Trends in
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Opinion

Finding order in chaos: influences of environmental complexity and predictability on development

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Environments are dynamic and complex. Some children experience more predictable early life environments than others. Here, we consider how moment-by-moment complexity and predictability in our early environments influence development. New studies using wearable sensors are quantifying this environmental variability at a fine temporal resolution across hierarchically structured physical and social features. We identify three types of predictability: periodicities ('at X time intervals, Y happens'), stability ('given state_x, state_{x+1} is known'), and contingency ('when I do X, Y happens'). We discuss how the temporal dynamics of environments may differ between individuals and the diverse developmental neural pathways through which this may influence outcomes, such as central nervous system (CNS) arousal and executive control. Finally, we discuss practical consequences and directions for future research.

Highlights

Self- and observer-ratings measuring chaos and unpredictability in a child's early environment predict diverse cognitive, psychological, and behavioural outcomes.

New generations of studies that use wearable sensors can quantify environmental variability at a much finer temporal resolution, which can adequately describe the hierarchical structures of physical and social features of an environment.

We discuss three types of environmental predictability (periodicity, stability, and contingency) and the pathways through which they directly influence development.

Child ↔ environment interactions are bidirectional; we explore example mechanisms of how this can lead to either regulation or dysregulation.

The influence of environmental unpredictability

> Ask not what's inside your head, but what your head's inside of
>
> [William Mace, 1977]

The developing brain is acutely responsive to its surroundings. Previous research has demonstrated how biological hazards (e.g., malnutrition, environmental toxins) and social hazards (e.g., maltreatment, domestic violence) are associated with diverse psychological, behavioural, and physical-health sequelae in children [1]. A range of pathways have been suggested that may mediate these effects. These include biological pathways affecting glucocorticoids or oxidative stress [2,3] as well as experiential pathways, such as prenatal adversity, causing abnormal cortical maturation [4].

Other research has examined the relationship between environment and brain development from alternative perspectives – by exploring, for example, how the availability and distribution of resources within an environment influences an individual's tendency to explore versus exploit [5]; or by considering how the expectation of environmental reward affects whether behaviours such as delaying gratification are adaptive [6,7].

We consider a different, complementary feature: how the temporal dynamics of complexity and predictability across multiple, hierarchically structured aspects of a child's early environment may affect developmental processes. We know that, across both atypical and typical development, self- and observer-ratings that measure chaos and unpredictability in a child's early

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home environment predict diverse cognitive, psychological, and behavioural outcomes [8–10]. Here, we consider why.

We explore the notion that children's brains operate, just like adult brains do, by generating and testing predictions based on regularities in our environmental input [11,12] and that statistically tracking patterns of change in our surroundings allows us to detect unpredictable incoming sensory input [13–15]. We consider how a consistent lack of predictability in early environments might affect these developmental processes [16].

We also discuss how a child's experience is not solely a passive flow of information from the environment to the child [17]. In reality, interactions with the world are bidirectional: my own actions determine what information I in turn receive back from the world [18]. Each child has a unique profile of predictability due to the varied experiences of predictable or unpredictable environments they experience across different timescales, locations, or situations [19]. We discuss how an agent's state at one moment can determine what they choose to sample from the world at the next moment in time and how children, by choosing what they sample from the world and when, can drive both self-**regulation** (see Glossary) (through a process known as **allostasis**) and dysregulation (through **metastasis**).

New approaches to measuring early life environments

Most current research uses questionnaires to measure early life environments. These reduce environmental variability to a static (time-invariant) snapshot that often agglomerates across levels of explanation. For example, research shows that children from low-income households will, on average, experience living environments with more noise and less light, with caregivers who are more anxious and depressed, and less responsive, and also experience greater day-by-day variability in the availability of food and resources [20]; but a single 'static snapshot' offers little opportunity to tease apart how each of these individual overlapping environmental factors influences development.

More recently, researchers have started to use wearable devices worn by the child and household members in home settings to capture day- and week-long recordings of how a child's physical and social environment changes over time [21–23] (Figures 1 and 2). In addition to tracking low-level visual and auditory features, such as light and sound fluctuations [21,24], machine learning classifiers can also be applied to automatically identify higher-level features, such as visual and auditory objects and scenes [25] and the mood [26] or responsiveness [27] of social partners, and auto-transcription [28] can identify semantic and contextual factors or thematic elements in speech [29].

Multi-feature extraction allows researchers to study variability across multiple hierarchical levels. These range from the low-level, temporally fine-grained (e.g., sub-second volume and pitch fluctuations in speech) to higher-order levels of explanation (e.g., meanings, contexts, and intentions). Higher-order levels of explanation tend to operate across more coarse-grained temporal scales (Figure 2).

In this article, we will explore different ways in which environments can vary in predictability over differing timescales (Figure 2) and the pathways through which each type may influence early development. First, we consider **periodicity** and how it drives neural and physiological entrainment to environmental rhythms. Then, we consider **stability** and how it may influence the development of hierarchical, predictive processing of events. Lastly, we consider **contingency** and how what children choose to sample from their environment and

Glossary

Allostasis: the active process by which homeostasis (i.e., internal, physiological equilibrium) is maintained by an organism.
Attention control: the capacity to choose what we pay attention to and what we ignore.
Attractor: transient self-sustaining patterns of activity, for example, engagement between an agent and objects and people around them.
Contingency: when I do X, Y happens.
Metastasis: the opposite of allostasis – processes through which increases and decreases are not corrected for, but instead become progressively amplified over time, leading to disequilibrium.
Periodicity: at X time intervals, Y happens.
Prediction error: caused by an unexpected event – prior expectations are compared with incoming sensory input, any discrepancy generates a prediction error signal.
Regulation: the ongoing, dynamic, and adaptive modulation of internal states (e.g., emotion, cognition) or behaviour, mediated by central and peripheral physiology.
Stability: given state$_x$, state$_{x+1}$ is known.

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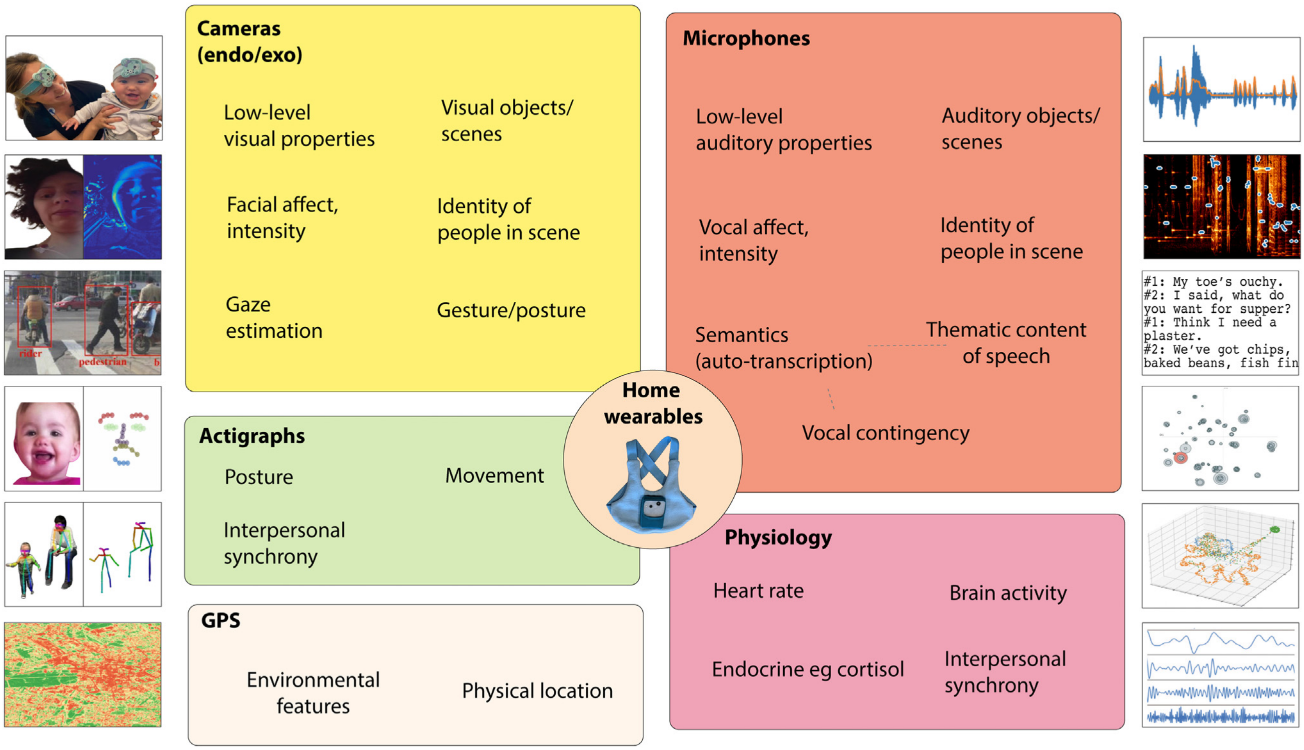

Figure 1. Examples of aspects of home environments that can be measured with wearables. The use of wearable recording equipment in research, worn by children and household members over days/weeks, allows researchers to capture how a child's physical and social environment changes over timescales that can range from seconds, to days, to months. The centre panels show the different types of information that can currently be extracted using widely available classifiers, from wearable microphones, cameras, actigraphs, physiological monitors, and GPS units. Left column shows illustrations of analyses applied to camera and GPS data. From top to bottom, the images show: mother and child wearing head cameras; sample frame from a head camera, analysed for flicker (low-level luminance) (using scripts from [94]); sample frame analysed to object (person identification) (using [95]); sample frame analysed for facial features and facial affect (using [96]); sample frame analysed for body position (using [97]); sample map showing normalised difference vegetation index (from GPS data) (using [98]). Right column shows illustrations of analyses applied to microphone and physio sensor data. From top to bottom, the images show: raw amplitude; raw spectrograms and fundamental frequency of voice (from [99]); sample text transcriptions (from [28]); intertopic distance map (from [100]); 2D spatial representation obtained using Uniform Manifold Approximation (from [101]); raw plot multi-modal data acquired from physiological sensors.

when they choose to sample can drive both regulation (via allostasis) and dysregulation (via metastasis [30]).

Environmental periodicities, entrainment, and coupled oscillators

Periodicities are present in a child's environment across varying temporal scales, from the exaggerated rhythms occurring at the sub-second scale in infant-directed speech [31] to the daily, weekly, or monthly routines adhered to by households [10,32]. Periodicities are also observed at numerous levels of biological structures within a child. From early life, we show cyclic organisation of feeding, digestion, sleep, and vigilance [33], as well as rhythmic physiological changes in respiration and heart rate [34], through to spontaneous sub-second oscillatory brain activity [35]. Although speculation exists regarding how precisely oscillatory entrainment is achieved [36], there is considerable evidence supporting that, as endogenous oscillators, children entrain to external periodicities across these varying scales [37–39].

During early life, caregiver–infant co-regulation ensures infants maintain optimal CNS arousal [40] within a critical state between over- and under-excitation [41] throughout fluctuations driven by

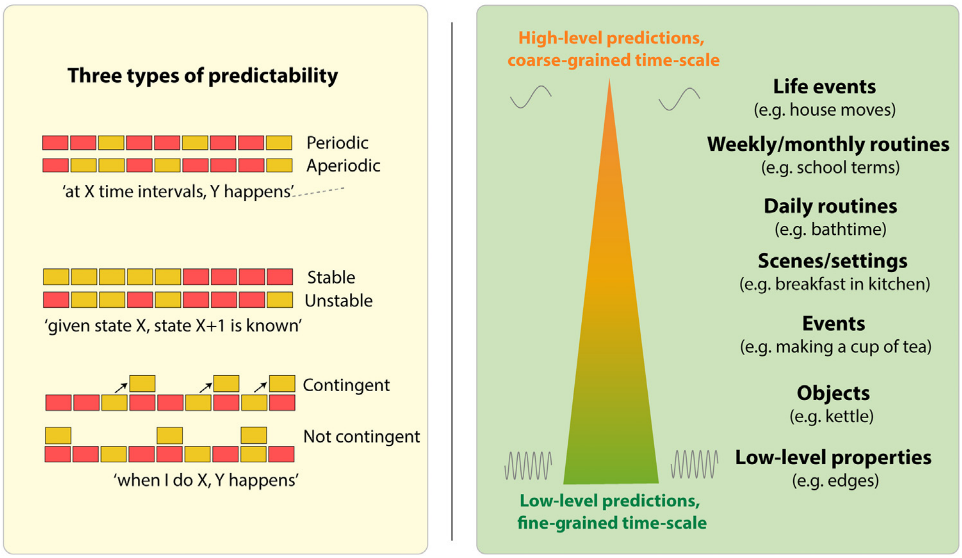

Figure 2. Types and scales of environmental predictability. Left: different types of predictability. Schematic illustrating the three types of predictability discussed in this article: periodicity (top), stability (middle), and contingency (bottom). Right: environmental predictability across multiple, hierarchical scales. The schematic illustrates how environmental predictability can occur across multiple hierarchical scales, ranging from the low-level predictions based on luminance differentials (for example), tracked at a fine-grained temporal scale, through to high-level predictions based on semantic and contextual factors, tracked at a more coarse-grained temporal scale.

feeding and sleep/wake cycles, stochastic variability, and environmental changes [42,43]. Over time, regulation of these cyclical, physiological functions influences the ability to self-regulate more complex functioning, firstly emotional and socio-communicative functions and, later on, cognitive and epistemic processes [43,44].

Stable oscillatory activity enables the management of inhibitory/excitatory balances [35]. For example, young infants whose attention patterns are more cyclic show faster learning and discrimination [45]; and greater sleep–wake cyclicity during early life also predicts superior emotion regulation during later development [46]. Over a larger timescale, rhythms that arise on a daily basis due to family routines are also associated with superior child mental health during stress [10]. The influence of a lack of predictability may be amplified when these environmental periodicities of differing scales interact with one another.

Environmental rhythms influence internal rhythms via a process known as passive environmental entrainment (Figure 3, middle row, left box). Thus, more stable environmental rhythms are associated with more stable internal rhythms. But there are also other, more subtle ways in which periodicities may influence perception. For example, periodic external stimulus features (e.g., 'sharp' events in the speech acoustics, which cause transient increases in brain activity in listeners [47]) may allow a child's oscillatory neural responses to that speech stream to be selectively greater, relative to other aperiodic features [36,38]. This causes selective entrainment driven by environmental periodicities (Figure 3, middle row, left box). This may produce effects that are similar to directed **attention control**, where it is known that directing attention (e.g., paying attention to one talker in a multi-talker environment) causes neural responses to the attended-to speech stream to be selectively enhanced [48]. But in this case, the selective enhancement is driven purely by external properties (periodicities) of the stimulus. This may be one reason why early language-based

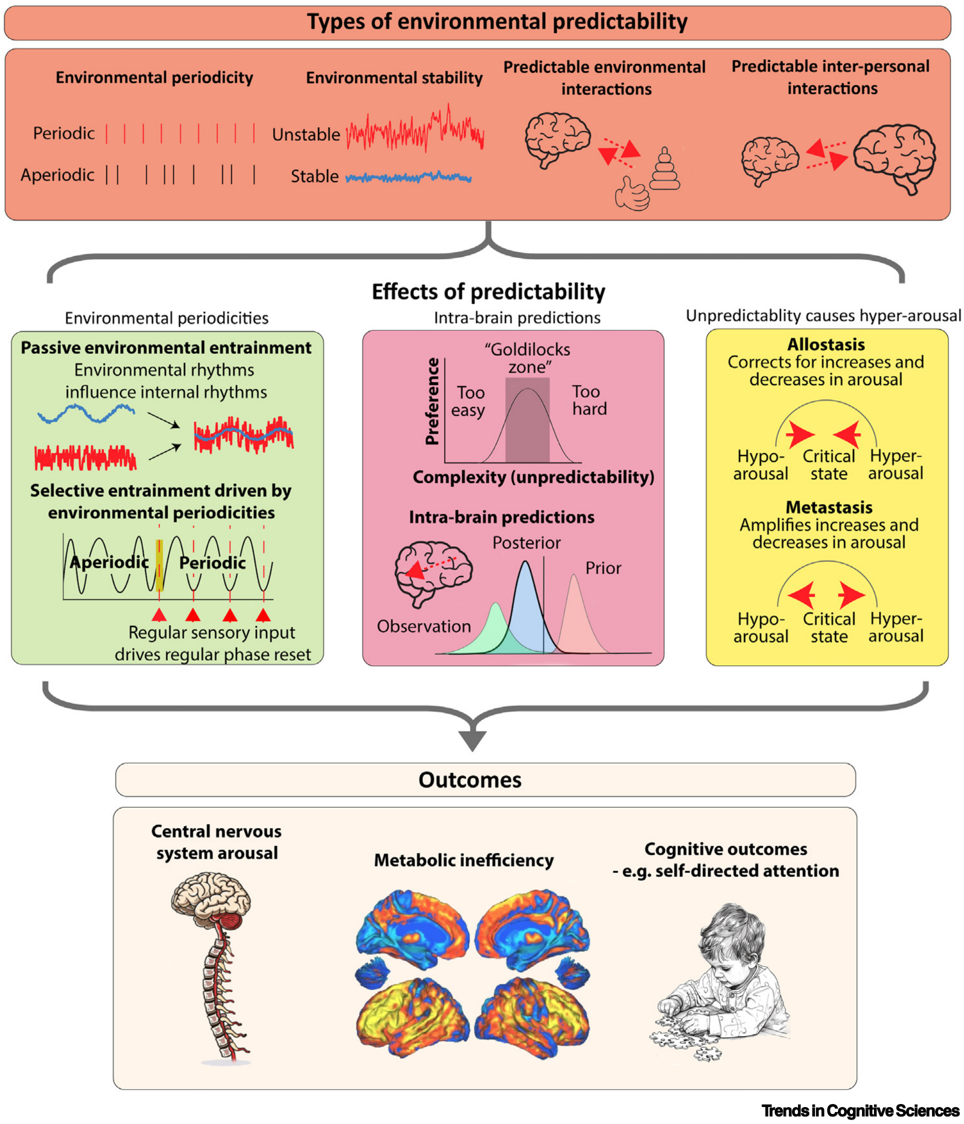

Figure 3. Dynamic environments and brain development. First (top row), we considered the three different ways in which environments can be predictable: environmental stability, environmental periodicity, and predictably contingent environmental interactions (either with the physical environment, or inter-personal). Next (second row), we consider the effects of environmental predictability. In the section entitled 'Environmental periodicities, entrainment, and coupled oscillators' we considered how environmental periodicities can drive both passive environmental entrainment; and the special case of how selective entrainment to periodic features of environment can also arise (e.g., in rhythmic child-directed speech) (left box). In the sections entitled 'Environmental stability and inference' and 'Predictive learning and metabolic efficiency' we considered environmental stability and the development of predictive neural coding (centre box). In the sections entitled 'Arousal and allostasis' and 'Metastasis and gene-evoked environments' we discussed how children, by choosing what they sample from the world and when, can drive both self-regulation (through a process known as allostasis) and dysregulation (through metastasis) (right box). Finally (bottom row), we consider three outcomes that are thought to be affected by environmental predictability: central nervous system arousal, metabolic efficiency of brain function, and cognitive outcomes, such as self-directed attention.

interactions often rely more heavily on nursery rhymes and rhythmic singing [49] and why children's brains show stronger cortical tracking of child-directed speech, which contains exaggerated rhythms [50].

Environmental stability and inference

Whereas a periodic stimulus is always stable, a stable stimulus can also be aperiodic (Figure 2, left panel). We define stability as the likelihood that the next state of a feature of the environment can be inferred, given its current state. The stability of moment-to-moment variation in both physical features (e.g., household noise) and social features (e.g., the continuous behaviour of a caregiver) [51] can be approximated using information-theoretic measures of entropy, which quantifies the average level of uncertainty, or surprisal, assigned to a variable's potential outcomes [52]. Children raised in environments with higher stability tend to demonstrate advanced cognitive development according to multiple measures [53].

Research into how our brains learn to predict the subsequent state of the environment given its current state is most well advanced in studies that measure the neural tracking of natural language within the narratives of media clips. The use of a deep neural network (GPT-2) to quantify contextual predictability has shown that the brain's processing of words in an audiobook is modulated by predictions, with high-level (e.g., contextual) predictions informing low-level (e.g., phoneme) predictions [54]. When stories are presented in a scrambled order, the higher-order contextual predictions, represented by whole functionally-connected brain networks, are lost [55]. Comparable research in 12-month-old infants whilst viewing TV and film clips established neural representations for longer events only, and not for shorter events, even in early visual regions of the brain [56], indicating that a timescale hierarchy has yet to develop at this age [57].

It is likely, although untested, that similar principles guide how the adult brain processes hierarchically structured layers of predictability in real-world settings. In younger viewers, semantic and contextual factors may be less likely to influence the predictability of a given event [56]; but, to our knowledge, this is currently untested. It is also possible that the development of a timescale hierarchy of predictions may be influenced by the stability of early life experiences; but this idea is also, to our knowledge, untested. Future research could, for example, measure this by transcribing dialogue in home settings using an automatic speech recognition model [58] and analysing this in combination with postural, gestural, and positional information [59]. In this way, the higher-order contextual and semantic predictability in children's home environments, and how it varies between settings, could be measured.

Interactive contingencies

Thus far, the child's environment has been considered in a passive, non-interactive lens (i.e., information flows solely from the environment to the child). But in reality, much of the data in the world is latent without direct interaction with it [60]. Through picking up a toy or smiling at someone, we alter what information we receive back from the world. Interactive contingency allows us to predict how one's actions on the world will in turn influence what information we receive back, whether this is a physical interaction (e.g., a child banging a spoon on a table will hear a noise) or social interaction (e.g., a child who smiles at someone will generally be smiled back at).

Even from early life, children are highly sensitive to contingency. For example, they show neural sensitivity to contingent responsiveness from a social partner by the age of 1 year [61,62]. From as early as 6 months, infants hold expectations about the social efficacy of their behaviours [63]. The caregiver's model of the infant influences in turn how the caregiver reacts to the infant, based on how they predict they will think, feel, or behave [64]. This results in mutual prediction driving neural activity during social interaction [65].

When children self-select what information they receive from the world, whether through social interaction [66] or physical toy play [60], their selections tend to be 'bursty' (i.e., to contain periods where the same element is sampled repeatedly, interspersed with periods where it is not). This tendency has been linked to the idea that learners repeatedly sample from the same source as long as they are learning something new, reducing **prediction error** [67]. When the contingency has been learnt and prediction error diminishes, the learner moves on to novel problems [60].

Predictive learning and metabolic efficiency

When we are both passively perceiving information in our environment as well as actively interacting with it, we generate predictions that increase our perceptual sensitivity to anticipated events [15]. In real-world settings, as we discussed earlier, predictability is a function of both the low-level audio-visual properties of the scene and the higher-order properties derived from semantic and contextual factors. An unexpected sensory event can be functional for an infant if it facilitates information gain, with intermediate levels of new information (e.g., uncertainty) considered optimal [68,69].

Learning occurs through generating predictions and consequently updating current states and goals: this process involves 'bottom-up' and 'top-down' processes acting both independently and collectively [15] (Figure 3, middle row, centre box). Computational modelling has shown that when training recurrent neural networks to minimise energy consumption while operating in predictive environments, networks naturally self-organise into prediction and error units [70]. Persistent and successful predictions selectively reinforce and strengthen the connectivity between bottom-up and top-down processes.

In novel settings, infants show a preference for learning from social partners who act predictably compared with unpredictably [71]. This may correspond to the optimal amount of unexpectedness that facilitates information gain and is therefore functional for an infant [68].

Behavioural evidence suggests that short-term predictability is associated with short-term increases in attention control. For example, reliably contingent caregiver feedback extends infant attention durations [72], and experimental manipulations show that when children (and adults) receive information about upcoming tasks, they engage attention control proactively in anticipation of the task more often when the information accurately predicts the future task, than when the information is made unreliable [73]. Over longer time-frames, individuals raised in more predictable environments demonstrate a greater ability to self-sustain attention states [74]; and children who receive more contingent feedback from their primary caregiver show more response-eliciting behaviours, even with unfamiliar adults [63,75].

However, the long-term neural mechanisms that subserve these behavioural findings remain poorly understood. One potential postulation is that because reducing uncertainty involves minimising the brain's free energy [76], the brains of children growing up in more uncertain environments ought to be metabolically less efficient [16]. Additionally, as discussed earlier, there may also be individual differences in how hierarchical brain processing develops, such that children raised in more unpredictable homes show atypical neural tracking of higher-order semantic/contextual factors but not low-level audiovisual properties. As yet, though, both of these possibilities remain, to our knowledge, untested.

Arousal and allostasis

Exposure to environments in which we cannot make accurate predictions leads to increases in CNS arousal [77,78]. Behaviourally, when people feel uncertain, they shift to hypervigilance, where attention allocation is determined primarily by environmental salience rather than 'top-down' control [79,80]. These state-like traits may progress to trait-level features over time, defaulting to more metabolically-saving cognitive processing as an adaptive response to uncertainty. For example, individuals raised in more unpredictable environments show more 'bottom-up', reactive attentional styles during lab-based visual searches when uncertainty is introduced [81], as well as reduced exploratory behaviours [82].

An agent's state at one moment in time can determine what they choose to sample from the world at the next moment in time. Allostasis is the active process that drives self-regulation; it allows us to maintain a critical state between over- and under-excitation [83], or expected and actual sensations [84] (Figure 3, middle row, right box). When there is a discrepancy between the current level of activation and the optimal level, or range, for a given situation, the organism engages in behaviour that shifts activation or perception to reduce this discrepancy [85]. For example, in response to hyper-arousal, an infant may close their eyes or avert their gaze, which reduces sensory stimulation and, thus, decreases arousal [78]; or they may engage in co-regulation-eliciting behaviours, such as crying. Children raised in unpredictable environments show increased metabolic markers of 'allostatic load' [86], thought to index the summed costs of repeatedly engaging in allostasis, whereby the metabolic costs of stress outcompete with longevity-promoting growth, maintenance, and repair [87].

Metastasis and gene-evoked environments

Allostasis, then, informs how behavioural changes can be used to shift activation to reduce the discrepancy between our current level of arousal and the optimal range for a given situation. But this may not be the only way in which an agent's state at one moment can determine what they choose to sample from the world at the next moment. For example, recent research that examined moment-by-moment fluctuations in arousal in naturalistic settings found that both high and low-arousal states are more long-lasting than intermediate-arousal states [21]. This is the opposite of what would be predicted based on allostasis, which predicts that high- and low-arousal states should be corrected.

One possible explanation for this is that the opposite of allostatic processes exist – which in the past we have described as 'metastatic' (from the Greek word 'meta' meaning beyond). Metastatic processes are those in which increases in arousal can lead to changes in behaviour which further amplify the child's arousal state. Possible examples of this may include a hyper-aroused child either becoming increasingly oppositional towards adults [88], exhibiting increased attention bias to threat [89], or creating a messy or chaotic physical environment, all of which further amplifies arousal (Figure 3, beige box). These atypical environmental cascades manifest as **attractors** (i.e., a transient, self-sustaining state characterised by elevated stability; 'getting stuck in a state') [88] (Figure 4).

Relatively little previous research has documented how these processes develop. Sometimes it seems that children can correct for the effects of environmental features through their own behaviours (through allostasis); at other times, they can actively amplify them (through metastasis). Understanding how and why we transition between allostatic and metastatic processes may, in the future, be useful for understanding the gene-evoked environment [90] (e.g., how two children growing up in the same family in the same home may still experience markedly different home environments because their experiences are determined by how they interact with the objects and people around them). In addition to allostasis and metastasis, child behaviours can also influence the periodicity and the stability of the environments that they experience, and so understanding the role of the child as an active agent is crucial for understanding all of the developmental neural mechanisms we have described in this article.

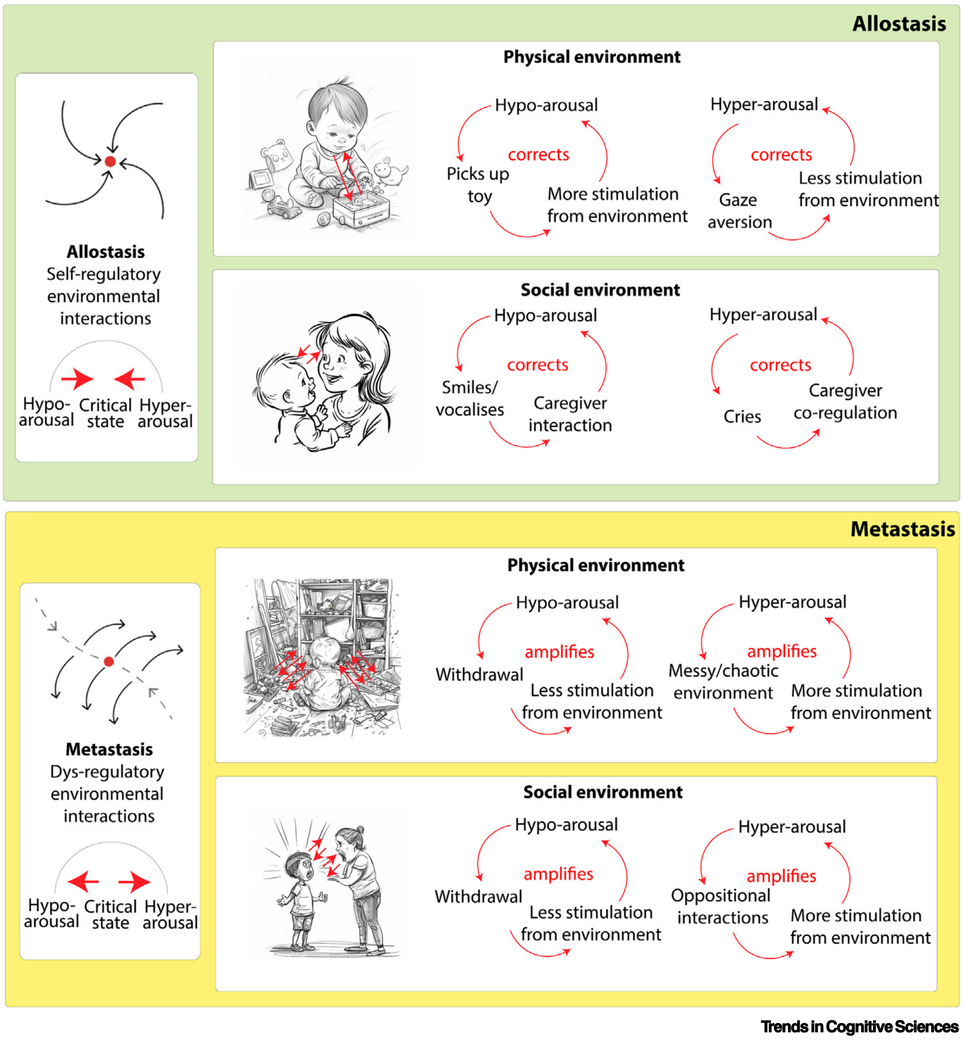

Figure 4. Allostasis, metastasis, and the gene-evoked environment. Recent approaches are starting to measure not just how the environment affects the child (environment → child influences), but also how children evoke different experiences of their environment through their behaviour (child ↔ environment interactions). This bidirectional flow of information is demonstrated in several mechanistic examples above. Interactions with our environment can operate via the physical environment or the social environment, and can lead to regulation (via allostasis) (top) or to dysregulation (via metastasis) (bottom).

Concluding remarks and future perspectives

Studying environments is crucial for understanding typical and atypical development. Questionnaire-based research has made crucial strides in showing how global features of environments are associated with long-term outcomes. In the future, more fine-grained research using wearables to record from real-world environments will allow us to uncover which specific features of environments are most developmentally relevant for children. From this, concrete and practical interventions can be generated to improve long-term outcomes [91].

These new techniques still, of course, have limitations. Achieving accurate depictions of environments often limits studies to day- or week-long recordings and expanding beyond this to longer timescales, such as months or years, can limit coverage. Long-form home recordings also raise

Outstanding questions

Do real-world home environments differ in how hierarchically structured they are (i.e., the degree to which low-level predictions can be made based on higher-order contextual factors)? For example, do children raised in more unpredictable homes show atypical neural tracking of higher-order semantic/contextual factors, but not low-level audiovisual properties? If so, how can early learning environments be tailored to take advantage of this?

Does being able to predict relate to being predictable? In other words, does a child's ability to track information in their environment by generating low-level predictions based on higher-order semantic and contextual factors relate to their ability to generate events (e.g., during play) that are hierarchically structured? If so, what are the neural mechanisms that might drive this?

Does the predictability of a child's early environment relate to their ability for self-directed executive control? If so, is this due to short-term mechanisms (e.g., moment-by-moment fluctuations in their ability to generate predictions based on events that they perceive), or to long-term mechanisms (e.g., altered structural/functional connectivity), or to a combination of both?

What drives children to seek out more versus less stimulation from their environments? Do different individuals differ in their 'critical state' – such that a given level of stimulation might be too low for one individual, leading to active upregulation, but too high for another individual, leading to downregulation?

How, and why, do we transition between self-regulation (via allostasis) and dysregulation (via metastasis)? Are these trait- or state-level features?

Do children differ in the levels of predictability that are optimal for them? For example, would children raised in more unpredictable home settings benefit more from predictable educational settings?

numerous ethical and practical issues of safe data handling and management that need to be considered carefully [92]

Nevertheless, the potential of these techniques for addressing foundational questions about early development is considerable (see Outstanding questions). For example, no research has examined hierarchical structures within real-world environments (i.e., the degree to which low-level predictions can be made based on higher-order contextual factors), let alone assessed individual differences between different settings and families. Just as current research is using large language models (LLM's) to track hierarchically ordered events within TV clips and movies [55] to measure how the brain makes different types of prediction based on low-order features versus higher-order contextual factors (Figure 2), so future research can apply similar techniques to quantify multiple layers of meaning and predictability in real-world environments.

In addition to quantifying how environments differ, we can also explore children's active role in choosing what they sample from their environments and when. A child's experience of their environment is not just passive and non-interactive. Interactions with the world are bidirectional: behaviours generate experiences. Children's early interactions with the world may be stochastic [93] but, over time, they become predictable in a number of different ways. At times, children can correct for the effects of these environmental features through their own behaviours, but at other times they can actively amplify them. Understanding these dynamics is crucial for the future of early life research.

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Declaration of interests

No interests are declared.

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