breaking away from broken windows: Baltimore neighborhoods and the nationwide fight against crime, grime, fear, and decline*. Boulder: Westview Press.

Tinbergen, N. (1963). On aims and methods of ethology. *Zeitschrift fur Tierpsychologie*, 20, 410–433.

van den Akker, O. R., van Assen, M. A., Van Vugt, M., & Wicherts, J. M. (2020). Sex differences in trust and trustworthiness: A meta-analysis of the trust game and the gift-exchange game. *Journal of Economic Psychology*, *81*, 102329. https://doi.org/10.1016/j.joep.2020.102329

Veissière, S. P., Constant, A., Ramstead, M. J., Friston, K. J., & Kirmayer, L. J. (2020). Thinking through other minds: A variational approach to cognition and culture. *Behavioral and Brain Sciences*, *43*. e90. https://doi.org/10.1017/S0140525X19001213

Wilson, D.S. (2011) *The neighbourhood project: Using evolution to improve my city, one block at a time.* New York: Little, Brown and Company.

Wilson, J. Q., & Kelling, G. L. (1982). Broken windows. *Atlantic Monthly*, *249*(3), 29-38.

Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, *28*(4), 1060-1092. https://doi.org/10.3758/s13423-020-01859-9

Yarbus, A. L. (1967). Eye movements during perception of complex objects. In *Eye movements and vision* (pp. 171-211). Springer, Boston, MA.

Table 2 *All of the Outcome and Covariate Measures*

Data Category	Variable Type	Variable Name	Description
Outcome Measures	Behavioural	Social Trust Score	"The residents of this stree
	Physiological (Eye-tracking)	Total Dwell Time (gaze duration)	Time spent fixating on area
		First Fixation Index	Temporal order of fixation
Covariate Measures	Demographics	Age	Participant age in years
		Sex	Biological sex
		Ethnicity	Ethnic background
		Region	Geographic origin
	Developmental	Developmental Environment	Micro-level developmental
	Socioeconomic Position	SEP	Combined household inco
		Single-parent family	Number of parents in hous
	Psychological Measures	Mini-K Score	Life history strategy (20-ite
		GHQ-12 Caseness	Mental health screening (1

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	Psychological Measures	Mini-K Score	Life history strategy (20-ite
		GHQ-12 Caseness	Mental health screening (1

Table 2 *Descriptive Summaries for Outcomes and Covariates*

Social Trust Rating	Mean(SD)	4.04 (1.25)
Dwell Duration	Mean(SD)	1520 ms (1255)*
First Fixation Index (*N* 3880)	Mean(SD)	7.80 (8.44)*
Age	Mean(SD)	23.72(9.72)
Sex	Female**	76.29%
	Male	23.71%
Mini-K Score	Mean(SD)	1.12 (.61)
GHQ12 Caseness	Three and below**	64.95%
	Case (four and above)	35.05%
Single-parent family	Two Parents**	68.04%
	One Parent	31.96%
Dev environment	Urban**	46.39%
	Suburban	35.05%
	Rural	18.56%
Ethnicity	White**	53.61%
	Non-White	46.39%
Region	UK**	69.07%
	EU	12.37%
	Non-EU	18.56%
SEP	High**	44.33%
	Medium	35.05%
	Low	20.62%
(*N* 97)		

Note. * = Untransformed data; ** = Reference category;
Dev Environment = Developmental Environment; SEP = Socioeconomic Position.

Table 3 *Multilevel Regression Analysis for Models Estimating Social Trust Score as a Function of Maintenance, Mini-K Score, and Covariates*

Variable	Null	Model 1	Model 2	Model 3	Model 4
Intercept	4.04*** (0.08)	3.67*** (0.08)	3.67*** (0.08)	3.35*** (0.15)	3.11*** (0.31)
Maintenance		0.74*** (0.03)	0.74*** (0.04)	0.74*** (0.04)	0.74*** (0.04)
Mini-K score				0.28* (0.12)	0.38** (0.12)
Single-parent family					0.16 (0.18)
Age (ref: 18 and 19)					
20 to 29					-0.06 (0.17)
30 and over					0.19 (0.26)
Sex (ref: Female)					
Male					-0.02 (0.19)
Dev environment (ref: Urban)					
Suburban					0.01 (0.17)
Rural					-0.16 (0.22)
Ethnicity (ref: White)					
Non-White					0.30 (0.20)
Region (ref: UK)					
EU					0.29 (0.25)
Non-EU					-0.47* (0.22)
SEP (ref: High)					
Medium					-0.05 (0.17)
Low					0.20 (0.21)
Variance components					
Level 1 Variance	0.52*** (0.04)	0.53*** (0.04)	0.55*** (0.04)	0.52*** (0.04)	0.46*** (0.04)
Level 2 Variance	1.04 (0.01)	0.90*** (0.01)	0.89*** (0.01)	0.89*** (0.01)	0.89*** (0.01)
Random slope Maintenance			0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Correlation of random slope Maintenance and intercept			-0.20 (0.17)	-0.22 (0.17)	-0.24 (0.19)
N	3880	3880	3880	3880	3880
AIC	11475.9	10929.8	10922.1	10918.5	10929.3
ICC	0.334	0.369	0.381	0.368	0.343
Log likelihood	-5734.9	-5460.9	-5455	-5452.2	-5446.6

Note. Standard errors in parentheses

Dev environment = Developmental environment; SEP = Socioeconomic Position.

*P<0.05; **P<0.01; ***P<0.001

Table 4 *Multilevel Regression Analysis for Models Estimating Dwell Duration as a Function of Maintenance, Mini-K Score, Mental Health, and Covariates*

Variable	Null	Model 1	Model 2	Model 3	Mode
Intercept	35.15*** (0.46)	39.85*** (0.53)	39.85*** (0.63)	39.24*** (1.00)	40.74***
Maintenance		-9.39*** (0.51)	-9.39*** (0.59)	-9.39*** (0.59)	-9.39***
Mini-K score				0.55 (0.69)	
GHQ 12 Caseness					-2.54**
Age (ref: 18 and 19)					
20 to 29					
30 and over					
Sex (ref:Female)					
Male					
Dev environ (ref: Urban)					
Suburban					
Rural					
Ethnicity (ref: White)					
Non-White					
Region (ref: UK)					
EU					
Non-EU					
SEP (ref: High)					
Medium					
Low					
Variance Components					
Level 1 Variance	13.80*** (1.48)	14.36*** (1.48)	25.99*** (2.75)	25.38*** (2.73)	24.29***
Level 2 Variance	271.34*** (3.12)	248.71*** (2.86)	246.49*** (2.87)	246.49*** (2.87)	246.49 (2.87)
Random Slope Maintenance			8.68*** (2.41)	8.69*** (2.41)	8.69***
Correlation of random slope Maintenance and intercept			-1.56* (0.74)	-1.49* (0.67)	-1.71 (0
N	3880	3880	3880	3880	388
AIC	32865.8	32538.3	32524.2	32525.6	3251
ICC	0.0484	0.0546	0.0954	0.0934	0.089
Log likelihood	-16429.9	-16265.2	-16256.1	-16255.8	-1625

Note. Standard errors in parentheses
Dev environ = Developmental environment; SEP = Socioeconomic Position.
*P<0.05; **P<0.01; ***P<0.001

Table 5 *Robust Linear Regression Analysis for Models Estimating First Fixation Index (Transformed) as a Function of Maintenance, Mini-K Score, Mental Health, and Covariates; Accounting for Clustering*

Variable	Model 1		Model 2		Model 3		Model 4	
Intercept	2.283***	(0.036)	2.291***	(0.080)	2.306***	(0.043)	2.159***	(0.096)
Maintenance	0.258***	(0.047)	0.258***	(0.047)	0.258***	(0.047)	0.258***	(0.047)
Mini-K Score			-0.007	(0.057)				
GHQ 12 Caseness					-0.064	(0.069)		
Age (ref: 18 and 19)								
20 to 29							0.080	(0.059)
30 and over							0.123	(0.091)
Sex (ref: Female)								
Male							-0.190**	(0.067)
Dev Environment (ref: Urban)								
SubUrban							0.021	(0.066)
Rural							0.165*	(0.079)
Ethnicity (ref: White)								
Non-White							0.06	(0.079)
Region (ref: UK)								
EU							0.033	(0.100)
Non-EU							-0.137	(0.094)
SEP (ref: High)								
Medium							0.012	(0.073)
Low							0.304***	(0.077)
N	3880		3880		3880		3880	
R^2	0.008		0.008		0.009		0.020	
R^2 Adjusted	0.008		0.008		0.008		0.017	

Note. Standard errors in parentheses

Dev environmentt = Developmental environment; SEP = Socioeconomic Position

*P<0.05; **P<0.01; ***P<0.001

Table 6 *Multilevel Regression Analysis for Models Estimating Social Trust Score as a Function of Dwell Duration, Maintenance and Mini-K Score*

Variables	Null	Model 1	Model 2	Model 3	Model 4
Intercept	4.039*** (0.075)	4.396*** (0.084)	3.826*** (0.086)	3.825*** (0.088)	3.503*** (0.158)
Dwell Duration		-0.010*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
Maintenance			0.704*** (0.032)	0.704*** (0.039)	0.704*** (0.039)
Mini-K score					0.287* (0.118)
Variance Components					
Level 1 Variance	0.523*** (0.039)	0.533*** (0.040)	0.530*** (0.040)	0.554*** -0.043	0.524*** -0.041
Level 2 Variance	1.043 (0.012)	1.014 (0.012)	0.898*** (0.010)	0.885*** -0.01	0.885*** -0.01
Random slope Maintenance				0.051*** -0.01	0.051*** -0.01
Correlation of random slope Maintenance and intercept				-0.220 (0.172)	-0.234 (0.173)
N	3880	3880	3880	3880	3880
AIC	11475.9	11374.6	10915.5	10908.1	10904.4
ICC	0.334	0.345	0.371	0.385	0.372
Log likelihood	-5734.9	-5683.3	-5452.7	-5447.0	-5444.2

Note. Standard errors in parentheses
*P<0.05; **P<0.01; ***P<0.001