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The social-ecological learning framework: perception, action, and learning in a changing world

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A B S T R A C T

Interactions among and between human and non-human agents across scales are central to social-ecological systems (SES) and their dynamics. Among the emergent processes vital to navigating change, social learning, especially across cultural and onto-epistemological perspectives, has gained traction for building adaptive capacity, fostering collaboration, and enabling transformative governance. Yet, many learning theories in SES research offer limited insight into the fine-grained, embodied, and relational dynamics through which learning unfolds.

This paper bridges Pahl-Wostl's social learning framework with the predictive processing (PP) paradigm from cognitive science to illuminate micro-level mechanisms of perception, action, and learning in SES. As we show, PP offers a biologically grounded, process-based account of how internal models are formed and revised through recursive loops of perception and (inter-)action with complex environments.

Acknowledging that theorizing learning in SES requires recognizing the inseparable entanglement of the social and the ecological, we introduce the concept of social-ecological learning. This lens highlights how human–human and human–nature relations co-shape what and how agents learn, emphasizing that social learning in SES is always ecologically situated, and vice versa.

Finally, we integrate PP's distinctions between parametric and structure learning with loop learning theory to offer a novel entry point for examining learning across scales—from incremental updates to deep shifts in assumptions and worldviews, and from individual sense-making to broader societal change.

Our framework bridges theoretical silos and contributes to sustainability science by advancing a relational, embodied, and embedded understanding of learning in SES–essential for fostering transformative capacity in an uncertain, rapidly changing world.

1. Introduction

Humanity is facing accelerating and unprecedented global change, which manifests in complex, intertwined social-ecological sustainability challenges such as climate change, biodiversity loss, and geopolitical instability. These crises disrupt established patterns, structures, and relations in social-ecological systems (SES) (Folke et al., 2021; Steffen et al., 2018) and call for fundamental rethinking of how individuals, communities, and societies at large relate to one another and to the more-than-human world (e.g., O'Brien, 2012, 2021; Wamsler et al., 2021; West et al., 2020, 2024). Learning has emerged as a key leverage point for transformative change, particularly forms of learning that engage deeper structures underpinning current behaviors, beliefs, and systems (Baird et al., 2014; Herrfahrdt-Pähle et al., 2020; Pahl-Wostl, 2009). Mutual learning and knowledge co-production are increasingly seen as essential for weaving diverse knowledge systems and for meaningfully including Indigenous peoples and local communities' knowledge and perspectives in sustainability transformation; an endeavor both crucial and challenging (Subramanian et al., 2025; Tengö et al., 2017). Supporting such processes demands a more nuanced understanding of the fundamental dynamics through which learning takes place in SES. This paper advances understanding of learning in SES by drawing on predictive processing (PP), a cognitive scientific framework that conceptualizes perception, action, and learning as processes of navigating uncertainty. By linking PP with SES learning theories, we explore the embodied and relational processes through which learning unfolds and may be fostered across disciplinary, cultural, and onto-epistemological diversity.

A range of concepts have been employed to study learning in SES contexts, including transformative learning (Mezirow, 1991; Moyer and

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Sinclair, 2020), policy learning (Gerlak and Heikkila, 2011), experiential learning (Kolb, 2014; Toderi et al., 2007), and knowledge co-production (Pohl et al., 2010). Among these, social learning—commonly defined as *"a change in understanding that goes beyond the individual to become situated within wider social units or communities of practice, through social interaction"* (Reed et al., 2010, p. 6)—has become especially influential in literature on natural resource management and environmental governance (Gerlak et al., 2019; Reed et al., 2010; Suškevičs et al., 2018). Several influential frameworks have advanced understanding and practice of those learning processes in SES (e.g., Armitage et al., 2008; Cundill & Rodela, 2012; Pahl-Wostl et al., 2007). Yet, the concept of learning remains ambiguous and is often used interchangeably to refer to both processes and outcomes (Gerlak et al., 2019; Jadallah and Ballard, 2021).

Recent syntheses highlight the need for greater theoretical clarity and stronger integration with learning theories from adjacent fields (Ernst, 2019; Gerlak et al., 2019; Jadallah and Ballard, 2021; Suškevičs et al., 2018). Persistent gaps include limited conceptual and empirical focus on (transformative) learning dynamics at the level of individual agents (Ernst, 2019; Wijermans et al., 2023), an emphasis on outcomes—such as improved resilience, trust, or shared understanding—over learning processes (Folke, 2006; Plummer et al., 2017; Suškevičs et al., 2018), and a lack of mechanistic understanding of how learning unfolds across individual, collective, and system levels (Jadallah and Ballard, 2021). Although the embeddedness of individual and collective learning trajectories in the broader social, cultural, political, and natural contexts is generally acknowledged, it remains underexplored (Jadallah and Ballard, 2021, p. 7).

To address these limitations, scholars have increasingly called for cross-pollination with research from psychology, cognitive science, education, and adult development (Gerlak et al., 2019). This aligns with a growing trend in the field of SES research, which is moving towards more dynamic, integrative understandings of human behavior and cognition. These accounts emphasize their relational, embodied, and context-dependent character (Constantino et al., 2021; Schill et al., 2019; Weber et al., 2023). Together, these efforts indicate mounting interest in the mechanisms, conditions, and relational dynamics that shape learning as a transformative force in navigating sustainability. In this paper, we explore the strong potential of predictive processing (PP) in this regard. PP rests on the core premise that the brain fundamentally functions as a predictive system (Clark, 2013; Friston, 2013; Walsh et al., 2020). It casts perception, action, and learning as inferential processes. Their tight coupling enables them to serve the unifying objective of minimizing uncertainty and maintaining an agent's bodily integrity over time (Pezzulo et al., 2024; Shaffer et al., 2022). PP agents do not passively await sensory input. Instead, they proactively predict their sensations based on generative models shaped by past experience (Friston et al., 2016). These top-down predictions contextualize and guide learning (Parr et al., 2022). This resonates with SES concepts such as mental models and cognitive maps, while offering a dynamic and mechanistic account of how such models are formed, adapted, and guide situated action (Craik, 1943; cf. Hutchinson and Barrett, 2019; Johnson-Laird, 1983; Tolman, 1948). Learning from a PP perspective is active and inherently relational. It unfolds through recursive loops of embodied interaction with the social and ecological world, rather than through passive processing confined to the brain (Allen & Friston, 2018; Parr et al., 2022; Veissière et al., 2020, cf. Turner and Berkes, 2006).

We do not present predictive processing (PP) as a substitute for established social learning theories, but as a complementary, integrative lens enhancing understanding of learning dynamics at finer-grained, processual levels. To bridge these perspectives, we integrate core insights from PP with Pahl-Wostl's influential social learning framework (Pahl-Wostl, 2009; Pahl-Wostl et al., 2007). The latter, like PP, highlights the interplay of individual, collective, and institutional levels, and the importance of both content- and relational dimensions in learning. However, both frameworks diverge in their emphasis, engendering a mutual complementarity. Whilst PP offers a process-based, biologically grounded lens to zoom in on individual and interactive dynamics, Pahl-Wostl's framework foregrounds governance, institutional, and systemic change. We advance integration by exploring the potential of PP's distinctions between perception, parametric, and structure learning[1] to inform and deepen existing concepts of loop learning in SES research. This offers a more granular understanding of learning processes across levels, particularly how individuals update their mental models in response to (interactive) experience, and how such shifts may scale up to collective or systemic change.

In what follows, we demonstrate how predictive processing (PP) can advance current perspectives on social learning and mental models by illuminating the entangled dynamics of perception, action, and learning. For clarity, we focus on core insights of PP most relevant for understanding learning and enacting change in SES. To render these concepts accessible to a wider readership, we mostly rely on non-technical language, while providing a glossary that maps these approximations to the corresponding technical terms. In addition, further explanations are offered in intuitive terms and PP formalism for readers wishing to explore the topic more deeply (see Appendix A). In Section 2, we introduce our framework and further refine it in Section 3. Appendix B complements our elaboration by applying these principles to the case of mutual learning and knowledge co-production across cultural and onto-epistemological differences, particularly between Western scientific and traditional and local knowledge systems. We conclude by reflecting on the broader implications of this integration for SES research and outline future directions.

2. The social-ecological learning framework

This section introduces predictive processing (PP) as a complementary lens for conceptualizing and analyzing the learning dynamics at the core of Pahl-Wostl's social learning framework in greater detail. In particular, we focus on how agents[2] actively navigate uncertainty by finessing generative models of, and exercising control over, their worlds.

In a nutshell, PP, particularly the subset of theories aligning with active inference that we draw on here, offers a unifying perspective on perception, action, learning, and decision-making. These are regarded as different expressions of a single shared imperative: minimizing prediction error in long-term average to ensure continued existence in an ever-changing, volatile world (Friston et al., 2017a; Hohwy, 2016; Parr et al., 2022).

The basic idea is as follows. Living systems, such as human agents, engage in a continuous process of inferring the hidden states of the world—both internal (e.g., bodily states or self-concept) and external (e.g., social dynamics or ecological conditions)—that give rise to their sensory experience. These inferences are guided by generative models that predict what sensations should occur given an agent's beliefs about the world, which are informed by past experiences and learning. Subsequently, a comparison is made between prior beliefs[3] and incoming sensations, thereby forming a posterior belief in a process approximating

[1] Broadly speaking, parametric learning refers to updating parameters within an existing model, whilst structure learning refers to revising the model structure itself (see Section 3.2 for a more detailed discussion).

[2] In PP, the term agent is applied to a broad range of systems capable of self-organization, from single cells and synthetic agents to human collectives. In this paper, we focus on natural agents: humans and other entities in the natural world that exhibit patterns of adaptive behavior and learning. For brevity, we refer to individual humans as agents and to other such entities as non-human agents (e.g., animals, plants, ecosystems). When addressing shared principles, we use natural agents as an inclusive term. This usage remains open to diverse ontological perspectives that recognize forms of agency beyond the human or cognitive.

[3] In PP, beliefs are formal statistical constructs (probability distributions over latent causes within a generative model). See the glossary for details.

Bayesian inference. Prediction errors, that is, discrepancies between priors and sensory evidence, can fuel learning about the causal structure of the world (Friston et al., 2017b; Hutchinson & Barrett, 2019). Crucially, generative models are hierarchically structured, allowing agents to interpret and anticipate the unfolding of events at multiple temporal and spatial scales (Friston et al., 2018; Parr et al., 2022).

In line with one of SES's core ideas, PP hence conceptualizes agents and their environments as reciprocally coupled (De Vos et al., 2025; Seth & Tsakiris, 2018; Stephan et al., 2016). This coupling affords agents with two complementary routes for minimizing prediction error. By revising their models (perception and learning) or by acting to align the world with their expectations (goal-directed action) (Friston et al., 2010). Through this dynamic interplay, agents not only adapt to change, but also actively participate in shaping their ecological and social niches, calibrating the fit between their models and the worlds they inhabit (Ramstead et al., 2016; Veissière et al., 2020).

Fig. 1 illustrates how bridging core insights from PP with the social learning framework offers a rich, integrative perspective on learning trajectories and enacting change in SES.

The story of PP is still unfolding, and its conceptual landscape is too vast to be fully captured here (Hohwy, 2020). Rather than presenting a comprehensive account, we propose a generative roadmap, which

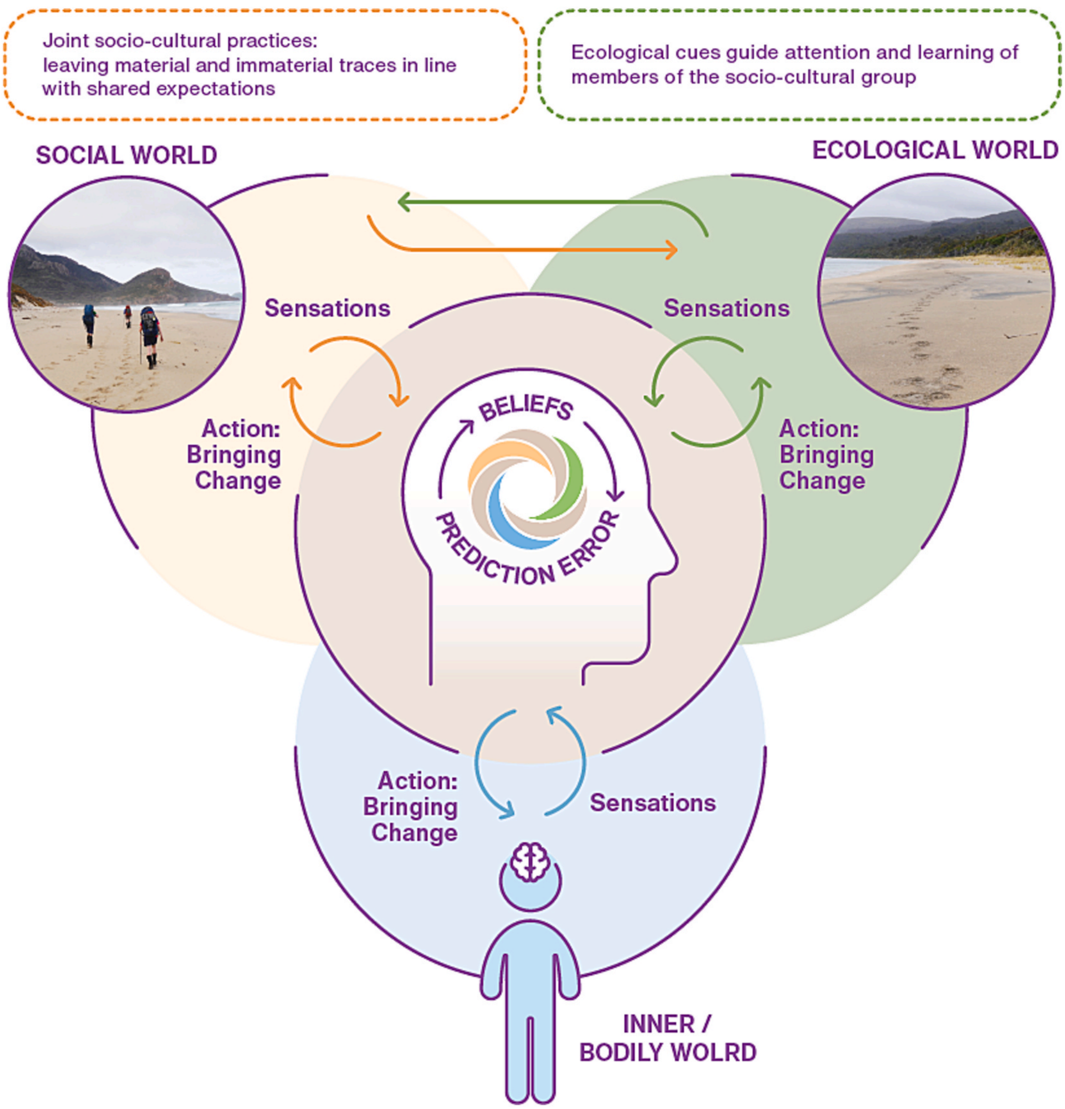

Fig. 1. The social-ecological learning framework. A highly schematic representation of how individuals learn about and in their social-ecological world. At the core, the human agent is constantly generating multisensory predictions about incoming sensations, their meaning, and the optimal plans of action, drawing on past experiences and the current context. These predictions are then checked against sensations arriving from its social, ecological, and inner worlds. Should mismatches occur, agents can either alter their minds (perception and learning) or alter the world to match their predictions (action). The action-perception loop/feedback loop above the agent's head illustrates how individual perception, action, and learning are linked to, and scaffolded by, dynamics in the broader social-ecological context. As socio-cultural group engage in shared practices, they alter their ecological surrounding in material and discursive ways, inscribing shared meaning into its fabric in the form of tools, institutions, narratives, and so forth. These traces shape how other agents perceive and act in the world, though the intelligibility of some of these traces depends on shared histories and cultural familiarity. Over time, this looping mechanism creates local social-ecological niches where learning unfolds differently depending on agent's histories and relations, and contributes to the transmission of cultural expectations across generations. By participating in shared practices, including those in nature, the agent internalizes culturally shared expectations, which will guide how it attends to and makes sense of nature's patterns and dynamics. When engaging with nature's cues in line with shared expectations, the agent contributes to reinforcing both. Conversely, engaging with these cues in unexpected or non-established ways can open space for innovation, reinterpretation, and transformative change. As a whole, the framework underscores that social-ecological learning is not a discrete event isolated to a single disembodied mind, but a socially-ecologically situated process, sustained through embodied engagement with materially and discursively mediated local worlds. *For further explanations and references, please refer to the main text. Photos: Bosse Sottmann.*

delineates core threads that may guide further exploration of learning within SES.

In the following sub-sections, we unpack how learning emerges over time from cycles of action and perception that couple (i) brains with bodies, and embodied agents with their (ii) social and (iii) ecological worlds. For analytical clarity, we temporarily treat the inner, social, and ecological dimensions as if they were distinct, while recognizing that in lived experience they are deeply entangled. We return to this entanglement in Section 3.

2.1. Learning is embodied

The capacity to learn is frequently treated as a matter of information intake. Yet, common experiences, such as difficulties with focusing, absorbing information, or adjusting one's thinking when hungry, anxious, or stressed, serve as reminders of the intimate interconnection between learning and bodily states. From a PP perspective, the body is not merely a backdrop for cognition but a dynamic part of the inferential machinery that underpins learning. The body matters in three interrelated ways: agents learn with their bodies; their learning ability is constrained by the body's energetic regulation (or, more precisely, the brain's beliefs about that); and what is learned is shaped by how the body is represented in the brain (Pezzulo et al., 2015; cf. Seth, 2021).

(1) Learning *with* the body: Perception and learning do not arise from passive observation, but from an active, embodied cycle. Agents use their bodies to seek information in a variety of ways, including moving, looking, listening, touching. This active exploration of the world enables them to test and refine their internal world model, a process known as action-perception loop (Clark, 2016; Friston et al., 2010).

At each moment, agents use their generative models to generate predictions about what they expect to sense, leveraging on past experiences and current goals. These predictions guide their way of engaging with the world. Each action changes the conditions for future sensing, either by altering the environment or by changing the way it is sampled (e.g., shifting gaze). These alternations yield new sensory data, which is compared to prior predictions. Should a prediction error occur, the brain can update its model accordingly, generating new predictions that inform subsequent action. The cycle starts anew. Over time, these micro-adjustments accumulate into learning, yielding a refined model capable of more effectively navigating the world. Thus, learning is inseparable from action; it emerges *through* ongoing brain-body-environment interaction. In SES, this is visible in how local actors build expertise in farming, fishing, or forest stewardship, using embodied engagement to make sense of uncertain, dynamic environments (Berkes, 2017).

(2) Learning is constrained by energy regulation. Belief updating is metabolically costly. Agents thus tend to favor parsimonious explanations that minimize surprise with minimal complexity. Intuitively, they are inclined to change their minds as little as possible (Neacsu et al., 2022; Sterling & Laughlin, 2015). In practice, this means the brain will only invest in belief updating when it expects that doing so will meaningfully reduce future prediction error (Feldman and Friston, 2010; Parr and Friston, 2017).

The trade-off between accuracy and complexity is governed by precision weighting, which reflects the brain's estimate of the reliability or trustworthiness of incoming sensations and the confidence in prior beliefs. Noisy or ambiguous input may be discounted, while priors held with strong confidence (e.g., from long-standing experience) tend to resist change but become enacted. Generally, model updates will only be triggered by prediction errors that are deemed vital and/or trustworthy (i.e., precise). As such, precision weighing allows for context-sensitivity in learning, guiding the balance between action and perception. Put simply, confident beliefs support action, while uncertain beliefs and trustworthy input favor perceptual updating. This mechanism has been linked to attention, understood as selectively amplifying reliable signals (Feldman and Friston, 2010).

In the here and now, prediction error can be resolved by changing minds or changing the world. However, human agents are also endowed with the capacity to plan ahead, accounting for prospective prediction errors. Alternative action strategies are evaluated in terms of both epistemic value (expected information gain) and pragmatic value (goal fulfillment), with the objective to optimize both. Unlike classical reinforcement learning and utility theory focused solely on expected rewards (equivalent to pragmatic value), PP acknowledges that epistemic foraging is valuable in its own right (Friston et al., 2017b; Parr & Friston, 2017). Through exploration, agents can refine their models, supporting more efficient goal fulfillment in the long run (Friston et al., 2017b; Seth & Friston, 2016). The balance between exploration and exploitation is again shaped by precision. Agents with strong preferences (high-precision priors) are more likely to settle quickly on explanations, acting to fulfil their goals. Conversely, agents with weaker preferences tend to explore longer, remaining curious, and often learning more as a result (Neacsu et al., 2022).

Crucially, due to agents' strong preference for maintaining physiological integrity, when resources are scarce (e.g., lack of sleep, illness, chronic stress), the costs of belief updating may outweigh the benefits of a more accurate model. This may manifest as a reduced sensitivity to, or proactive avoidance of, disconfirming evidence, resulting in greater reliance on established beliefs (for further information on the link between brain and body metabolism, see Stephan et al., 2016; Theriault et al., 2021).

(3) Learning is shaped by the brain's model of current and future bodily states. A leading hypothesis under PP is multisensory integration. An agent's percept of itself in the world arises from integrating across worldly and bodily sensory streams, filtered through the lens of priors (Petzschner et al., 2017; Seth, 2021). Generative models encode beliefs not only about the external world (exteroception), but also about the body's position (proprioception) and internal physiology (interoception). The latter directly follows from the imperative to maintain key physiological variables, such as blood sugar or core temperature, within viable, phenotype-congruent ranges to ensure survival (Barrett & Simmons, 2015; Seth, 2013). Interweaving these streams gives rise to perception, rendering it inherently subjective. Agents do not perceive the world as it is, but as it is meaningful for them, given their model. It also follows that the brain's interpretation of bodily states directly contributes to how external events are perceived and learned from, and vice versa (Barrett, 2022; Seth, 2019).

Predictions about how external events will affect physiology may underwrite affective and emotional experience. From this perspective, emotions are not reactions to the world, nor added layers on top of perception. Instead, they reflect the brain's best beliefs about the meaning of interoceptive cues within context, shaped by past learning (Barrett, 2017; Seth & Friston, 2016). Misattributions may arise. Where internal disruptions, such as a racing heart, could mean "I am anxious" or "I am stressed", they might also be mistakenly attributed to outside causes, for example, "He is a bad guy", with ensuing consequences for attention, action, and learning trajectories (Fridman et al., 2019).

Even the agent's self may be part of the generative model, constituting the best explanation for recurring patterns of sensations and actions over time (Hohwy and Michael, 2017; Seth and Tsakiris, 2018). Self-related beliefs, whether bodily or psychological, are typically assigned high precision and are thus resistant to change. This is adaptive insofar as a coherent identity renders an agent more predictable to itself, scaffolding goal-directed behavior and offering a stable framework for anticipating the future. In doing so, it reduces the energetic burden of ongoing prediction (Bouizegarene et al., 2024; Seth, 2021). Yet, this stability can challenge transformative learning that requires revisiting deeply held values and beliefs about the self and one's relationship to nature.

In sum, consistent with existing PP accounts, learning is embodied, context-sensitive, and path-dependent. Even shared environments or experiences, such as drought or policy change, may lead to divergent learning trajectories across agents depending on their internal states, histories, and goals. Likewise, the same agent may learn differently across contexts.

2.2. Learning is embedded in social structures and relations: The role of the social world

Social learning is neither one-sided, nor passive observation, nor is it separable from the relationships in which it unfolds. Learning from and with others involves inferring the hidden causes behind the sensory streams generated by them, including not only actions and speech, but also deeper mental states like intentions, desires, and emotions (Koster-Hale and Saxe, 2013; Lehmann et al., 2024; Palmer et al., 2015). The accuracy and depth of these inferences, in turn, depend on interaction dynamics and the quality of social relationships. When extended to interactive inference, PP clarifies why social relations and interactions are foundational to effective, transferable learning.

Social learning research within SES has long emphasized the importance of interaction and relationship-building for shared understanding and collaborative action (e.g., Bodin and Prell, 2011; Pahl-Wostl et al., 2007). PP resonates with this perspective, while offering a process-based account of why and how social interaction enhances learning that can generalize across contexts.

From a PP lens, learning minimizes prediction error by updating generative models to better account for sensory input. In complex environments where multiple, interacting causes unfold over different spatiotemporal scales, efficient prediction error minimization requires hierarchically deep models, capable of tracking both rapidly changing surface patterns and more stable, abstract regularities that underlie them (Parr et al., 2022). For instance, deciding when to bring an umbrella benefits not only from noticing rain, but also from understanding how rainfall patterns vary across seasons (Hohwy and Michael, 2017, p. 368). Social learning likewise benefits from modeling regularities that span multiple levels of abstraction (Palmer et al., 2015). Social inference ranges from higher-level, more abstract beliefs about a person's traits or worldview, through inferences about emotions and intentions, to lower-level, more concrete anticipations of tone of voice or movement (Schurz et al., 2021). These levels are hierarchically ordered to enable flexible transfer of what has been learned across situations.

When encountering new people, agents typically start with generic priors about how "someone like this" is likely to behave, think, feel etc. These predictions are informed by past learning and sociocultural scaffolding. Through interactive inference, these priors are tested and refined in real-time. Agents predict others' behavior and mental states, act accordingly, and adjust their models based on calculated prediction error (Gendron and Barrett, 2018; Theriault et al., 2021). Over time, this can yield nuanced, accurate, and personally tailored agent-models. Importantly, complexity is itself metabolically and computationally costly (Friston et al., 2017b). Therefore, as with underfitted models, overly complex ones should be avoided. The optimal balance depends on the context. Shallow models and broad heuristics may suffice for imitating behavior under stable environmental affordances. However, when future cooperation is aspired, when the goal is to comprehend underlying, transferable strategies rather than context-specific actions, or when model divergence is likely (e.g., across cultural boundaries), investing in richer, more nuanced models of others becomes advantageous.

Crucially, in social interaction, the other is not a passive object, but an embodied agent simultaneously predicting us. With rare exceptions, such as far-distant observation, social interactions are best conceptualized as two (or more) embodied agents coupled via action-perception loops, each modeling the other while being modeled in return (De Jaegher and Di Paolo, 2007; Lehmann et al., 2024). This mutual engagement leads to complex, nested inference, involving recursive predictions such as "I believe that you believe that I believe…", probed moment-to-moment in embodied exchange (Ramstead et al., 2016; Theriault et al., 2021).

Across persistent or repeated interactions, generative models tend to align. This improves mutual prediction and reduces prediction error, with downstream metabolic and affective consequences (Hesp et al., 2021; Theriault et al., 2021). Interacting becomes increasingly fluent and metabolically efficient, phenomenologically likely to be experienced as rewarding and less stressful. Mutual liking tends to increase, inviting further engagement that fine-tunes social inference even more. This creates a positive feedback loop that strengthens social cohesion (Theriault et al., 2021). At the same time, occasional breakdowns in synchrony, such as moments of miscommunication, can be productive. They generate prediction errors that, when resolved, enhance mutual understanding (Gendron and Barrett, 2018).

Crucially, social learning also involves learning how trustworthy and reliable others' signals are. Initially, agents estimate this precision based on social factors such as trust, likeability, and perceived social status, and expertise, refining their estimates over time. Fig. 2 illustrates how such precision judgments shape the degree to which agents allow others to influence their understanding (Hofmans and Van Den Bos, 2022; Otten et al., 2017), underscoring the significance of strong, trusting bonds in effective learning.

Strong social bonds affect alignment processes across multiple levels, from shared preferences and emotional attunement (typically associated with empathy) to embodied resonance, including gestures and heartbeat synchronization (Cristaldi et al., 2024; Shamay-Tsoory et al., 2019). Close, supportive relationships promote greater alignment, reducing metabolic burden and freeing resources that can be invested in learning and creativity. As Barrett notes, "*[w]hen people work in an environment where they can learn to trust one another, they'll have less burden on their body budgets, saving resources that can be invested in new ideas.*" (Barrett, 2020, p. 86).

Social learning may also require adjusting the confidence attributed to one's own prior beliefs (see Fig. 2). Agents' models of the world are specific to their histories and, shaped by cultural influences. The strands of PP, which we draw on here, challenge the assumption that psychological categories such as "emotion," "perception," or "memory" map cleanly onto distinct cognitive or neural processes. Scholars argue that such categories may reflect culturally shaped explanatory frames, representing modes of organizing experience that are useful because they are widely shared, not because they are universally valid (Parr et al., 2022; Shaffer et al., 2022). Consequently, these categories support social learning exclusively when mutually held. In cross-cultural, interdisciplinary, or transdisciplinary contexts, such alignment cannot be taken for granted. For instance, cultures vary widely in their conceptualizations of emotions and the degree to which mental state inferences are evoked (Barrett, 2017; Gendron et al., 2020; Hoemann et al., 2019). What one agent interprets as hidden causes behind another's behavior may differ from how the other agent experiences and understands their own actions. In these situations, social learning may benefit from humility, involving loosening ingrained assumptions and attending more closely to how others model the world (Barrett, 2020). This approach fosters learning at increasingly abstract levels, yielding knowledge that can be applied across contexts.

The 2018 Environmental Flow Needs Conference illustrates this well. Rather than opening with technical discussions, Indigenous leaders began by sharing the *Enowkinwixw* framework, rooted in a relational cosmology. By emphasizing the cultural framing, participants were encouraged to reflect on how others make sense of the world and model each other's perspectives more deeply. This created space for learning that could travel across contexts and future collaborations (Okanagan Basin Water Board, Canadian Water Resources Association, 2018).

In sum, social learning emerges through reciprocal inference, as agents co-construct their models of self, others, and the world. When the goal is to generate insights that can be transferred across contexts, for example in efforts of Western societies to learn from Indigenous practices, investing in social interaction and relational quality is essential to understand not only what others do, but also why they do it.

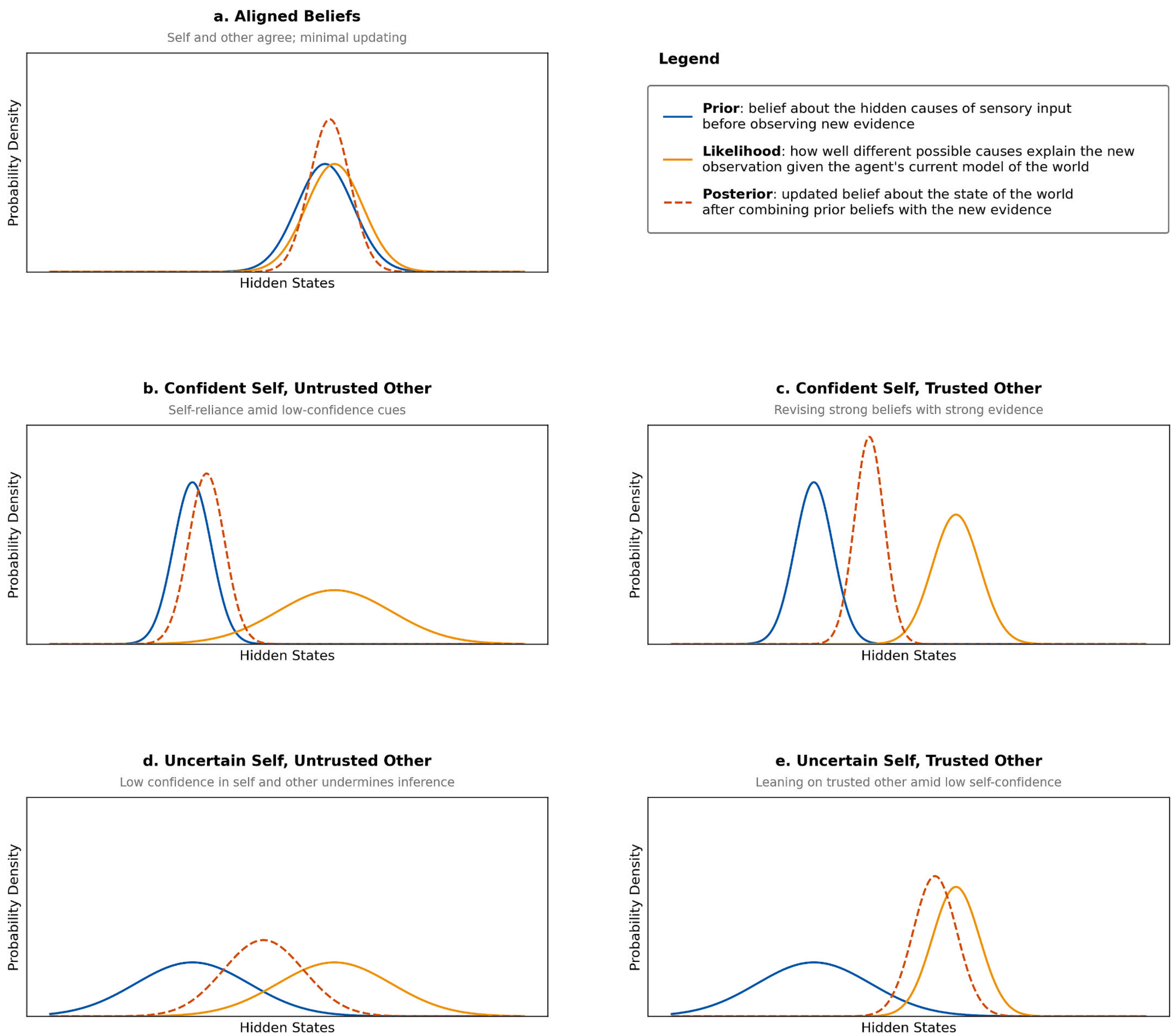

Fig. 2. (Mis-)Alignment and (un-)certainty in social inference. Prior beliefs are combined with evidence from new sensory input (likelihood) to form an updated belief (posterior). Sensory input may come from social others through words, tone of voice, gestures, facial expressions, or actions. Heuristically, the mean of each curve represents the belief content, while the width (variance) indicates its precision. Narrow curves denote high confidence or low uncertainty, whereas wide curves reflect low confidence or greater uncertainty, respectively. The relative precisions of prior and likelihood determine how much prediction errors (differences between prior and likelihood) drive belief updating. Panel (a) depicts aligned beliefs, where prior expectations and incoming signals closely match, resulting in minimal updating. Panels (b–e) show four scenarios of belief conflict, arranged in a 2 × 2 grid according to (rows) trust in others and (columns) confidence in one's own beliefs (presented in clockwise order). High self-confidence combined with low trust in others leads to rejection of conflicting input (b), whereas high trust in others allows belief revision despite strong priors (c). Low self-confidence coupled with high trust in others results in posterior beliefs being largely shaped by external input (e), while low trust in both self and others generates unresolved uncertainty and persistent ambiguity (d). This figure is inspired by illustrations found in Otten et al. (2017, p. 16) and Hofmans and Van Den Bos (2022).

2.3. *Learning is embedded in human-nature relationships: The role of the ecological world*

Agents learn in and through interactions with particular places, landscapes, species, and other parts of nature (hereinafter non-human agents). Although this domain remains underexplored in the PP literature, the accounts we build on assume that the inference mechanisms underpinning learning, and indeed *"all the human mind is and does"* (Hohwy, 2016, p. 260), generalize across social, physical, and bodily domains (Parr et al., 2022; Petzschner et al., 2017). This assumption allows us to sketch how understanding of the environment, nature connectedness, and attunement may emerge through repeated, embodied engagement with non-human agents.

Much like in social interactions, repeated encounters with particular non-human agents allow individuals to fine-tune generative models. Over time, sensory evidence from such interactions is integrated with prior beliefs. The formation of these beliefs is shaped by a variety of factors, including one's own lived experience, such as fishing in the same coastal waters over decades, and socio-cultural learning, for example, through stories about when berries ripen or rivers flood. Model refinement frequently leads to increasingly fluent predictions, reduced uncertainty, and a growing sense of familiarity or even affinity. This, in turn, can motivate further engagement and exploration, establishing a positive feedback loop that may deepen human-nature relationships (cf. Nisbet et al., 2009).

Analogous to social inference, it may not only be the frequency of interaction that matters, but also its relational quality. Factors such as trust, respect, felt responsibility, and attachment toward non-human agents, can modulate the precision assigned to environmental cues, making them more salient and informative. Intuitively, relational depth shapes how attentively people "listen" to nature. When precision is high, even minimal variations (such as subtle shifts in animal behavior) are more likely to prompt model updating. For instance, agents who have a strong connection to a wetland or forest may notice and interpret small changes that others overlook. Respect or reverence may similarly heighten sensitivity to nature's signals, amplifying their epistemic relevance.

Many ecological systems follow their own rhythms, such as seasonal cycles, tidal flows, and migratory patterns. These patterns can serve as reliable high-level priors for agents who have learned to attune to them (Hohwy and Michael, 2017). They introduce temporal structure into the sensory stream and help connect faster, more variable fluctuations. For those who have internalized them, such rhythms reveal deeper scaffolding behind events that might otherwise appear isolated or random. In human-nature interactions, hierarchical depth (just as in social interaction, see Section 2.2) supports efficient prediction and planning, thereby reducing cognitive burden and enhancing the capacity to attend more closely to subtle changes. Social inference relies on high-level models of others' minds to contextualize behavior (Koster-Hale and Saxe, 2013; Proietti et al., 2023). Attunement to nature relies on learning the enduring regularities that govern surface-level variation.

In this sense, attuning to and aligning with nature's rhythms can serve a function similar to social-co-regulation. While mostly lacking neurophysiological substrates for classical co-regulation (e.g., shared gaze, affective mirroring), nature provides its own temporal "beat" with which generative models can entrain. This may yield physiological and psychological regulation, openness to subtle change, and deeper engagement with the non-human world.

Empirical research across disciplines lends support to these dynamics. Across cultures, people report that specific landscapes or natural beings elicit calmness, restoration, or a sense of belonging (Bratman et al., 2019; Masterson et al., 2017; Ness and Munkejord, 2021). Nature relatedness increases with time spent in nature, and vice versa (e.g., Nisbet et al., 2009). Moreover, nature exposure has been shown to restore attention (Berto, 2005), enhance working memory (Bratman et al., 2015), and foster relaxed yet alert states, similar to those cultivated in mindfulness practices (Koivisto et al., 2022). Crucially, such effects do not stem from nature per se, but depend on the meaning and memories that individuals associate with natural cues (Koivisto et al., 2022). These findings align well with PP's claim that meaning is not passively received, but arises from the ongoing coupling of a particular embodied agent, with particular goals and experiences, and its environments.

For natural cues to serve as trusted anchors, an agent's generative model must assign them high precision, usually either because those cues are vital for agents' well-being, culturally valued, or personally meaningful. For instance, Indigenous fishers along the Pacific Northwest coast, deeply attuned to tidal rhythms and salmon behavior, often detect disruptions in migration timing early on. This allows them to adapt their practices well before any large-scale declines or stock collapses (Turner and Berkes, 2006). Their models, shaped by generations of interaction, support both accurate prediction and sensitivity to subtle ecological change. Recent discussions on empathy with nature and its role for sustainability (e.g., Brown et al., 2019; Tam, 2013) may capture such a heightened sensitivity to changes in natural rhythms paired with ontological, often culturally shared, beliefs about agency and sentience of non-human agents. For those whose survival and flourishing depends on these patterns, deviations can carry strong affective consequences, as generative models link these changes to risks for physiological and psychological integrity. When agents conceive non-human agents as sentient beings, these affective responses may be experienced as a sharing of nature's feelings.

Prediction depends on pattern matching. When ecological rhythms are reliable, agents can gradually refine their models, learning to anticipate change and prepare ahead. In the Anthropocene, however, many of those rhythms are collapsing (Rockström et al., 2009). Change, in itself, is not the problem. If variation is structured, it becomes predictable/learnable. Even disruptions can be integrated if they stabilize into new dynamic equilibria. However, when systems shift into chaotic dynamics, that is dynamics marked by continuous non-linearity and instability, where regularities no longer emerge or hold, agents struggle to regain a stable grip on their world. Persistent and compounding prediction error has downstream consequences for physiological and mental well-being. When efforts to reduce uncertainty remain ineffective, agents may experience a loss of confidence in their models, negative affect, and diminution of their sense of agency and self-efficacy (Hesp et al., 2021; Stephan et al., 2016). Ultimately, agents may disengage from nature altogether, a strategy that may conserve energy in the short term, but that will limit opportunities for learning and long-term adaptation. Psychological phenomena, such as eco-anxiety or climate grief, which appear to be increasing in prevalence (Hickman et al., 2021), may be conceptualized as arising from a chronic model-world mismatch. Nevertheless, some agents remain engaged. Rather than withdrawing, they continue to observe, learn, and act. The mechanisms underlying such sustained engagement remain unclear. In Section 3.1, we propose that a reinforcing loop between social relations and connection to place may help explain such sustained engagement, suggesting that relational practices in meaningful natural settings can support both social cohesion and ecological connection. This, in turn, may help to stabilize agents' engagement even in the face of disruption.

3. Enacting change

> "Yesterday I was clever, so I wanted to change the world. Today I am wise, so I am changing myself."
>
> —Rumi in Parr et al., 2022.

3.1. Social-ecological learning: Re-entangling social, ecological, and inner worlds

A hallmark of SES scholarship is its emphasis on the deep entanglement between social and ecological systems, which co-evolve through feedback loops giving rise to complex dynamics and emergent patterns (Folke et al., 2021; Schlüter et al., 2019). Recent research in PP explores the role of such loops in guiding individuals' attention in their sensory-rich worlds in ways that are culturally valued and shared (see top of Fig. 1). These dynamics help explain how cultural expectations are transmitted across generations, and shape learning and action trajectories within specific social-ecological contexts (Ramstead et al., 2016; Veissière et al., 2020).

The PP framework holds that agents' priors are shaped by multiple forces. While some are inherited evolutionarily, many are acquired through socio-cultural learning. Priors pertain to different aspects of the general model, encompassing both the content of beliefs and the reliability or relevance assigned to beliefs and sensations. Patterned cultural practices, such as storytelling, rituals, or ecological monitoring, play a central role in installing these priors, especially those governing attention and salience. Beyond merely transmitting explicit content, such practices guide individuals toward trusted sources of information and teach them where to expect high epistemic value. Through immersive participation, agents often implicitly learn where to look, whom or what to trust (e.g., elders, spiritual leaders, cloud patterns, seasonal smells), and which cues carry high epistemic value. Ultimately, they acquire so-called "regimes of attention": culturally valued ways of attending to and sampling the world (Ramstead et al., 2016).

Priors, including those culturally shaped, are inscribed not only in agents' minds but often also in the environment, leaving behind material traces, such as footpaths, ritual spaces, and tools, as well as immaterial traces, such as narratives, institutions, and protocols. For those skilled in navigating them, these features act as external scaffolds, cueing epistemic value and soliciting culturally appropriate responses (Constant et al., 2018; Veissière et al., 2020). Through processes of niche construction, cultural expectations are effectively outsourced to the environment, such that environments, in a sense, "learn" the expectations of their inhabitants (Constant et al., 2018, 2019). By engaging with these affordances (e.g., walking familiar paths, retelling ancestral stories), agents re-enact and reinforce the very norms and expectations that led to their formation (Ramstead et al., 2016).

Social learning, defined as *"a change in understanding that goes beyond the individual to become situated within wider social units or communities of practice, through social interaction"* (Reed et al., 2010, p. 6), thus unfolds through dynamic feedback between people, practices, and places (Ramstead et al., 2016; cf. Berkes, 2017). Via these two routes, i.e., regimes of attention and niche construction, cultural expectations shape how individuals perceive, learn, and act (Veissière et al., 2020). Drawing upon these perspectives, even seemingly solitary learning in nature might never be purely individual. An agent's very first encounter with a natural agent is already filtered through cultural expectations encoded in its neural network and sedimented in the environment. Conversely, immersing oneself in another culture's practices can open up entirely new ways of attending to the world, offering a powerful means of reshaping perception and engagement.

These insights also allow us to clarify how ontological pluralism can be naturally integrated into our framework. From a PP perspective, local ontologies can be understood as culturally shared expectations (Ramstead et al., 2016) regarding the kinds of beings that exist in the world, how they relate to one another, and how one ought to engage with them. Along the looping mechanisms just described, local ontologies guide attention, structure action-perception loops, and scaffold learning. However, much of environmental governance still implicitly rests on a Western-naturalist ontology. This ontology understands humans as active agents, nature as passive resource to be managed. In contrast, many Indigenous and relational worldviews treat natural entities as agentic, fellow living beings deserving care and respect (Ingold, 2002; Latour, 2009; Linton and Pahl-Wostl, 2023). Consistent with PP, we argue that we do not need to adjudicate between ontologies. What matters is what agents believe. (Ontological) Priors guide perception, engagement, and sense-making regardless of their objective truth (cf. Otten et al., 2017). Kimmerer (2013) illustrates this vividly in Braiding Sweetgrass. The same scene—asters and goldenrod—affords different meanings and invites different questions when viewed through the lens of scientific botany or the relational attentiveness of Indigenous ways of knowing grounded in kinship and reciprocity.

In addition to the agent's entanglement in the social and ecological, the embodied agent is enmeshed in these worlds, perceiving, acting, and learning to reduce long-term prediction error and preserve physiological integrity. As discussed in Sections 2.2 and 2.3, repeated interaction with people and places can promote predictive fluency, reducing metabolic and computational demands, fostering mutual liking, and ultimately strengthening relational ties.

Building on this, we hypothesize that relational practices in valued natural environments, such as ritual landscapes or community gardens, can strengthen social bonds and, in doing so, further deepen agents' connection to place. Familiar environments imbued with positive affect reduce ecological prediction error, thereby potentially increasing overall confidence in one's model and liberating resources for social inference. This may engender greater tolerance for ambiguity and openness to differing perspectives. As social models are fine-tuned, social fluency improves, and interpersonal bonds are consolidated. Drawing on the multisensory integration hypothesis and recent work on deep affective inference (Hesp et al., 2020, 2021), we further suggest that agents may come to experience not only their social relations, but also their natural surroundings as more predictable, safe, and meaningful. This points to a feedback loop in which social and ecological learning dynamically co-regulate one another, reinforcing both social cohesion and connection to place over time. The dynamics are bidirectional. Strong, trusting social ties can buffer the cognitive and physiological strain of environmental disruption. During times of high ecological prediction error—e.g., under conditions of rapid change or degradation—secure social relations may support internal regulation and affective attunement with the social-ecological context. In turn, such relations could help sustain exploratory engagement, while preserving a sense of agency and self-efficacy (Stephan et al., 2016). In this way, social cohesion nurtures the conditions that enable learning and adaptive engagement to persist, even under adverse circumstances. Fig. 3 illustrates these dynamics across contrasting scenarios, ranging from states of instability and high prediction error to scaffolded inference in trusted social-ecological relations.

Taken together, the mechanisms outlined above illustrate that traditional notions of "social learning" may be too narrow to capture the reciprocal loops connecting individuals, communities, their practices, and places. We propose the term social-ecological learning to better reflect these entanglements, serving as both a conceptual lens and analytical tool. This framework foregrounds the deep intertwining and inseparability of social and ecological processes in shaping both what is learned and how learning unfolds.

Emerging research on outdoor educational and recreational practices lends support to our hypothesis of a positive feedback loop between social bonds and connections to nature (Gilbertson et al., 2023; Henderson et al., 2024). In brief, across both strands of literature, being outdoors with others—whether for learning or leisure—is associated with increased sustainable action, nature and social connectedness, mental well-being as well as the development of social cohesion and care for human and non-human others (Pirchio et al., 2021; Puhakka, 2021; Van Tol and Wals, 2025). By foregrounding the interplay between immediate interactions, past experiences, and broader social-ecological dynamics, our framework can help trace and explain these patterns and their unfolding over time. In doing so, it may also guide the design of curricula that leverage social and ecological entanglements for sustainability.

3.2. Learning loops and the dynamics of transformative change through a PP lens

To this point, our discussion of learning has remained general, without explicitly distinguishing between different types or loops of learning as SES scholars might expect from a comprehensive account. In the social learning literature, learning loops typically range from incremental behavioral adjustments to revisiting underlying assumptions and deeper transformations of socio-institutional structures in which learning unfolds (Pahl-Wostl, 2009). Recent advancements in PP have likewise begun to differentiate types of learning that, as we show, map closely onto the loop concept. While we only sketch this connection here, the PP approach provides a promising lens for theorizing loop learning at the level of individual agents, including the conditions that may support transformative change.

PP distinguishes three interrelated types of learning, each optimizing world-model fit at different timescales and levels of abstraction (e.g., Da Costa et al., 2020; Neacsu, 2024; Smith et al., 2020).

1. *Perceptual inference*: rapid, moment-to-moment updating of beliefs to accommodate sensory input, modulated by precision.
2. *Parametric learning*: slower, cumulative tuning of model parameters, such as expected values or precision estimates, based on prediction errors repeatedly resolved in perceptual inference over time. This

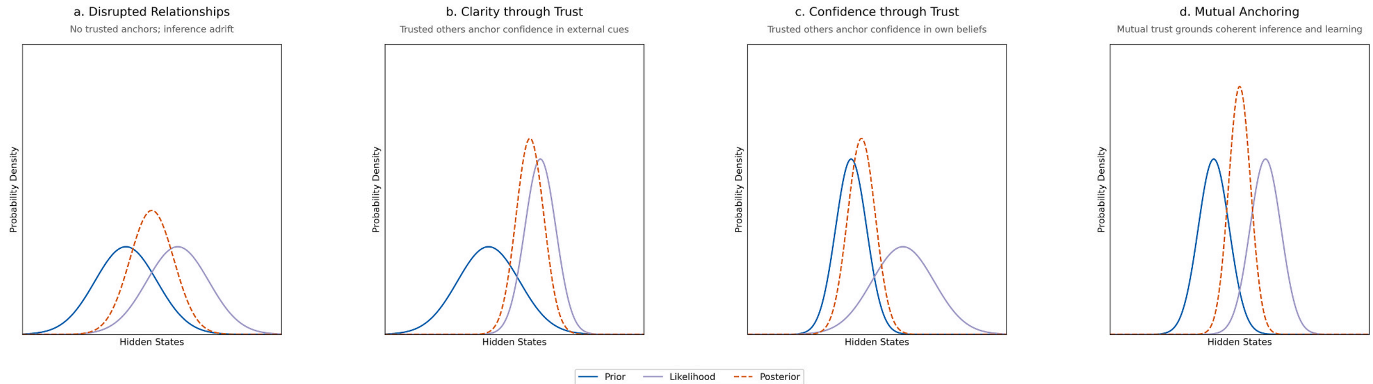

Fig. 3. Trusted relations as scaffolds for navigating uncertainty. This figure illustrates how being with trusted human (non-human) others can scaffold learning, sense-making, and decision-making by stabilizing inference in uncertain ecological (social) environments. Each panel shows how an agent integrates prior beliefs (prior curve in Fig. 3 a-d) and sensory evidence from the social-ecological world (likelihood curve in Fig. 3 a-d) to form a posterior belief (posterior curve in Fig. 3 a-d), accounting for the relative trustworthiness of both prior and likelihood. (a) In the absence of trusted human or non-human others, inference is destabilized, cognitively taxing, and affectively straining. An example might be having to navigate disrupted ecological dynamics alongside unfamiliar or distrusted social others. Panels (b) and (c) show two complementary routes through which trusted others – human or non-human – can stabilize inference. In (b), trusted others enhance the perceived reliability of external cues through shared attention (e.g., gaze, gestures, or ecological signaling) and support of internal state regulation. This fosters bottom-up learning. In (c), trusted relational context increases confidence in internal models and a priori expectations, stabilizing inference from the top-down. This might be particularly crucial for navigating transformative change, where uncertainty is high and experimentation is needed. Low model confidence tends to promote habitual, cautious behavior (Hesp et al., 2020, 2021), whereas greater confidence in beliefs leads to more vigorous actions (Stephan et al., 2016). Panel (d) reflects both (bottom-up and top-down) processes working in tandem. Scaffolded by trusted others the agent has learned to navigate initially uncertain circumstances. Inference is fluent, reinforcing trust and fostering deeper engagement with the social–ecological world. Over time, social trust has scaffolded ecological trust, and vice versa. Together, they reinforce learning and experimentation, both key capacities for navigating transformation under uncertainty. *Please refer to the main text and Fig. 2 for further explanation and references.*

fine-tuning preserves the model's structure and maps biologically onto synaptic plasticity.

3. *Structure learning*: reorganizing the model's architecture itself, including the addition, pruning, or restructuring of causal relationships and concepts. Unlike the former two, this process generally transpires offline (e.g., during rest, sleep, or reflection) and is triggered by persistent prediction error that cannot be resolved within the existing model structure.

Collectively, these mechanisms help agents balance model stability and adaptability, supporting flexible engagement with dynamic environments (Neacsu et al., 2022).

There is a striking alignment between PP's learning types and the concepts of single-loop and double-loop learning. Both frameworks differentiate between model-conserving and model-revising forms of adaptation.

- Single-loop learning and Parametric learning: incremental, experience-dependent adjustments within an existing model that refine interpretation or action without challenging core assumptions.
- Double-loop learning and Structure learning: revision of the model itself, enabling concept-level change and a reframing of the problem space.

Structure learning, therefore, offers a powerful entry point into understanding transformative change, as it reshapes the conceptual lens through which past, present, and future are made sense of (Bouizegarene et al., 2024). While parametric learning is cumulative, structure learning *"goes beyond [that], granting […] agents the capacity for an instantaneous, or rapid type of learning"* (Neacsu, 2024, p. 66), and may underpin the familiar "Aha"-moments where things finally click into place. Crucially, however, this does not detach structure learning from past experiences. Instead, it is typically triggered by a cognitive impasse, in which chronic, unresolved prediction error signals that the current model architecture is no longer adequate or helpful (Servajean and Wiese, 2024). Although such moments of concept learning may appear sudden, they are rooted in extended trajectories of cumulative experience and unresolved dissonance that gradually build pressure for reorganization. This insight is critical for SES research, as it suggests that learning should be understood not as isolated events, but as longer-term trajectories unfolding across lived experience. Linking structure learning to double-loop learning also underscores the value of reflective spaces within relational practice (Pahl-Wostl et al., 2007), which may support the offline processes necessary for conceptual reorganization.

How to integrate triple-loop learning into the picture? Triple loop-learning refers to a form of learning, which extends beyond belief revision to transforming the very conditions for learning, including normative, institutional, and structural dimensions (Pahl-Wostl, 2009). In line with PP assumptions, this can be partly explained by a shift in the balance of the action-perception cycle. When revised belief structures, formed through structure learning, are held with high confidence, they are more likely to become enacted in the world, even in the face of contradicting social feedback. In early stages, such enactment may only occur in solitude or safe spaces, where the risk of disconfirming evidence is low. As agents gain confidence, these concepts become robust enough to withstand public scrutiny. In acting upon revised models, agents modify the environment they share with others, thereby altering the sensory inputs and affordances available to them. These changes, in turn, may elicit updates in others' models, allowing one agent's structure learning to seed change beyond the self. As such change ripples through social networks, it can initiate cascades of shared belief revision and behavioral adaptation. Ultimately, these dynamics may scale into triple-loop learning and broader socio-cultural transformation (cf. social tipping dynamics, Otto et al., 2020; Weber et al., 2023).

Importantly, as outlined above, belief precision is socially modulated. Beliefs are more likely to be enacted when they are perceived as socially supported, validated by trusted peers, or aligned with shared narratives. This suggests that transitions from double- to triple-loop learning may hinge on social processes that foster shared confidence and mutual reinforcement.

In the sustainability community, calls for transformative shifts in values, beliefs, and worldviews have gained traction as essential for systemic change (e.g., Linton and Pahl-Wostl, 2023; Wamsler et al., 2021). Importantly, such changes to mindsets can emerge through action, not only through introspection, and PP offers a theoretical foundation for this pathway. As Hohwy and Michael (2017) argue, self-models can be revised when new patterns of enacted behavior repeatedly violate what would be expected under the current self-model (see also Barrett, 2017).

Crucially, not all behavioral changes lead to lasting transformation, as long established in behavioral sciences (e.g., Engel et al., 2008). From a PP perspective, this resistance is adaptive. Updating self-related priors in response to every fluctuation would risk overfitting to noise. Self-related priors typically carry high precision, meaning that their revision tends to necessitate persistent prediction error, likely accompanied by affective salience. Behavioral shifts are more likely to revise the self-model when they contribute to internal regulation, either directly or through alignment with significant others. Consequently, even actions initially undertaken for pragmatic or relational reasons (e.g., abstaining from eating meat out of respect for a vegetarian friend) may, if sustained and experienced as meaningful, gradually recalibrate one's self-model.

A compelling example is Cape Town's Day Zero water crisis. Initially, local actors conserved water in response to urgent external constraints, not out of a transformed relationship to water. Yet, long after the crisis, many continue to practice responsible consumption, reporting a deeper awareness and shift in perspective (Eakin and Shearing, 2025). What began as compliance led to a shift in self-model. Action preceded a change in mindset.

In essence, PP offers a powerful lens for elucidating the dynamics of loop learning. It strongly contributes to explaining how learning unfolds across time and scales, how action and belief co-evolve, and how transformation can begin not only in the mind, but in the world.

4. Conclusions

In this paper, we propose a novel framework for understanding relational learning in SES by embedding PP within the broader architecture of the social learning framework. This allowed us to illuminate the fine-grained mechanisms through which shared understanding, strong and trusting relationships, and both adaptive and transformative capacities emerge and evolve in social-ecological contexts. We offer a granular lens on how attention, sense-making, and (collective) action are shaped by feedback loops that span brain, body, communities, their practices, and ecological worlds; loops that can either reinforce existing systems or open space for transformation.

We see three core contributions emerging from our work.

First, our framework bridges micro-level processes, such as interoceptive regulation, attention, and trust, with macro-level social and ecological dynamics, including cultural expectations, institutional structures, and ecosystem change. In doing so, it offers a biologically plausible architecture for integrating the diverse cognitive, affective, experiential, and social dimensions of learning, which have thus far been discussed largely in isolation. Its integrative nature may help bridge conceptual divides by showing how seemingly disparate learning approaches are connected and emerge from the same predictive principles. While rooted in a different theoretical foundation – drawing from computational neuroscience, evolutionary biology, and the physics of sentient systems, among others – PP resonates with core insights from the social learning framework: learning is inherently relational, and the quality of relationships, both social and ecological, profoundly shapes learning dynamics and outcomes. What PP contributes is a mechanistic account of why this is the case, grounded in a state-of-the-art understanding of nervous system structure and functioning. As such, it may offer an entry point for those previously skeptical of approaches that foreground subjectivity, relationality, or the centrality of strong relational ties in learning.

Second, we introduce social-ecological learning as a novel conceptual framework more apt for capturing the deep entanglement of social and ecological dynamics that shape what and how agents learn in SES. This lens emphasizes the dynamic interplay between social relationships, environmental engagement, and internal regulation processes, offering a more integrated view of learning as it unfolds in real-world, dynamic contexts. It invites researchers to explore the interdependencies between learning from other people and learning from nature, and to consider how factors such as empathy, trust, and physiological regulation influence both. By highlighting these often-overlooked feedbacks, this lens opens space for new research questions and more nuanced intervention strategies, particularly those attuned to the affective and relational demands of navigating complexity and change. It also offers practical value. By understanding the relational conditions under which learning and adaptation flourish (or fail), practitioners can better support processes of collective sense-making, transformation, and resilience-building in SES.

Third, by conceptualizing loop learning through the lens of PP, we offer a novel contribution in response to the growing call for more rigorous theorizing on learning loops at the individual level (e.g., Wijermans et al., 2023). To our knowledge, this is the first attempt to link loop learning to parametric and structure learning as defined in PP. While only sketched here, in future work we plan to develop this connection further and explore its implications for agent-based modeling of learning and decision-making in SES. The mathematical formalism behind PP offers a promising toolset that could guide model development and improvement (e.g., Parr et al., 2022).

Adopting a PP perspective entails a shift in causal reasoning away from a Newtonian cause–and-effect logic toward a more encompassing relational ontology. In this view, the human mind might be fruitfully approached as a complex adaptive system (Barrett, 2022), much like the SES, in which it is embedded (e.g., Preiser et al., 2018). Learning, then, cannot be understood as a fixed trajectory leading to clearly defined outcomes, only modulated by contextual factors. Instead, it unfolds through dynamic, non-linear interactions in which context—including the researcher—plays a constitutive role. Methodologically, this requires *"cast[ing] much wider observational nets"* that attend to multiple scales and influences (cf. Barrett, 2022, p. 904). Suitable research approaches would capture influences across bodies, brains, individual and socio-cultural histories, social-ecological relations, and so on, while also requiring reflexivity regarding researcher positionality. Not all of these dimensions are accessible through social science methods alone, pointing to the value of interdisciplinary and transdisciplinary approaches. Ultimately, this also calls for a rethinking of what counts as successful learning. In a PP sense, every encounter involves some degree of model updating, much of which remains unconscious, before eventually manifesting as observable or reportable change. Fully elaborating on these implications lies beyond the scope of this paper. However, we hope that our conceptual contribution, together with emerging empirical work (e.g., Hoemann et al., 2020), inspires others to develop methodological designs that are better suited to capturing learning as a dynamic, relational, temporal and spatially extended process.

We see this framework as a scaffold – a first step toward translating the rich insights of PP into the context of SES learning. Our goal was to surface key threads particularly relevant to SES, leaving space for further conceptual layering and elaboration. Many promising strands, especially from more recent PP literature, remain to be woven in, including accounts of the role of socio-cultural narratives (Bouizegarene et al., 2024), social conformity (Constant et al., 2019), and the emergence of generative models of group-level agents (Thestrup Waade et al., 2025). These and other developments could further enrich and deepen the framework in future work.

Of course, the strength of our framework depends in part on the validity of the PP paradigm itself, which remains an evolving and debated field. Yet, PP continues to gain empirical and theoretical support and has offered compelling explanations for phenomena that remain puzzling under classical models of perception, cognition, and behavior (e.g., Hutchinson and Barrett, 2019; Otten et al., 2017). We view PP as one of the most integrative and plausible frameworks currently available. In line with PP principles, our framework is designed to remain dynamic and adaptive—updated and refined as new insights emerge.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used DeepL and ChatGPT in order to assist with English language editing and readability improvements. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Carolin Janssen: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Conceptualization. **Philipp Gorris:** Writing – review & editing, Visualization, Methodology, Conceptualization. **Claudia Pahl-Wostl:** Writing – review & editing, Methodology, Conceptualization. **Luana Schwarz:** Writing – review & editing, Visualization, Methodology, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2026.103159.

Data availability

Data will be made available on request.

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