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Innovations for Healthy Landscapes: Review and Perspective on Technologies for Assessing and Understanding Human Responses to Environmental Stimuli

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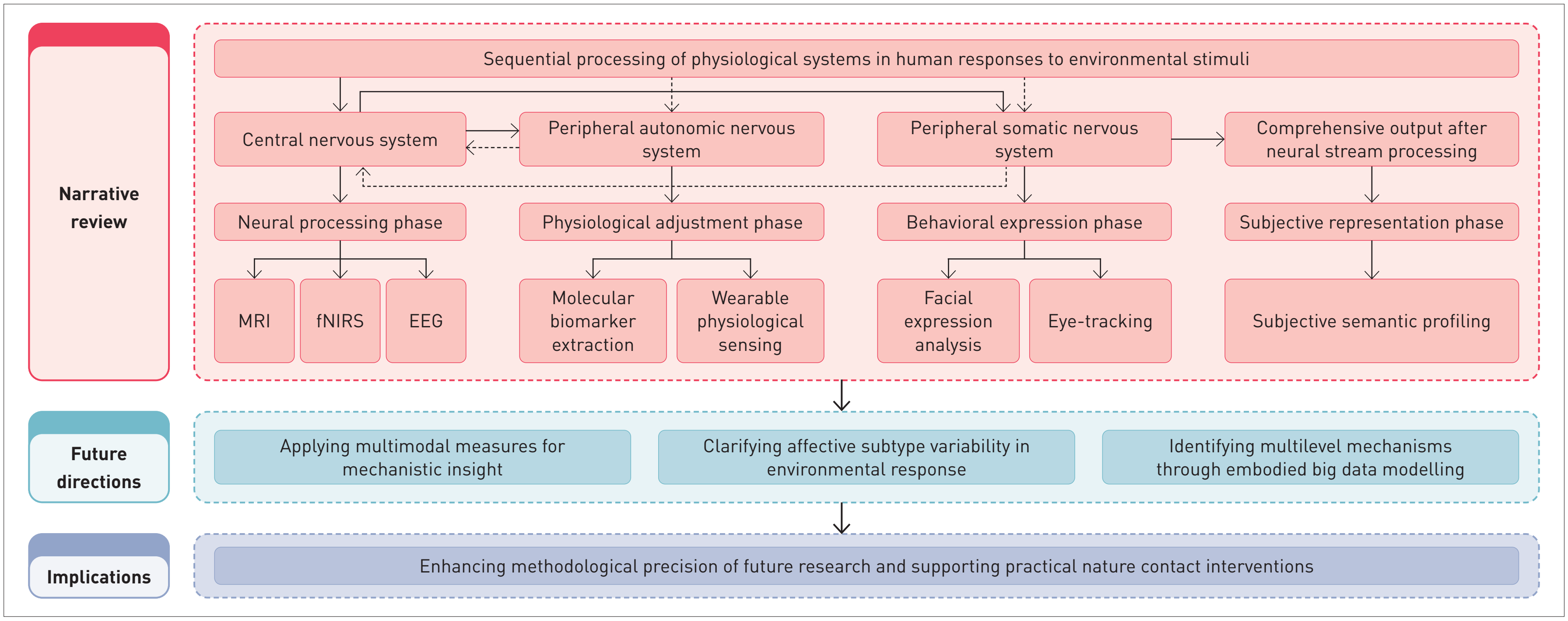
GRAPHICAL ABSTRACT



ABSTRACT

Mental health disorders have become a growing challenge globally. As research continues to emphasize the restorative properties of the environment, natural landscapes are increasingly recognized as an effective means to reduce disorders. Research on healthy landscapes may be enhanced and, in some cases, uniquely informed by human response data; however, the existing literature provides limited and insufficient synthesis on this topic. To address the gap, this study first proposes a four-stage classification framework for new measurement technologies based on the intrinsic processing phase through which individuals respond to environmental stimuli—

neural processing, physiological adjustment, behavioral expression, and subjective representation—each aligned with its corresponding phase of the body's response. Within each stage, a narrative review then synthesizes current technologies, their key indicators, applications, and potential mechanisms in healthy landscape research. Finally, we identify three emerging healthy landscape research directions based on the current research gaps, following: 1) applying multimodal measures for mechanistic insights, 2) clarifying affective subtype variability in environmental response, and 3) identifying multilevel mechanisms through embodied big data modeling. Overall, this work provides a theoretical lens and methodological foundation for probing complex human–environment interactions and for designing precision interventions in the digitally enhanced healthy landscapes.

KEYWORDS

Environmental Exposure; Human Health Response; Psychology; Physiology; Neuroscience; Landscape Architecture

HIGHLIGHTS

- Defines a four-stage human response framework for healthy landscape studies
- Maps neural, physiological, behavioral, and subjective measurement tools to each response phase
- Synthesizes emerging digital sensing indicators for fine-grained human–environment interactions
- Advocates for multimodal measures to uncover mechanisms and affective subtype differences
- Proposes embodied, multilevel data modeling to enable precision landscape interventions

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1 Introduction

Mental health disorders have been among the most pressing global health challenges of the 21st century, affecting an estimated 970.1 million people worldwide in 2019, a figure that represents a 48.1% increase over the past two decades[1]. Meanwhile, nature contact has gained increasing recognition as a comparatively accessible, low-cost, and non-pharmacological approach to support mental health promotion and secondary prevention[2–3]. This demand has driven scholarly interest in healthy landscapes. Underpinned by the therapeutic landscape paradigm, healthy landscapes refer to urban environments intentionally designed to support multi-dimensions of human health, including mental, physical, and social and behavioral[4–5].

1.1 Limitations of Traditional Data

Traditional data sources, such as self-report surveys, interviews, and observational data, have dominated early healthy landscape research in assessing the influence of nature exposure on mental health. Such tools allow the gathering of data from large population samples, place minimal procedural and technical demands, and allow for direct measurement of subjective experiences of mental states and environmental perceptions[6–10]. However, they have significant shortcomings in eliciting fine-grained, embodied information about human–environment interactions.

In particular, the coarse temporal resolution of traditional data masks the fast psycho-physiological fluctuations within the human body during real-world environmental exposure. Conventional data in the form of questionnaire surveys and periodic sampling usually provide information on daily to monthly cycles, whereas autonomic responses to environmental stimuli take place on the millisecond timescale[11]. This temporal mismatch limits the ability of traditional data to capture critical dynamics and thus undermines efforts to establish causal relationships.

Another concern is reporting bias in psychological states. Retrospective questionnaires rely on memory and are affected by the current mood of the participants, which systematically misestimates longer-term emotion[12]. Relying on such measures can hinder causal inference and limit the full spectrum of human–environment interactions, particularly at physiological and neural levels.

Even under conditions of minimal reporting bias, the inherent limitations of the rating scales may serve as another constraint on detectability. An independent yet equally critical limitation that is likely to occur is the presence of floor effects and ceiling effects, which reflect constraints inherent in the measurement scale that restrain participants' responses at the lower and upper limits[13]. In practice, participants may cluster at the scale extremes, limiting the capacity to detect mild or emerging changes and reducing sensitivity to psychological variation[14].

1.2 Human Response Data and Their Scientific Value

Human response data, are defined as high-resolution, embodied indicators of neural, physiological, behavioral, or subjective states captured through emerging technologies[15]. This type of data holds great promise for overcoming the limitations of traditional data in the evolving healthy landscape research, where the field has moved incrementally from simple identification of effects to a focus on cumulative effects and mechanisms.

Specifically, human response data offer high spatio-temporal resolution for mechanistic modeling. Traditional instruments yield sparse and infrequent data points, thereby constraining statistical power and hindering the fitting of dynamic or multilevel models that characterize continuous physiological changes. In contrast, sensing-based data acquisition yields high-density, high-frequency streams through which researchers trace temporal dynamics of how the human body responds and adapts to environmental stimuli. For example, functional near-infrared spectroscopy (fNIRS) can detect changes in cerebral hemodynamics on a sub-second timescale after stimulus onset and generate large volumes of real-time data[16]. These temporally rich datasets enable fine-grained modeling of dose–response relationships, stress–recovery trajectories, and cross-system interactions, thereby revealing process-level mechanisms.

Furthermore, human response data enable sensor-based objectification of experiential processes. Conventional self-reported measures quantify only the subjective outcomes detached from the underlying perceptual processes[17]. In contrast, the new sensor-based approaches transform the internal processes into continuous objective data that examine how landscape experiences temporally unfold while reducing reporting bias and floor and ceiling effects. This transformation is particularly valuable for healthy landscape research, as it clarifies how perceived environmental features evoke specific patterns of physiological change. For instance, eye-tracking can record fixation duration, saccade paths, and blink frequency, thereby quantifying the dynamics of visual perception in real time[18]. Such ability enables new research topics in constructing visual salience and attention-allocation models that reveal which landscape components raise continuing interest.

Human response data also have constraints, such as high equipment costs, increased technical complexity, and contextual interpretation of human response signals. However, when carefully designed and appropriately interpreted, such data uniquely add mechanistic insights and retain considerable value for advancing research on healthy landscapes.

1.3 Mapping Human Response Systems: A Neurophysiological Basis for Layered Measurement

Human response data originates from the measurement of human responses. These responses arise from the processing of external environmental stimuli by multiple human body systems. To provide a clear theoretical basis for the subsequent synthesis of human response data and their measurement, we first describe how the body processes environmental information and the roles played by the relevant human body systems.

The human process of receiving and responding to environmental information involves the coordinated activity of various physiological subsystems[19–22]. At the forefront of this process is typically the central nervous system (CNS), which integrates sensory inputs, interprets environmental stimuli, and initiates appropriate responses. The peripheral nervous system (PNS) transmits signals between the CNS and the rest of the body. Within the PNS, the somatic nervous system controls voluntary motor functions and supports overt behavioral responses, while the autonomic nervous system (ANS) regulates involuntary physiological functions such as heart rate (HR), pupil dilation, and sweat gland activity. The endocrine system modulates slower but longer-lasting internal changes via hormonal signaling, often in close interaction with the ANS during stress and recovery processes. Finally, the motor system, composed of skeletal muscles, bones, and joints, executes physical actions under instructions from the somatic branch of the PNS, providing the structural basis for environmental interaction. Although these subsystems generally follow a temporal sequence, their activation windows often overlap and interact dynamically[23]. Generally, neural processing in the CNS tends to occur first, while downstream systems such as the motor system depend on neural commands relayed via the PNS before initiating behavioral output. These behavioral responses do not necessarily occur only after neural processing is complete; rather, the two often unfold in parallel and remain interdependent, with ongoing neural activity continuing to influence behavior even after it has been initiated.

1.4 Knowledge Gaps

While there is considerable promise for human response measurement technologies in furthering healthy landscape research, the application of these technologies is fragmented across different disciplines. To the authors' knowledge, no comprehensive review to date has synthesized and evaluated these technologies. This has created a complex foundation from which scholars can choose appropriate tools and measures for researching more challenging topics in healthy landscape studies. What is needed is a comprehensive synthesis of emerging human response measurement technologies within the context of a structured framework that outlines their roles and applications and provides guidance for future research.

2 Research Framework and Methodology

2.1 Research Framework

This paper first proposed a response-based framework situated in the human process of receiving and responding to environmental information. Following the framework, it then reviewed emerging technologies, synthesized key indicators, applications, and possible mechanisms to explain human–environment interaction. It concluded by providing three overarching directions for future research.

2.2 Methodology

A narrative review approach was adopted to accommodate the interdisciplinary scope of this study, which spans landscape architecture, environmental psychology, cognitive neuroscience, and physiological sensing. This approach is particularly suitable for synthesizing diverse theoretical perspectives and methodological practices, enabling the integration of conceptual insights, comparison of measurement techniques, and identification of emerging research gaps[24].

To guide the literature search, we first outlined a sequential information-processing framework of human responses involving multiple body systems. For each system, we referred to representative measurement reviews to select device families along with quantitative indices that are sensitive to system-specific changes[25–29]. This mapping relationship between human systems and measurement indicators guided the keyword strategy for this narrative review, particularly for terms related to measurement technologies and indicators.

The narrative literature search was conducted across databases of Web of Science, Scopus, Google Scholar, and ScienceDirect, using combinations of keywords from three thematic clusters: research domains ("healthy landscape," "green space exposure," "nature exposure," "nature contact," and "environmental psychology"); measurement technologies ("EEG," "MRI," "fNIRS," "molecular biomarker extraction," "PPG," "EMG," "facial expression," "eye tracking," and "sentiment analysis"), and main indicators ("cortisol," "CRP," "IL-6," "sAA," "BVP," and "EDA")①. To ensure specificity and relevance, each cluster was searched independently and iteratively combined. The chosen literature explicitly examined the relationship between nature contact and psychological or physiological outcomes and employed at least one quantifiable human response measurement technique. Moreover, eligible publications were limited to English-language original research articles published between 2010 and 2025. This time frame was chosen to capture the methodological evolution of the most recent years, during which the field has witnessed both the emergence of new digital sensing technologies and the renewed application of earlier physiological methods through advanced data-processing approaches and evolving research questions.

3 A Narrative Review: Hierarchical Classification of Human Response Measurement With New Technologies

Building on the sequential flow of information described in Section 1.3, we delineated a temporally ordered framework comprising four functional stages—neural processing, physiological adjustment, behavioral expression, and subjective representation—each corresponding to specific measurement approaches detailed below (Fig. 1).

The neural processing phase, centered on the CNS, primarily takes place in the brain. It captures brain activity through technologies such as EEG, MRI, and fNIRS. These methods quantify electrical signals, levels of cerebral blood oxygenation, and hemodynamic responses.

The physiological adjustment phase, driven by the ANS and the endocrine system, captures internal adaptive changes from peripheral organs or tissues. It focuses on bodily responses recorded via two primary approaches: molecular biomarker extraction and wearable sensing. The former includes techniques for analyzing multiple physiological biomarkers in blood, hair, and

① EEG stands for electroencephalogram; MRI stands for magnetic resonance imaging; fNIRS stands for functional near-Infrared spectroscopy; PPG stands for photoplethysmography; EMG stands for electromyography; CRP stands for C-reactive protein; IL-6 stands for interleukin-6; sAA stands for salivary alpha-amylase; BVP stands for blood volume pulse; and EDA stands for electrodermal activity.

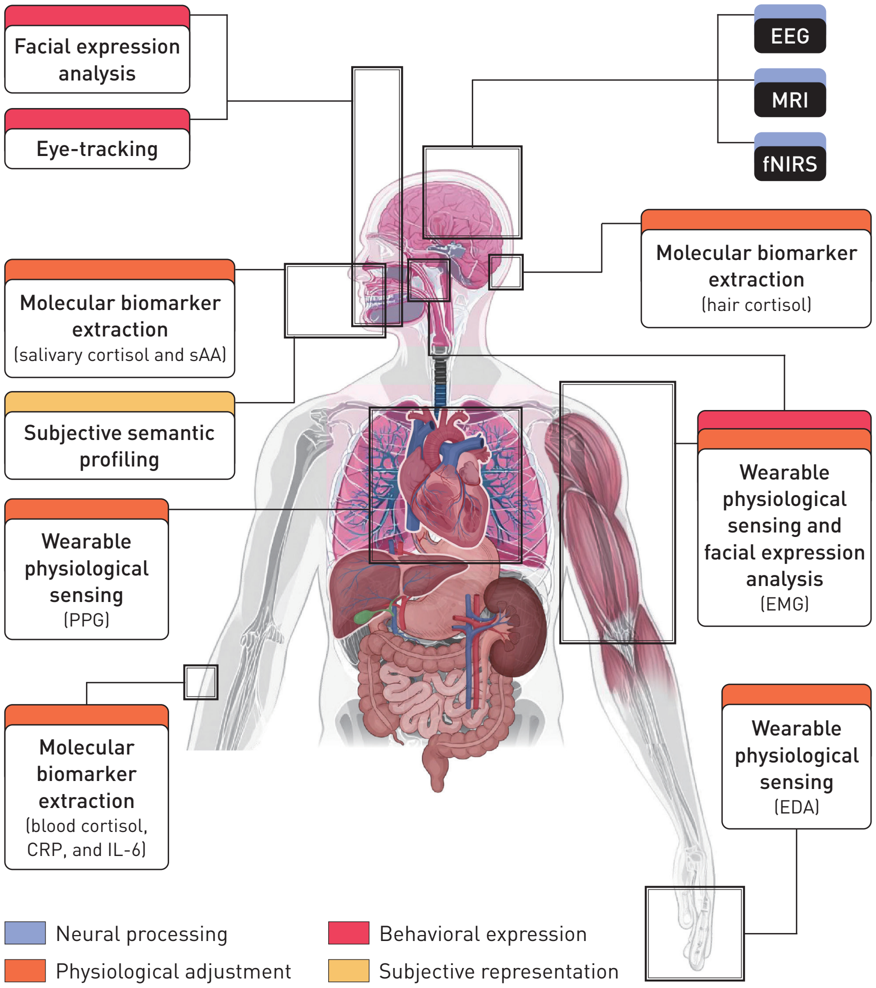

Fig. 1 Four functional stages and corresponding measurement.

saliva. The latter involves devices that measure EDA and heart rate variability (HRV).

The behavioral expression phase, driven by the somatic nervous system and motor system, quantifies motor-based outputs and involves the detection of externally observable behaviors using eye-tracking systems and facial expression analysis. These technologies collect data such as gaze fixation duration, saccade frequency, and facial muscle activity.

The subjective representation phase assesses psychological states through the analysis of individuals' verbal or written expressions. Emerging techniques such as subjective semantic profiling based on natural language processing (NLP) are used to extract features like emotional tone, word frequency, and thematic patterns from participant narratives.

3.1 Neural Processing Measures

Measurement of the neural processing phase focuses on capturing how the brain processes environmental stimuli, reflecting the activity of the central nervous system. This phase includes three main techniques: EEG, MRI, and fNIRS. Although all three techniques can be used to characterize brain activity, EEG captures neural responses through neural electrical activity, whereas MRI and fNIRS rely on hemodynamic signals; moreover, MRI offers whole-brain coverage, while fNIRS is largely restricted to cortical regions.

3.1.1 EEG

EEG is a technique that records electrical signals generated by the synchronous firing of cortical neuron populations, collected through electrodes placed on the human scalp[30]. Traditional EEG systems rely on stationary installations and thus are usually applied in controlled laboratory settings. More recently, however, portable EEG recorders have become increasingly popular with the rise of mobile neuroscience[31]. In healthy landscape research, EEG, especially portable devices, offers key advantages, including low weight, wireless connectivity, and high temporal resolution. These devices allow researchers to detect rapid fluctuations in cognitive states during real-world environmental exposure, improving ecological validity compared with laboratory-based EEG[32]. However, EEG continues to face restrictions regarding poor spatial resolution and the potential influence of muscle activity and ambient electromagnetic noise[33].

In terms of measurement indicators, EEG data can be transformed into a series of canonical bands. The amplitude measure for these bands has commonly been used as an indicator for cognitive and emotional processing[32], though their interpretation may vary across experimental contexts and task demands (Table 1).

Table 1: EEG frequency bands and their associated psychological states

Frequency band	Frequency range	Common psychological state
δ	0.5 ~ 4 Hz	Deep sleep, reduced consciousness
θ	4 ~ 8 Hz	Relaxation, imagination, drowsiness
α	8 ~ 13 Hz	Calmness, relaxation, quiet wakefulness
β	13 ~ 30 Hz	Focus, thinking, tension
γ	> 30 Hz	Higher-order cognition, memory, learning

Empirical findings from EEG studies on healthy landscapes have highlighted several characteristic changes in neural activity. Most prominently reported are increased α power associated with stress reduction, with studies showing that exposure to natural environments, such as forest walks or viewing nature scenes, can provoke these EEG changes[34–36]. In the realm of attention measurement, reduced θ/β ratio (TBR) has been used as a neural index of increased attentional arousal, with findings showing a significant decrease in frontal TBR following nature exposure[37]. Some studies further find decreases in γ power following nature exposure, interpreted to reflect lower cognitive resource demands, though such interpretations require further empirical confirmation[38].

In terms of potential mechanisms, nature exposure seems to work via two different EEG-based pathways. The stress–recovery pathway, whose putative core mechanism involves decoupling of the interoceptive and affective-salience channels[39]. This decoupling is reflected by a reduction in δ-band coherence between the anterior insula, a region integrating interoceptive signals, and the subgenual anterior cingulate cortex, a region modulating visceral and autonomic responses to stressors. This pattern is consistent with a downshifting of interoceptively driven emotional amplification and autonomic load. Another pathway is the attention-recovery pathway. Its putative core mechanism is inhibitory gating and resource reallocation within the thalamocortical circuit[40]. This is indicated by an α increase and a β decrease, where an α increase means stronger thalamocortical inhibitory gating that suppresses task-irrelevant inputs and lowers exogenous distraction, and a β decrease indicates reduced activity within basal ganglia–thalamus–cortex circuits, which normally support sustained and selective attention as well as sensorimotor coupling, freeing processing capacity. Under nature exposure, this pattern is interpreted as reallocating resources toward control nodes, including the dorsal ACC (canterior cingulate cortex), anterior insula, and prefrontal cortex, thereby reducing bottom-up attentional capture and restoring top-down regulation.

3.1.2 MRI

MRI includes several techniques to characterize brain properties, among which functional MRI (fMRI) and structural MRI (sMRI) are used more frequently for environmental and health-related research[41]. fMRI measures neural activity indirectly through hemodynamic responses, namely blood-oxygen-level-dependent (BOLD) signals, whereas sMRI outlines the structural and volumetric features of the brain. In particular, MRI offers very good spatial resolution and whole-brain coverage so that brain properties can be localized with accuracy for both cortical and subcortical regions. However, the application of MRI is rather limited in naturalistic settings since it requires large, stationary, and expensive equipment[42].

fMRI detects region-specific neural activity by measuring fluctuations in BOLD signals. These fluctuations allow statistical inference of the activation or deactivation of brain regions during well-defined tasks or stimulus conditions, thus informing the degree of regional involvement in information processing[43]. Beyond regional activation, fMRI also assesses functional connectivity in neural activity across brain regions. Changes in connectivity are often interpreted as alterations in network-level coordination, although their functional significance depends on context[44]. Structural brain changes, such as volumetric differences across regions, are assessed using sMRI, and may reflect longer-term neural adaptation[45].

In fMRI studies on healthy landscapes, significant activation patterns have been reported across key brain regions involved in attentional control and negative emotions. More specifically, nature exposure has been shown to reduce BOLD signals in brain regions involved in self-referential negative emotions, such as the subgenual prefrontal cortex, as well as in portions of the posterior cingulate cortex believed to contribute to the maintenance of stress[46–47]. In similar experimental research, contact with nature has been found to result in the suppression of amygdala activity as well as decreased activity in the frontopolar cortex, insula, and hippocampal regions, reflecting reduced stress responses and emotional arousal[48]. Aside from these functional changes, sMRI studies also suggest that nature exposure could influence one's brain structure. Cross-sectional findings disclosed a positive relationship between the levels of one's exposure to residential greenness and both the volume of gray matter[49] and cortical thickness[50], suggesting that nature exposure may potentially impact cognitive performance.

The potential mechanisms of nature contact are revealed through the connectivity of brain regions. Natural viewing is found to increase the functional connectivity of the dorsal attention network (DAN) and the ventral attention network (VAN), allowing top-down attention allocation[51]. The DAN, centered on the bilateral intraparietal sulcus and frontal eye fields, is responsible for top-down goal-directed orienting as well as the maintenance of attentional sets. The VAN, which comprises the right temporoparietal junction and ventral frontal cortex, is responsible for the detection of salient unexpected events triggering top-down orienting. In attentional tasks, the DAN is predominantly active while the VAN is inhibited. Yet with natural stimuli, this relationship shifts toward cooperative coupling: the dorsal network sustains a low-cost preparatory focus, while the ventral network remains ready for rapid reorienting, potentially reducing control demands and supporting attention restoration. In parallel, enhanced functional connectivity between the default mode network (DMN) and attention networks appears important for stress regulation during natural viewing[52]. The increased connectivity enables the DAN to impose top-down biased allocation by reallocating resources from threat or negative valence cues to more relevant cues for reappraisal and regulation.

3.1.3 fNIRS

fNIRS is an imaging technique that measures concentrations of oxygenated hemoglobin (O_2Hb) and deoxygenated hemoglobin (HHb), providing an indicator of local neural activation[53]. The portability, adaptability, and resistance to motion artifacts make fNIRS an ideal option for mobile lab studies, which adds to the ecological validity when compared with fMRI studies. The resolution of fNIRS has some limitations, however, as the device cannot scan deeper structures of the brain, such as the amygdala or hippocampus[54].

fNIRS can be used to assess cortical activities and functional connectivity between cortical regions under nature exposure. The interpretative logic is similar to fMRI in that hemodynamic changes reflect neural activity; typically, an increase in O_2Hb (often accompanied by a decrease in HHb) is interpreted as cortical activation[53].

fNIRS has been used to investigate cortical responses to nature contact, especially focusing on hemoglobin concentration changes in the prefrontal cortex regions. Such regions are known to be involved in the regulation of emotions and relaxation. A few studies have reported that exposure to natural settings is associated with decreases in O_2Hb levels in the right prefrontal cortex. This response is consistent with self-reported increases in relaxation and comfort, supporting the role of nature in emotional relief and physiological recovery[55–56]. Nature contact also suppresses activity in the orbitofrontal cortex (OFC), with reduced activation in the right OFC correlating with increased positive affect, such as pleasure and relaxation, which suggests that nature lowers emotional vigilance and promotes positive emotional states[57].

In terms of potential mechanisms, evidence remains sparse. Because of limited optical penetration, fNIRS only samples hemodynamics in the superficial cortex and cannot resolve deep nuclei or large-scale interactions central to stress and attention regulation, including the thalamus, basal ganglia, hippocampus, and distributed salience and control circuits.

3.2 Physiological Adjustment Measures

Measurement of the physiological adjustment phase focuses on monitoring internal physiological dynamics, particularly those involving the autonomic and endocrine systems. This phase includes two main measurements: 1) molecular biomarker extraction technologies, which detect endogenous biomarkers in biological samples to reveal cumulative physiological processes; and 2) wearable physiological sensing technologies, which use wearable devices to continuously track externally observable physiological signals.

3.2.1 Molecular Biomarker Extraction Technologies

Molecular biomarker extraction technologies are methods for detecting internal physiological responses by isolating indicators like proteins or metabolites from biological samples[58]. Commonly used immunoassay technologies include Enzyme-Linked Immunosorbent Assay (ELISA), Chemiluminescent Immunoassay (CLIA), and Radioimmunoassay (RIA), among which ELISA is the most widely applied and is therefore the focus of this section[59]. ELISA uses enzyme-labeled antibodies to recognize target substances and generates quantifiable color signals through an enzymatic color reaction. Standard procedures involve sample collection and refrigeration, centrifugation, incubation in antibody-coated wells, addition of enzyme-linked secondary antibodies and substrates for color development, and final absorbance reading with reference to a standard curve[60]. The method is technically mature, highly sensitive, and accommodates various sample types (e.g., saliva, blood, urine)[59].

ELISA has been widely applied to analyze various bodily fluids in healthy landscape research. In saliva samples, salivary cortisol, a classic indicator of stress, consistently tends to decrease following exposure to nature. This reduction has been observed across a range of conditions, from watching videos of nature scenes[61], short rest in natural settings[62], to forest walking[63], which suggests that nature contact can attenuate both acute and chronic stress responses. In addition, salivary α-amylase, though not assessed using the ELISA method, can also indicate sympathetic nervous system arousal. It is usually observed to decrease following nature exposure, indicating a shift from vigilance to relaxation, though findings remain mixed[64–65].

In blood samples, common ELISA targets include cortisol, CRP, and IL-6. Serum cortisol, known as the "gold standard" for stress research, has been found to decrease after exposure to nature, as seen in both an exercise-in-nature study[66] and a forest bathing experiment[67]. In recent years, CRP and IL-6 have gained more prominence in determining the impact of nature exposure on chronic inflammation. One study showed that exposure to natural forest vapors rich in volatile terpenes led to a decrease in IL-6 and CRP levels, suggesting immune-mediated stress relief[68]. However, as blood sampling is invasive and may cause physical stress, caution should be maintained when linking blood-derived biomarkers to stress[69].

In hair samples, measuring hair cortisol concentration (HCC) represents one of the most prominent applications. A common approach involves segmenting the strands into 1 cm sections, with each section representing roughly one month of stress exposure. Leveraging this property, some studies have employed HCC as a biomarker to evaluate the effects of nature exposure[70]. Both a two-month mindfulness-based intervention and a six-month outdoor space optimization activity program in the natural environment have reported significant reductions in HCC, indicating the stress-relieving effect of long-term nature exposure[71–72].

From a mechanistic viewpoint, a possible interpretation for the effect of being in nature is that changes in anti-inflammatory markers and cortisol produced by nature contact indicate a vagal anti-inflammatory-HPA downregulation pathway[70,73]. In this pathway, nature contact enhances parasympathetic activity, engages the cholinergic anti-inflammatory reflex, and directly lowers peripheral inflammatory markers such as IL-6 and CRP. The dampening of peripheral inflammation reduces HPA-axis activation, leading to downshifted secretion of circulating cortisol. This lower level of cortisol, in turn, stabilizes the HPA axis via negative feedback and further limits inflammation, thereby consolidating a low-stress state.

3.2.2 Wearable Physiological Sensing Technologies

3.2.2.1 PPG

PPG is a broadly used biologic monitoring technique in wearable biosensors. Based on the principles of optics, the technique requires the transmission of wavelengths of light onto the skin and the detection of reflected changes in light to estimate periodic variations in capillary blood volume, thus forming the basis for the assessment of cardiac dynamics[71–72]. Due to its non-invasive, portable, and online nature, PPG is particularly suitable for continuous biologic monitoring in realistic settings. However, it is susceptible to motion artifact and illumination sensitivities, which might limit its accuracy during intense activity and bright environments[74]. Skin tone and sensor location might also affect accuracy[75].

In terms of indicators, the BVP signal is the raw data directly obtained from PPG, capturing temporal fluctuations in peripheral blood volume. By preprocessing the BVP waveform and detecting pulse peaks, inter-beat intervals (IBIs) can be calculated to form an IBI time series, which allows for the derivation of instantaneous HR and serves as the basis for HRV analysis. Common HRV features are typically classified into two domains: time-domain indicators include the root mean square of successive differences (RMSSD), the standard deviation of NN intervals (SDNN), and the proportion of NN intervals differing by more than 50 ms (pNN50); frequency-domain indicators include low-frequency power (LF), high-frequency power (HF), and the LF/HF ratio[76]. These metrics are widely used as correlational indicators associated with individuals' stress levels, emotional arousal states, and recovery capacity[77]. Physiologically, the magnitude of BVP tends to decrease as levels of psychological stress increase, with short IBIs, that is, higher HR, being characteristic under high-stress conditions[76,78]. RMSSD, SDNN, and pNN50, measures of time-domain HRV, tend to decrease with increasing levels of stress. In the frequency domain, higher stress tends to be linked with higher LF, lower HF, and higher LF/HF ratio. However, since LF reflects both sympathetic and parasympathetic activity and is not uniquely indicative of stress responses, there is a need for caution in deriving stress-related inferences based on LF. Moreover, the LF/HF ratio does not uniquely map onto sympathetic versus parasympathetic dominance, so its interpretation as an index of autonomic balance remains debated[76].

In healthy landscape research, PPG-derived indicators have been widely used. For example, walking in natural environments has been associated with lower HR and longer IBI, suggesting a more relaxed and comfortable physiological state[79]. Analysis of HRV in the time domain also exhibits similar outcomes, with an increase of 104% in RMSSD, as well as an increase of 47% in SDNN, signifying a decline in physiological stress experienced by the individual because of nature-based walking as a health-enhancing activity[80]. Consistently, frequency-domain analyses of HRV have shown that exposure to natural settings is associated with increased HF and decreased LF/HF ratio[81].

In terms of mechanism, changes in PPG-derived indicators elicited through nature contact underscore the shift between two autonomic modes[80]. A vagal-dominant mode is inferred when indicators such as HF, RMSSD, SDNN, and pNN50 increase, and IBI lengthens; all are signatures of parasympathetic predominance and more compliant vascular tone. By contrast, a sympathetic-dominant mode corresponds to the opposite pattern of these indicators, signaling a higher-load, stress-reactive state. Shifts toward the first pattern after nature exposure indicate reduced stress load and greater recovery capacity. It should be noted that such mechanistic interpretations are plausible but inferred, as PPG cannot directly measure autonomic drive and instead reflects correlations with underlying physiological patterns.

3.2.2.2 EDA

EDA is a non-invasive physiological measure widely used in emotion and stress research. The measure indicates the degree of sweat gland activity by detecting skin conductance responses provoked by a small electrical stimulus. EDA offers high temporal resolution, tending to be very sensitive to psychological states such as stress, alertness, and arousal. However, the accuracy of the EDA signal may be affected by several factors, among which are the quality of the electrical contact at the skin electrodes, environmental temperature and humidity, the participant's task engagement, as well as inter-individual variations of sweat gland density[82].

Changes in EDA reflect shifts in physiological arousal, with higher values generally indicating increased sympathetic activation and lower values associated with relaxation[83]. In addition, EDA is represented as the time-series skin conductance signal that shows two distinct patterns. These patterns include the tonic component, referred to as skin conductance level (SCL), and the phasic component, denoted by skin conductance responses (SCR)[84].

SCL measurements are more often used compared with SCR in studies of nature exposure. Most of the results have shown that nature exposure is more effective in reducing SCL compared with urban settings. Factors such as virtual exposure to forest pictures or classroom settings with views of plants have been found to effectively decrease SCL, thereby contributing to less stress and faster physiological recovery within natural environments[61,85–86]. However, some studies have failed to show significant differences in SCL in natural settings; some have found lower SCL levels in urban settings or have found no difference between environments[40]. These outcomes have been attributed to several factors, such as sequence effects of exposure, physiological adaptation, and sweat interference caused by electrode location[87].

In terms of mechanism, EDA offers a narrow window. High levels of EDA indicate sudomotor activity mediated by the sympathetic cholinergic nervous system[26]. Therefore, reduced EDA in nature-exposed subjects is more consistent with reduced sympathetic arousal. Mechanistic claims should remain conservative and be triangulated with other measurements to improve inference.

3.3 Behavioral Expression Measures

Measurement of the behavioral expression phase focuses on individuals' observable responses to environmental stimuli. Driven by neural commands via the somatic nervous system, these observable responses are captured through external data such as images, audio, and interaction logs, reflecting individuals' emotional states and cognitive demands. The phase involves two main measurements: 1) facial expression analysis based on image recognition to identify emotional responses and stress, and 2) eye-tracking technology to assess attention allocation and cognitive load.

3.3.1 Facial Expression Analysis

Facial expression analysis is a technique used to infer an individual's emotional state by identifying changes in facial features. The analysis has three main methodological approaches. The first is the Facial Action Coding System (FACS), developed by Paul Ekman, which decodes facial expressions by identifying specific Action Units based on basic emotion theory. Even though it minimizes researcher bias and offers structured coding, it requires strong emotional signals and is time-consuming to implement[88]. The second approach, EMG, uses surface electrodes to measure subtle facial muscle activity, offering high sensitivity. However, EMG can be technically complex and difficult to apply in realistic settings with low-arousal states in nature exposure[89]. The most recent and popular method among the three is an AI-driven facial expression recognition approach. Based on computer vision and machine learning, it automatically detects faces, tracks dynamic facial landmarks, and classifies emotions via trained algorithms, enabling rapid, consistent, and scalable recognition of emotional states such as joy, sadness, and anger[90]. As the most advanced approach in facial expression analysis, AI-driven recognition is the focus of this section.

AI-driven facial expression analysis has been applied in multiple empirical studies to explore whether nature exposure can elicit specific emotional expressions. For instance, an experimental study used AFFDEX 8.1 software to analyze participants' emotional expressions while viewing images of nature, where the results showed that joy was dominant over other emotional expressions[91]. Another field study conducted using FireFACE™ software showed that people exposed to forests were happier than those exposed to urban environments. Additionally, emotional expressions were affected by participant characteristics and time factors, with forests increasing joyful expressions among mid-aged female participants in the morning hours[92]. However, results are mixed, with one study finding no significant differences in facial expressions between natural and urban images, possibly due to low stimulus strength, limited environmental realism, or individual variability[93].

In terms of mechanism, facial cues have low levels of evidentiary utility. They are best seen as indexing overt affect and social appraisal, displaying only weak and nonspecific links to central-autonomic coupling and to endocrine mechanisms. Facial assessments can therefore best be considered phenotypic products for decomposition in terms of environment; for inference at the pathway level, they are best combined with other measures of human response.

3.3.2 Eye-Tracking Technology

Eye tracking is a technique for inferring individuals' visual attention and emotional states by recording eye movement patterns. Modern systems adopt the pupil-center corneal reflection principle, using infrared light and corneal-pupil positioning to estimate gaze direction in real time[94]. Eye-tracking devices now range from traditional glasses-style systems to screen-based software and portable USB modules for mobile devices, enabling users to track gaze behavior across a wide spectrum of contexts. Despite potential motion artifact and ambient illumination conditions, this technique maintains benefits regarding cost, high spatial and high temporal resolution, and high ecological validity in field assessment[95].

Common eye-tracking metrics include fixation, scanpath, pupil size, and blink rate. Fixation duration is one of the most used metrics, and increased fixation duration is often associated with a higher processing effort[96]. Scanpath patterns are used to assess the allocation of attention in visual space. Short and compact scanpaths are associated with focused allocation of attention to specific objects, while longer scanpaths are associated with higher levels of executive control over attention[97]. Increased pupil diameter and decreased blink rate are associated with higher levels of attentional and emotional effort[98], while increased blink rate may reflect mental fatigue[99].

In the fixation and saccades dimension, nature exposure typically enhances attentional focus and reduces cognitive load. For example, a study found that, compared with non-biophilic scenes, participants in biophilic environments showed fewer fixation counts, shorter fixation durations, and fewer saccade counts in OSPAN working memory tests, suggesting that biophilic environments may improve cognitive efficiency by reducing mental workload[100]. Pupillary responses to nature exposure show mixed effects, which some researchers link to differences in emotional arousal and hedonic valence of the stimuli used in experiments[101–102]. For blink frequency, some studies have shown that blink frequency increases when viewing urban scenes compared with natural scenes, reflecting higher cognitive load during information processing[103–104].

In terms of mechanism, eye tracking, like facial measures, does not deliver neurophysiological evidence and chiefly reflects overt attention allocation, so it is best treated as a phenotypic output for decomposing environmental effects. Within this framing, one potential mechanism is a perceptual fluency-mediated reduction in oculomotor load[103]. Perceptual fluency is the ease and speed with which visual input is parsed and integrated into a coherent representation. Natural scenes often exhibit mid-range fractal scaling, smooth contours, redundant statistical regularities, and lower visual clutter that align with visual priors and efficient coding constraints. Consequently, attention can be paid to fewer but longer fixations, fewer saccades, and lower blink rates.

3.4 Subjective Representation Measures

Measurement of the subjective representation phase focuses on automated subjective semantic profiling techniques that analyze people's verbal expressions to infer their internal psychological experiences based on language features. These techniques typically rely on NLP algorithms, such as sentiment lexicon analysis and emotion classification models, to extract structured features related to emotional valence, attentional focus, and cognitive state from interview transcripts, real-time speech, or self-report texts. The tools are cost-effective, have high ecological validity, and can, therefore, be applied in real-time, complex environments. However, its effectiveness depends on input quality and training data, has limited cross-cultural generalizability, and is susceptible to linguistic ambiguity and sarcasm[105].

In recent years, there has been increasing utilization of language processing techniques to identify subjective emotions evoked by interactions with natural environments. Dictionary methods have been utilized to determine the incidence of emotion words and tendencies in nature-based situations[106]. In one such study, happiness levels were identified by analyzing 1.5 million tweets from 25 cities across the US through the labMT sentiment dictionary. The results showed that there was a stronger incidence of positive words in messages posted inside parks, with the strongest effect present in parks larger than 100 acres (approximately 40 hm^2)[107]. More recently, machine learning and deep learning approaches have been used to model relationships between semantics and emotions with better contextual sensitivity. For instance, a study used random forest models to analyze 55,000 Weibo posts from Beijing parks and found that larger parks and more water features were linked to higher positive emotion[108]. Another study applied TextBlob to classify the emotional valence of geo-tagged English and German tweets from 26 green spaces in Berlin. Results showed that activity-related features, such as open areas and swimming facilities, consistently enhanced positive affect across languages despite cultural differences[109]. These findings demonstrate the potential of AI-based language analysis to uncover emotion–environment relationships at scale.

In terms of mechanism, language-based semantic profiling also offers no neurophysiological evidence and chiefly reflects overt appraisal, so it is best treated as a phenotypic output for decomposing environmental effects. Mechanistic inference should be triangulated with other human response measurements.

3.5 Synthesis and Transition

Taken together, Sections 3.1 to 3.4 indicate convergent yet modality-specific evidence that nature exposure is linked to proximal regulation across phases. At the neural processing phase, studies show relaxation-oriented shifts, including modulations of prefrontal electrical activity and hemodynamic responses, alongside adjustments in functional coupling. In the physiological adjustment phase, endocrine and inflammatory markers tend to decline, while autonomic regulation shifts to a lower arousal profile. At the behavioral expression phase, biophilic contexts are linked to more efficient visual attention and lower processing demands. At the subjective representation phase, language-based analyses further reveal a more positive affective tone at scale. Despite this progress, several unresolved issues are evident in the reviewed literature.

1) Cross-modal attribution limitations exist within modality silos. The attribution of change to a single signal without intertemporal alignment among the modalities characterizes most of the work. This is due to the absence of synchronous data acquisition as well as intermodality constraints (e.g., cross-modal noise couplings in joint recordings of EEG and fNIRS). As a result, observed effects cannot be anchored to common perceptual events or traced across phases, leaving pathway mediation untested.

2) Evidence for heterogeneity remains under-resolved. Many findings are mixed or conditional across the included studies. This gap arises from predominant group-mean reporting and limited stratification or latent profiling (e.g., facial-expression outcomes vary by individual characteristics and time of day). As a result, these patterns underscore the importance and necessity of probing respondent subtypes and systematically modeling affective heterogeneity.

3) Temporal and contextual fragmentation of datasets. Most protocols are short, scene-bound, and siloed. This gap arises from the scarcity of long-duration, georeferenced integration across wearables, neural and physiological signals, behaviors, and languages. As a result, measurements predominantly capture short-term effects, yielding insufficient data volume and continuity for complex big-data modeling, which in turn impedes the identification of multilevel mechanisms.

These observations delineate the outstanding problems that follow from the current evidence base and motivate further methodological consolidation in subsequent sections.

4 Discussion

4.1 Future Directions

4.1.1 Applying Multimodal Measures for Mechanistic Insights

Unimodal approaches often detect general psychological responses to environmental stimuli but lack the capacity to identify their perceptual sources or underlying affective processes. However, multimodal measures enhance explanatory precision by combining complementary data streams[110]. For example, combining neural imaging with eye tracking allows researchers to link attentional restoration to specific gaze behaviors, offering more precise insights than neural data alone[111]. In line with this, studies have shown that integrating fNIRS with gaze features can improve mental workload classification by up to 19%, highlighting the interpretive advantages of multimodal methods[18]. In another study, both green spaces and urban third places led to reduced prefrontal activation and self-reported stress. However, only when sentiment analysis was added did researchers identify different emotional pathways—biophilic appreciation in nature and social connection in urban settings[112]. This demonstrates that combining multiple methods can reveal psychological mechanisms that single measures may miss. As a result, future studies should continue to apply additional multimodal approaches to better understand how environments affect mental states.

4.1.2 Clarifying Affective Subtype Variability in Environmental Response

Growing evidence in psychiatry and environmental psychology indicates that affective disorders comprise biologically distinct symptom subtypes with differential treatment and exposure responses[113]. Recent studies using neuroimaging and physiological techniques have begun to reveal subtype-specific differences in responses to environmental exposure. For example, evidence indicates nature exposure induces medial prefrontal deactivation in depressive individuals with high rumination, while those with high anxiety show amygdala downregulation[47]. These distinct neural recovery mechanisms, which are unlikely to be identified through self-report alone, often point to diverging intervention pathways and underscore the need for more personalized treatment strategies. Therefore, future research should prioritize examining affective subtype variability in environmental response using multimodal human response data to better inform the design of individualized nature-based therapies.

4.1.3 Identifying Multilevel Mechanisms Through Embodied Big Data Modeling

Big data in environmental research has traditionally referred to large-scale geospatial datasets. However, high-resolution physiological and neural recordings such as EEG, fMRI, and biosignal streams offer temporally and spatially dense information that, when accumulated over time, constitute a human-centered form of big data. These datasets support the application of high-dimensional modeling techniques, such as independent component analysis, canonical correlation analysis, hierarchical clustering, latent class modeling, and normative modeling, which allow researchers to uncover multilevel mechanisms linking environmental exposure, brain features, and mental health outcomes[114]. For instance, using multi-sparse canonical correlation analysis, researchers have identified a three-stage pathway in which distinct urban environmental configurations shape brain morphology, which in turn interacts with genetic sensitivity to predict emotional, anxious, or unstable phenotypes[115].

4.2 Limitations

This review has several limitations that warrant consideration. First, it adopts a narrative rather than a systematic approach, and the literature search was not intended to be exhaustive. Using specific terms for the literature search, such as “green space exposure,” might mean that literature was missed in cases where related concepts were framed using different terminology, for instance, as “contact,” “interaction,” or simply “experience.” Therefore, future literature reviews should widen the keywords to include a broader range of research. Moreover, the interpretation of neural principles related to nature exposure within this paper depends on the current technical feasibility of brain science studies. Considering the current state of measurements and limited knowledge related to interregional brain interactions, some of our discussions inevitably remain speculative. Finally, as the literature for this review is predominantly from academic sources, it inherently lacks insights from planning and design practitioners. Consequently, the applicability of our conclusions for directly guiding real-world practice remains to be further verified.

5 Conclusions

This review applies a four-phase response-based measurement framework to synthesize emerging technologies for assessing human responses in healthy landscape research. From this synthesis, it becomes evident that current applications remain fragmented, with the integrative potential of multimodal approaches yet to be fully realized, while advanced analytical and modeling methods are still underutilized for probing deeper mechanisms and fine-grained questions. In response to these findings, three future directions are proposed: integrating multimodal measures for mechanistic insight, addressing affective subtype variability, and identifying multilevel mechanisms through embodied big data modeling. These advances have the potential to enhance methodological precision and theoretical depth, supporting the development of healthy landscape interventions going forward.

AI Ethics Statement | During the preparation of this work, the authors used ChatGPT 5.2 in order to improve the readability of the manuscript and check for grammar errors. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Competing interests | The authors declare that they have no competing interests.

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为健康景观而创新：关于测度并理解人类对环境刺激反应的技术的研究综述与未来展望

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摘要

心理健康障碍已成为全球范围内日益严峻的公共健康问题。随着相关研究不断强调环境的恢复性属性，自然景观正逐渐被视为减少精神障碍的有效途径。健康景观研究在很大程度上可通过人类反应数据得到强化，甚至在某些方面具有不可替代的启示意义；然而，现有文献在该领域内仍缺乏系统且充分的综合性梳理。为弥补这一不足，本文首先基于人体对环境刺激产生反应时所经历的内在加工阶段，提出一个面向新型测度技术的分类框架，包括4个阶段：神经处理、生理调节、行为表达，以及主观表征，分别对应于人体反应过程中的不同阶段。在此框架下，本文采用叙述性综述方法，对各阶段中应用于健康景观研究的相关技术、核心指标、证据实例及其潜在作用机制进行系统整合。最后，基于当前研究中的关键不足，提出健康景观研究的3个新兴发展方向：1）通过多模态测量获取机制层面的深入洞见；2）阐明环境反应中不同情感亚型的异质性特征；3）通过具身大数据建模识别多层级作用机制。总体而言，本文为探究复杂的人与环境相互作用提供了理论视角与方法学基础，并为数字赋能背景下健康景观的精准干预设计提供了支撑。

关键词

环境暴露；人体健康反应；心理学；生理学；神经科学；景观设计学

文章亮点

- 提出面向健康景观研究的人类反应4阶段框架
- 将神经、生理、行为与主观测量工具系统映射至各反应阶段
- 综合梳理用于精细刻画人与环境交互的新兴数字化感知指标
- 倡导采用多模态测量以揭示作用机制及情感亚型差异
- 提出基于具身大数据进行多层级数据建模的精准化自然干预路径

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