The Body, Brain and Environment: What Shapes What?

A.E. Eiben[1], G.S. Nitschke
a.e.eiben@vu.nl, gnitschke@cs.uct.za
[1]Department of Computer Science, Vrije Universiteit
Amsterdam, the Netherlands
Department of Computer Science, University of Cape Town
Cape Town, South Africa

Abstract

This chapter takes inspiration from the seminal book titled *"How the body shapes the way we think"*, which we paraphrase into *"How the body shapes the brain"*. The key idea is to invert the implication and consider how the brain shapes the body. The essence of our approach is to consider this in an evolutionary context, leveraging the fact that in evolving robot systems the bodies are shapeable. To this end we review two previously published studies and discuss them from a new perspective. We find solid evidence that system changes that affect the robot controllers (specifically, optimizing the brains during lifetime) can have paramount impact on the evolved morphologies. Encouraged by these insights we conclude the chapter by elaborating on promising directions and grand challenges for future research.

1 Introduction

Since the Cambrian explosion [Marshall, 2006], nature has produced a plethora of morphologically and behaviorally diverse organisms that have evolved to survive in even the most extreme environments on Earth [Rothschild and Mancinelli, 2001]. In contrast to current robotic systems that can operate only in specially structured environments [Carlson and Murphy, 2005, Bongard et al., 2006, Ermolov, 2020], natural organisms have evolved to survive in a diverse range of unstructured environmental niches, at least in part, due to *embodied cognition* [Barrett, 2011]. We argue that such embodied cognition (*embodied intelligence*) emerges from close coupling between an agent's body and brain and the environment. Thus if we are to solve the perennial problem in embodied autonomous systems [Rahwan et al., 2019] (and more generally Artificial Intelligence) of finding general problem-solvers that effectively function across and adapt to novel environments [Koos et al., 2013, Cully et al., 2015], then the evolutionary design of artificial and embodied agents (robots) must account for complexities in the evolutionary and developmental relationship between body, brain and environment [Eiben et al., 2021].

There is significant evidence supporting such body, brain, environment interactions in nature [Pfeifer and Bongard, 2007], and in various experimental artificial life [Sims, 1994] and embodied (robotic) [Lipson and Pollack, 2000] systems. Since this seminal work there has recently been an increasing volume of evolutionary robotics research investigating the impact of various morphology-controller evolutionary search [Pugh et al., 2021, Kriegman et al., 2020, Howison et al., 2021] on robot morphology-controller evolution [Weel et al., 2014, Cheney et al., 2018, Furman et al., 2019, Shah et al., 2021, Zardini et al., 2021, Nordmoen et al., 2021] across varying task and environment complexity [Auerbach and Bongard, 2014, Hallauer and Nitschke, 2020, Miras et al., 2020b, Spanellis et al., 2021]. One commonality of all such work, is clear demonstration that agent (robot) body (morphology) and brain (controller) determines attainable limits of learning and development, which is ultimately directed by environment complexity.

Most such evolutionary robotics work has focused on the rather intractable problem of jointly evolving both robot morphology and controller (in either simulated or physical systems), thus placing significant limitations on usable task environment complexity, given the enormity of the behavior-morphology search space. However, in this perspective we emphasize the importance of morphological materials available for body-brain evolution [Pfeifer et al., 2007, Pfeifer et al., 2012, Shah et al., 2020, Blackiston et al., 2021]. This is critical since materials available in the environment determine a robot's morphology, which constraints possible controller configurations which in turn determines possible problem-solving behaviors during robot-environment interaction. As in nature, the molecular and material building blocks present in any given environment significantly impact the evolution of organisms in these environments and thus direct body-brain development which then determines an organism's problem-solving behavior. This notion was most recently codified as the *multi-level evolution* process for automated robot design [Howard et al., 2019].

In embodied evolutionary robotics, the impact of *body-brain building-blocks*, and their material properties, on the evolution of body-brain (morphology-controller) configurations has been demonstrated across numerous studies. For example, Corucci et al. [Corucci et al., 2018], explore the impact of various material properties on the evolution of soft-robotic morphologies and behaviors for terrestrial and aquatic locomotion. In a study on evolving body-brain modularity, Bernatskiy and Bongard [Bernatskiy and Bongard, 2018], use embodied agents to demonstrate the influence of various evolved morphologies have on the concurrent evolution of *plastic* modular controllers. Kriegman et al. [Kriegman et al., 2018], present an *in silico* test-bed for evolving developmental embodied systems, demonstrating what they term *differential canalization*, in soft-body robot morphology (body) and controllers (brain) that concurrently adapt while robots interact with their environment. This phenomenon showed body-brain traits eliciting robustness in the environment become canalized in a developmental and evolutionary process akin to the *Baldwin effect* [Baldwin, 1896]. Similarly, Gupta et al. [Gupta et al., 2021] demonstrated the impact of lifetime learning on evolving beneficial robot morphologies (kinematic trees of interacting 3D rigid parts). Specifically, task environment complexity coupled with lifetime-learning and morphological evolution boosts the adaptation of task-accomplishing body-brain couplings. Also, a morphological Baldwin effect was observed where behavior-morphology couplings that learn faster during robot lifetimes are selected for and propagated over successive generations.

The following sections summarize two prevalent case-studies to demonstrate our perspective on the intertwined, close coupling between environment, body-brain material *building-blocks*, and controllers. We refer to such systems as: *Body And Brain Evolutionary Learning* (BABEL) systems. The first case study explores the impact of morphological material properties on evolving morphologies and thus behavioral adaptation in an artificial life system (section 2). The second case study investigates the impact of evolving modular robot morphologies and co-adapted neural controllers distributed throughout the modules in an embodied system operating in physical environments (section 3).

2 The Effects of Evolutionary and Lifetime Learning on Minds and Bodies

The first paper investigated the impact of evolutionary versus lifetime learning on agent minds (controllers) and bodies (morphologies) in an artificial society [Buresch et al., 2005]. Agents and plants (resources) populated the AEGIS artificial world [Buresch, 2004], where at each lifetime iteration agents could select to move, mate (with an agent of opposite sex), eat (a plant) or attack (another agent). Agent controllers were represented by three mental properties (*attack*, *food*, and *social*), determining propensity for executing a given action at each iteration of its lifetime. Similarly, agent morphology was represented by three physical properties (*gender*, *muscle* and *skin*), determining agent physical prowess and thus likely success at physical conflict. For each agent, these controller and morphological properties were coded as separate genes and represented as a single genotype evolved during an artificial evolution process.

Experiments compared *evolutionary* versus *lifetime* learning for controller adaptation, where for both experiment sets, agent morphology (skin and muscle attributes) was co-evolved. However, as control experiments, the controller with the highest overall task performance (denoted by average success of all actions executed during agent lifetime) was selected from the evolutionary and lifetime learning experiments. These *best* controllers were then executed in experiments where the controller was no longer adapted but where agent morphology was evolved.

Overall, the comparison of evolutionary versus lifetime learning for controller adaptation indicated each approach significantly influenced the co-evolution of morphologies. Specifically, agents using lifetime learning (figure 2) versus evolution (figure 1) adapted to occupy different regions of the morphological definition space (skin versus muscle attribute values), for a given environment.

Thus, the controller adaptation method influenced morphological evolution (over generational time), where agents using evolutionary controller adaptation evolved morphologies with physical attributes consistently confined to the lower-right quadrant of the skin-muscle density maps (figure 1). In this sense, such morphologies are considered stable across evolutionary time. Whereas, for the same environment, agents using lifetime learning for controller adaptation, evolved morphologies across all quadrants of the skin-muscle density maps (figure 2). Thus, comparatively, these are considered unstable across evolutionary time.

These results thus indicate the possibility that controller evolution enables the co-evolution of stable morphologies over successive generations, whereas lifetime learning to adapt controllers encourages the co-evolution of relatively unstable morphologies across generations.

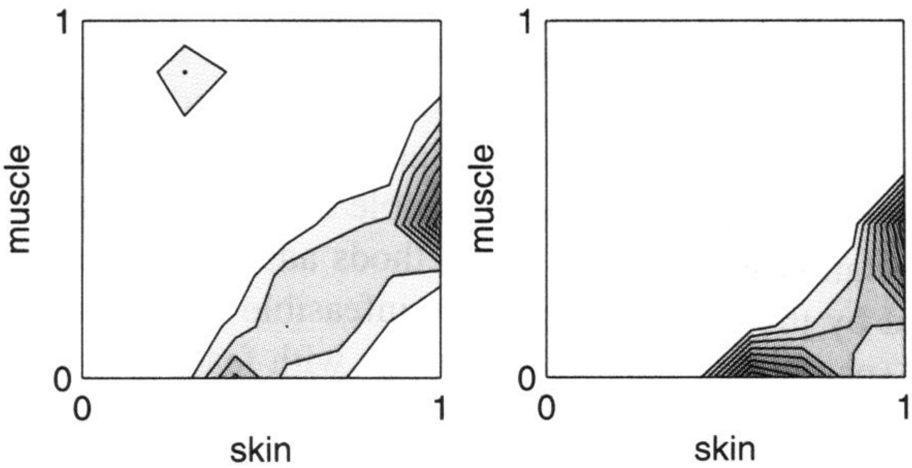

Figure 1: *Left:* Evolved agent morphologies given controller and morphology evolution. *Right:* Evolved morphologies given *best* controller (highest performer from evolving controller runs) and evolving morphology. Morphology muscle-skin density maps were computed for final generation populations (up to 10000 agents), averaged over 10 runs.

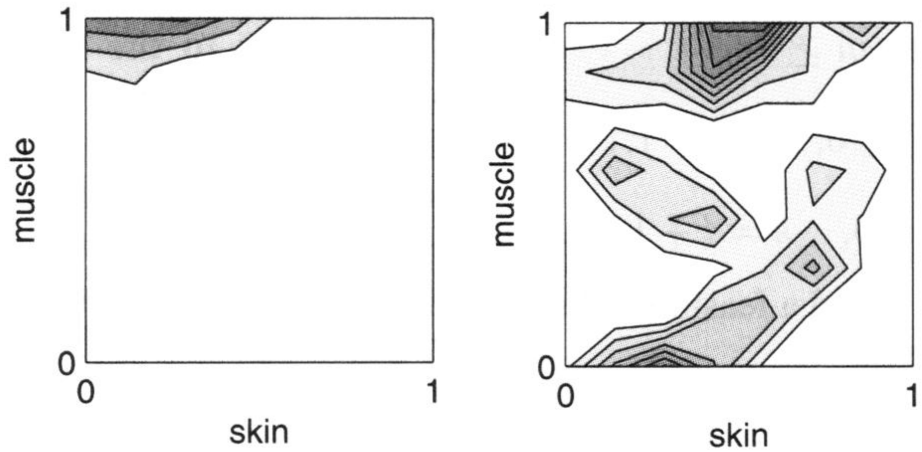

Figure 2: *Left:* Evolved agent morphologies given controller lifetime learning and morphology evolution. *Right:* Evolved morphologies given *best* controller (highest performer from lifetime learning controller runs) and evolving morphology. Morphology muscle-skin density maps were computed for final generation populations (up to 10000 agents), averaged over 10 runs.

3 Evolving Controllers versus Learning Controllers for Morphologically Evolvable Robots

The second paper studied the evolution of modular robots in simulation [Miras et al., 2020a]. The simulator, called Revolve [Hupkes et al., 2018], models robots that can reproduce and create offspring that inherit the parents' morphologies and controllers by crossover and mutation. The paper compares two approaches to evolving robots for fast locomotion. The robot morphologies are evolved the same way in both approaches, but for creating good controllers one method uses evolution only, while the other applies evolution and learning together. In the first one the controller of a robot child is inherited, that is, produced by applying crossover and mutation to the controllers of its parents. In the second one the controller of the child is also inherited, but additionally, it is improved after 'birth' by a applying a learning method to it.

The morphological design space is based on the RoboGen system [Auerbach et al., 2014], where a robot is composed from three different types of modules, one core component (head) that holds the controller board, the battery, and the camera (if present) and can attach to other modules by using its four lateral slots; a number of structural bricks (body modules) that have attachment slots on all four lateral sides; and a number of active hinges (joints) with servo motors that have two attachment slots on the opposite lateral sides. The joints can be positioned in two different ways, moving either vertically or horizontally. An important feature of the system is the bidirectional bridge between simulations and reality: all robots that can be built can also be simulated and all robots that can be simulated can be built in the real world. Figure 3 exhibits the physical as well as the digital 'incarnation' of three robots after [van Diggelen et al., 2021]. These robots are controlled by Central Pattern Generators (CPGs) [Ijspeert, 2008] arranged in a hybrid artificial neural network, called a Recurrent CPG Perceptron. For every joint in the morphology, there exists a corresponding oscillator in the network. The oscillators are not interconnected, and every oscillator may or may not possess a direct recurrent connection. The main goal of the paper is to investigate the effects of lifetime learning in evolving populations of such robots. As explained above, in the the baseline method the controller of the offspring is produced by applying crossover and mutation to the controllers of the parents. In other system controllers are not only inheritable (hence, evolvable), but also learnable. Here, the 'newborn' robot only uses its inherited brain to initialize a learning process and its actual behavior, and fitness, is determined by the learned brain.

The evolutionary process is using overlapping generations with population size $\mu = 100$. In each generation $\lambda = 50$ offspring are produced by selecting 50 pairs of parents through binary tournaments (with replacement) and creating one child per pair by crossover and mutation. From the resulting set of μ parents plus λ offspring, 100 individuals are selected for the next generation, also using binary tournaments. Evolution is terminated after 30 generations, thus all together 1.550 robots are generated and tested per run. The task for the robots is to acquire a good gait, thus the fitness function measures the speed (cm/s) of the robots: the displacement (distance between starting point and end point) divided by the duration of the test period (30 seconds). The resulting robot morphologies are compared quantitatively based on several morphological descriptors. Here we reproduce the outcomes regarding the evolution of *Size* and the *Number of Limbs* in Figure 4. These plots show that a change in the method to handle controllers can lead to changes in the evolved morphologies. For *Size* the difference is clear and significant, for the *Number of Limbs* the differences are prominent in the beginning, but diminish later as evolution settles on 'snake-shaped' robots. Recently it was shown that the dominance of 'snakes' is a consequence of a hidden bias of the representation; the L-systems have a strong tendency to converge to chain-shaped body plans, while other representations do not [Miras, 2021].

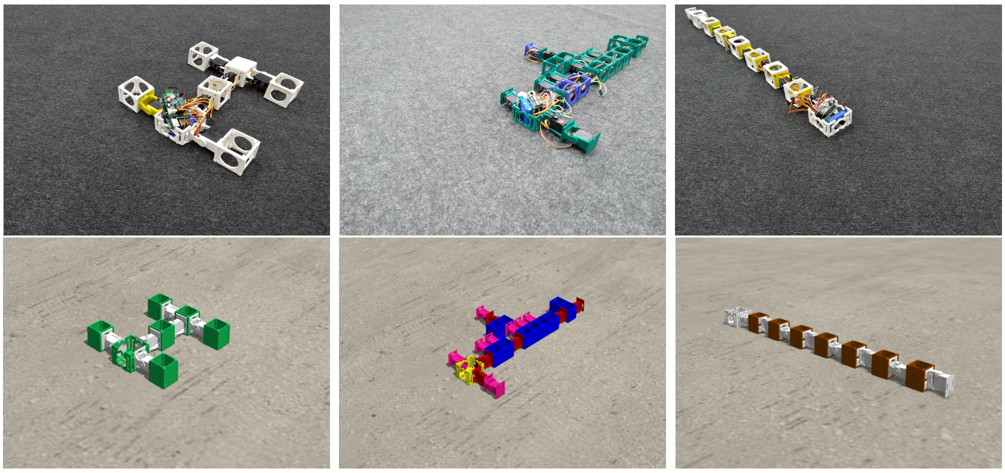

Figure 3: Examples of robots in reality and as rendered in the Revolve simulator, the Gecko (left), the Salamander (middle) and the Snake (right).

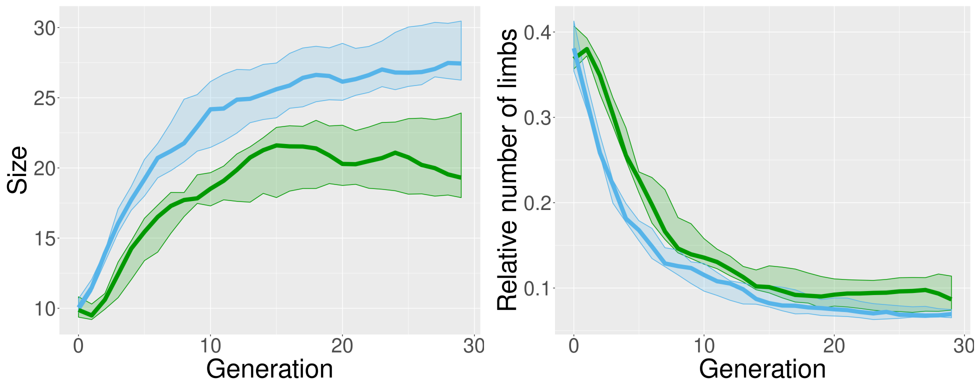

Figure 4: The evolution of morphological properties *Size* and *Number of Limbs*. The curves show the mean of the population for evolution only (green) and evolution plus learning (blue).

Another very interesting result is shown in Figure 5. It exhibits the average learning Δ per generation, that is, the speed after learning minus the speed before learning. Putting it differently, the learning Δ measures the performance difference between the inherited and the learned brains per generation. In Figure 5 we can clearly see that the learning Δ is growing across the generations. To be honest, this came as a surprise, because we have expected that as the bodies are becoming optimized for the task, there is less and less to gain by learning. However, the data suggests another effect: bodies are not only evolved for the task but also for their learning potential. As noted in the paper "*These observations suggest that the life-time learning led the evolutionary search to more quickly exploit the high performing morphological properties.*" To our best knowledge, these results are the first to demonstrate the evolution of morphological intelligence or the morphological Baldwin effect as phrased recently by Gupta et al. [Gupta et al., 2021].

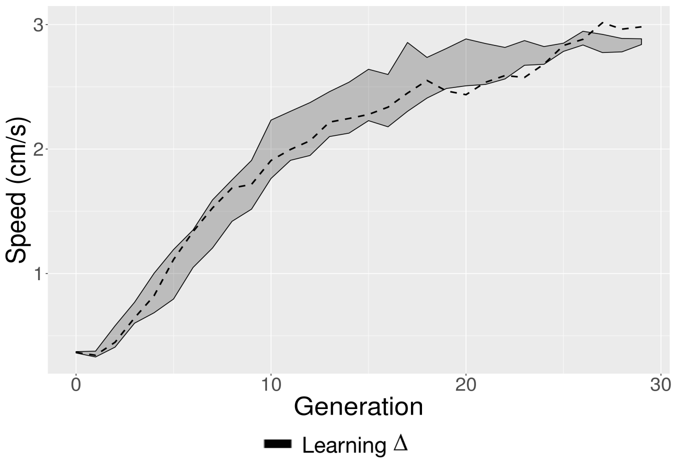

Figure 5: Average learning Δ per generation, that is, the speed after learning minus the speed before learning (quartiles over all runs).

4 Discussion

A plethora evolutionary robotics work [Lipson and Pollack, 2000, Bongard, 2011, Eiben et al., 2012, Brodbeck et al., 2015, Jelisavcic and et al., 2017, Spanellis et al., 2021] has demonstrated the impact of the environment and materials [Howard et al., 2019] available for robot morphology-controller (body-brain) evolution, as a key limitation of body-brain design and thus determinant of possible problem-solving behaviours [Pfeifer et al., 2007]. Specifically, the *body-brain building-blocks*, the material and controller constructs used by artificial evolution to synthesize body-brain couplings play an essential role in determining what path body-brain evolution can take in a given environment. This paper's first case study (section 2), examined robot body-brain evolution using simple parameterized morphological features (*skin* and *muscle*) linked to a probabilistic controller [Buresch et al., 2005] as the *body-brain building-blocks*, in a 2D artificial-life world. In this case, varying the body-brain adaptation significantly impacted the body-brain couplings evolved (figure 1: controller-morphology evolution versus figure 2: controller-morphology evolution and lifetime learning). Whereas, the second case study (section 3), examined robot body-brain evolution using sensor, actuator and joint modules defined in the *RoboGen* system [Auerbach et al., 2014], where individual modules are embedded with their own controllers, thus enabling formation of functional robot control when modules are assembled (figure 3). In this case, adding infant learning of controllers right after 'birth' significantly impacted evolved body-brain couplings and the task-accomplishing efficacy of evolved robot designs.

Although these case studies differ in several aspects and terminology, they investigate similar systems and follow a similar experimental protocol. In such *Body And Brain Evolution with Learning* (BABEL) systems, the *body-brain building-blocks* specific to each experimental protocol determines the limits of evolvable body-brain designs and thus what research questions such experiments can pose and subsequently answer. For example, in our first case study, experiments using simulated morphological materials (*skin* and *muscle*) coupled with simple probabilistic controllers, embodied as agents in artificial life simulation, were suitable and sufficient for addressing the impact of varying adaptive mechanism on evolving agent bodies and brains. However, for our second case study, use of the high-fidelity *Revolve* simulator and a broader array of *body-brain* *building-blocks* (various actuators, sensors and joints), was similarly suitable and sufficient for demonstrating the impact of an additional lifetime learning phase on evolving robot bodies and behaviours. Furthermore, these studies are also related by their surprising findings: system changes that adapt robot brains proved to affect the bodies. Specifically, that optimizing controllers during lifetime, have demonstrated significant impact on evolved morphologies. Reformulated, these studies demonstrated that while specific experimental setups support the hypothesis that the *body shapes the brain* [Pfeifer and Bongard, 2007], other experimental setups support the counter-wise hypothesis that the *brain shapes the body*.

Related work [Sims, 1994, **?**, Weel et al., 2014, Pugh et al., 2021], [Cheney et al., 2018, Furman et al., 2019, Kriegman et al., 2020, Hallauer and Nitschke, 2020], [Miras et al., 2020b, Howison et al., 2021, Spanellis et al., 2021, Zardini et al., 2021], has demonstrated the closely inter-twined dependency of body-brain evolution, depends upon the *body-brain building-blocks* (materials and coupled control mechanisms) available to such BABEL systems, which is in turn impacted by environmental and evolutionary conditions under which the *body shapes the brain*, while the *brain shaping the body*. For example, consider the generic system architecture for robot evolution conceptualized by the *Triangle of Life* methodology [Eiben et al., 2013]. In the *Triangle of Life*, a robot's lifetime consists of three phases: *Morphogenesis*, *Infancy*, and *Operational*. *Morphogenesis* is the process of creating a robot phenotype from its genotype. *Infancy* is when the newborn robot is learning to optimize its performance on a number of morphology dependent tasks and motor-actions such as locomotion, obstacle avoidance and terrain negotiation. The *Operational* phase is when the robot tries to survive in its environment, performs its tasks, and reproduces, thus starting a new robot lifetime cycle. An essential part of the *Triangle of Life* is lifetime learning, as the robot body does not change, but the embodied brain does. Specifically, learning is search through the space of all possible controllers that can be coupled with a given body and realize maximal control (effective task accomplishing behavior) [Eiben, 2021].

Lifetime learning is posited to be an essential factor in the inter-dependent evolutionary relationship between the *body shaping the brain* and the *brain shaping the body* [Eiben and Hart, 2020]. Consider that in stochastic based evolution of bodies and brains, there is no definite convergence upon inherited (reproduced) bodies and brains that are perfectly suited to each other achieving optimal task performance. That is, even though the parent robots may have suitably-coupled bodies and brains (otherwise they would not have been fit enough to be selected) randomized recombination and mutation can still result in a mismatch in the offspring. For example, an offspring's body may inherit actuators for which the inherited brain cannot suitably control. To mitigate this, newborn robots must quickly optimize inherited brains in order to adequately control the inherited body and thus survive in the environment. Also, in the search space of all possible brains, the inherited brain is just one possibility, meaning that the evolutionary search operator (reproduction), only considers one sample in the brain space. Thus, if lifetime learning can optimize brain architecture (robot behavior), then an ideal candidate brain can be found for any given inherited body.

This impact of lifetime learning on shaping the body (*the brain shaping the body*) is evident from our first case study (section 2), where significantly different agent morphologies evolved given lifetime learning and evolving morphology (figure 2) versus no lifetime learning and morphological evolution (figure 1) under the same environmental conditions. Our second case study provides experimental evidence for the same effect by the differences in evolved bodies when treating the brains differently (allowing infant learning right after 'birth'). Meanwhile, it also supports the inverse effect, *body shaping the brain*. Specifically, the notion of the *learning delta* introduced in that paper can be perceived as a quantifiable definition of *morphological intelligence*. This is in essence an attribute of the body that can indeed determine the types of behaviors (locomotion) elicited and the brains to generate them.

Returning to the pertinence of *body-brain building-blocks* in BABEL systems and implications for formulating worthwhile future research agendas, we can highlight multiple salient points. First, we need a suitable body-brain methodology to guide the setup and execution of fruitful evolutionary robotics experiments that take full advantage of the body shaping brain development and the brain shaping body development. The *Triangle of Life* framework [Eiben et al., 2013, Eiben, 2021] presents one such viable possibility. Second, given such a guiding methodology we have an excellent research instrument to better formulate experiments suitably elucidating the impact of specific *body-brain building-blocks* on the *shaping* of the body by the brain versus the *brain by the body*.

In summary, for future research into such issues we advocate using *shapeable* BABEL systems that are characterized by three principal features. First, there is an environment populated by organisms that have a dual makeup: bodies interacting with the environment and other organisms, where a brain is coupled as a controller of each body. Second, such organisms evolve as they can reproduce, generating new organisms with inherited features, and they undergo selection for reproduction and survival. Third, these organisms learn on either a *phylogenetic* (evolutionary) or an *ontogenetic* (individual lifetime learning) scale, or both, meaning that varying versions of brains are generated and tested in their given (evolving) body. Consider that this minimalist list of features implies further properties. The first feature implies that organism behavior is determined by the combination of their body and their brain. The second feature tacitly assumes that selection is based on the organisms' behaviour. This implies that evolutionary selection pressure is exerted on both the bodies and the brains. In other words, bodies and brains evolve simultaneously[1]. This is very different from the majority of evolutionary robotics literature [Trianni, 2014, Doncieux et al., 2015, Silva and et al., 2016], where only brains are evolved in fixed bodies. As discussed, this body-brain inter-dependency holds for both *artificial life* (section 2), *evolutionary robotics* (section 3) as well as biological systems [Pfeifer and Bongard, 2007], and determines what questions researchers can pose and have the system feasibly demonstrate.

To conclude, let us state a fundamental formula (1) behind embodied intelligence:

$$\textbf{BODY} + \textbf{BRAIN} + \textbf{ENVIRONMENT} \longrightarrow \textbf{BEHAVIOUR} \tag{1}$$

This formula states that, for any given environment, comprised of materials (*body-brain building-blocks* necessary for body-brain evolution) and defined by environmental features (such as the terrain and physical laws), the quality of behaviour, and hence organism fitness in an embodied artificial evolutionary system [Eiben et al., 2012, Eiben and Smith, 2015], is determined by both the body and the brain. Such *shapeable* evolutionary body-brain systems allow for some intriguing questions. Not only *"How the body shapes the brain?"* or *"How the brain shapes the body?"*, but also *"How the body and the the brain shape each other?"* or more precisely *"How the body and the the brain are shaped by evolution (and learning)?"*. Taking the environment and materials available for body-brain evolution into account can inspire further questions, for example *"Given an environment and a target behavior, what is more important, the body or the brain?"* and, whichever is more important, *"What materials, evolution and learning mechanisms are necessary to develop such bodies and brains?"*. Listing all possible questions is beyond this article's scope and purpose, which is to provide a new perspective for future artificial life and evolutionary robotics

[1]Several papers (including some of our older ones) incorrectly call this co-evolution of body and brain. However, co-evolution requires two species, which is not the case for the body-brain evolutionary systems referred to in this article.

research investigating *shapeable* evolutionary body-brain systems. First, to address the open questions of embodied intelligence, we must account for the complexities of body-brain interactions and inter-dependencies, in any BABEL system. Second, to address this first point, we must formulate research questions answerable by our experimental setup − that is, the environment, its constituent material properties (*body-brain building-blocks*), and underlying adaptive (evolution and learning) mechanisms.

Taking inspiration from nature, biology offers us countless examples of evolved body-brain couplings well suited to their environment, where body-brain evolution has made optimal use of materials in the environment. In such cases nature has produced organisms perfectly suited for survival in specific environmental niches [Coyne and Orr, 2004]. We thus hypothesize that future counterpart artificial embodied systems (extending current BABEL systems), will necessarily be derived with evolution and learning methodologies that fully account for the *phylogenetic* and *ontogenetic* complexities of body-brain interactions. A pertinent example are proposed artificial evolution and learning systems that will automate the production of problem-solving embodied (robotic) systems specially suited to solve given tasks in given environments [Nitschke and Howard, 2022].

References

[Auerbach et al., 2014] Auerbach, J., Aydin, D., Maesani, A., Kornatowski, P., Cieslewski, T., Heitz, G., Fernando, P., Loshchilov, I., Daler, L., and Floreano, D. (2014). RoboGen: Robot Generation through Artificial Evolution. In Sayama, H., Rieffel, J., Risi, S., Doursat, R., and Lipson, H., editors, *Proceedings of the Fourteenth International Conference on the Synthesis and Simulation of Living Systems*, pages 136–137. MIT Press.

[Auerbach and Bongard, 2014] Auerbach, J. and Bongard, J. (2014). Environmental Influence on the Evolution of Morphological Complexity in Machines. *PLOS Computational Biology*, 10(1):e1003399.

[Baldwin, 1896] Baldwin, J. (1896). A New Factor in Evolution. *The American Naturalist*, 30(1):441–451.

[Barrett, 2011] Barrett, L. (2011). *Beyond the Brain: How Body and Environment Shape Animal and Human Minds.* Princeton University Press, Princeton.

[Bernatskiy and Bongard, 2018] Bernatskiy, A. and Bongard, J. (2018). Evolving Morphology Automatically Reformulates the Problem of Designing Modular Control. *Adaptive Behavior*, 26(2):47–64.

[Blackiston et al., 2021] Blackiston, D., Lederer, E., Kriegman, S., Garnier, S., Bongard, J., and Levin, M. (2021). A Cellular Platform for the Development of Synthetic Living Machines. *Science Robotics*, 6(1):eabf1571.

[Bongard, 2011] Bongard, J. (2011). Morphological Change in Machines Accelerates the Evolution of Robust Behavior. *PNAS*, 108(4):1234–1239.

[Bongard et al., 2006] Bongard, J., Zykov, V., and Lipson, H. (2006). Resilient Machines through Continuous Self-Modeling. *Science*, 314:1118–1121.

[Brodbeck et al., 2015] Brodbeck, L., Hauser, S., and Iida, F. (2015). Morphological Evolution of Physical Robots through Model-Free Phenotype Development. *PLOS One*, 10(6).

[Buresch, 2004] Buresch, T. (2004). *Evolutionary versus Lifetime Learning of Agent's Controllers on a Gridworld.* VU Amsterdam, the Netherlands.

[Buresch et al., 2005] Buresch, T., Eiben, A., Nitschke, G., and Schut, M. (2005). Effects of Evolutionary and Lifetime Learning on Minds and Bodies in an Artificial Society. In *Proceedings of the Congress on Evolutionary Computation*, pages 1448–1454. IEEE.

[Carlson and Murphy, 2005] Carlson, J. and Murphy, R. (2005). How UGVs Physically Fail in the Field. *IEEE Transactions on Robotics*, 21:423–437.

[Cheney et al., 2018] Cheney, N., Bongard, J., SunSpiral, V., and Lipson, H. (2018). Scalable Co-Optimization of Morphology and Control in Embodied Machines. *Journal of The Royal Society Interface*, 15(20170937):dx.doi.org/10.1098/rsif.2017.0937.

[Corucci et al., 2018] Corucci, F., Cheney, N., Giorgio-Serchi, F., Bongard, J., and Laschi, C. (2018). Evolving Soft Locomotion in Aquatic and Terrestrial Environments: Effects of Material Properties and Environmental Transitions. *Soft Robotics*, 5(4):475–495.

[Coyne and Orr, 2004] Coyne, J. and Orr, H. (2004). *Speciation*. Sinauer Associates Inc., USA.

[Cully et al., 2015] Cully, A., Clune, J., Tarapore, D., and Mouret, J.-B. (2015). Robots that can Adapt like Animals. *Nature*, 521(1):503–507.

[Doncieux et al., 2015] Doncieux, S., Bredeche, N., Mouret, J.-B., and Eiben, A. (2015). Evolutionary Robotics: What, Why, and Where to. *Frontiers in Robotics and AI*, 2(4).

[Eiben, 2021] Eiben, A. (2021). Real-World Robot Evolution: Why Would it (not) Work? *Frontiers in Robotics and AI*, 8(696452):doi: 10.3389/frobt.2021.696452.

[Eiben et al., 2013] Eiben, A., Bredeche, N., Hoogendoorn, M., Stradner, J., Timmis, J., Tyrrell, A., and Winfield, A. (2013). The Triangle of Life: Evolving Robots in Real-Time and Real-Space. In Lio, P., Miglino, O., Nicosia, G., Nolfi, S., and Pavone, M., editors, *Proceedings of the 12th European Conference on the Synthesis and Simulation of Living Systems*, pages 1056–1063. MIT Press.

[Eiben et al., 2021] Eiben, A., Hart, E., Timmis, J., Tyrrell, A., and Winfield, A. (2021). Towards Autonomous Robot Evolution. In Cavalcanti, A. L. C., Dongol, B., Hierons, R. H., Timmis, J., and Woodcock, J. C. P., editors, *Software Engineering for Robotics*, pages 29–51. Springer.

[Eiben et al., 2012] Eiben, A., Kernbach, S., and Haasdijk, E. (2012). Embodied Artificial Evolution: Artificial Evolutionary Systems in the 21st Century. *Evolutionary Intelligence*, 5(4):261–272.

[Eiben and Smith, 2015] Eiben, A. and Smith, J. (2015). From Evolutionary Computation to the Evolution of Things. *Nature*, 521(7553):476.

[Eiben and Hart, 2020] Eiben, A. E. and Hart, E. (2020). If It Evolves It Needs to Learn. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, page 1383–1384, New York, NY, USA. Association for Computing Machinery.

[Ermolov, 2020] Ermolov, I. (2020). Industrial Robotics Review. In Kravets, A., editor, *Robotics: Industry 4.0 Issues and New Intelligent Control Paradigms. Studies in Systems, Decision and Control*, pages 195–204. Springer.

[Furman et al., 2019] Furman, A., Nagar, D., and Nitschke, G. (2019). Automating Collective Robotic System Design. In *Proceedings of the IEEE Symposium Series on Computational Intelligence*, pages 1465–1472. IEEE Press, Xiamen, China.

[Gupta et al., 2021] Gupta, A., Savarese, S., Ganguli, S., and et al. (2021). Embodied Intelligence via Learning and Evolution. *Nature Communications*, 12(5721):761–762.

[Hallauer and Nitschke, 2020] Hallauer, S. and Nitschke, G. (2020). Energy and Complexity in Evolving Collective Robot Bodies and Brains. In *Proceedings of the Congress on Evolutionary Computation*, pages 138–145. IEEE Press, Glasgow, United Kingdom.

[Howard et al., 2019] Howard, D., Eiben, A. E., Kennedy, D. F., Mouret, J.-B., Valencia, P., and Winkler, D. (2019). Evolving Embodied Intelligence from Materials to Machines. *Nature Machine Intelligence*, 1(1):12–19.

[Howison et al., 2021] Howison, T., Hauser, S., Hughes, J., and Iida, F. (2021). Reality-Assisted Evolution of Soft Robots through Large-Scale Physical Experimentation: A Review. *Artificial Life*, 26(1):484–506.

[Hupkes et al., 2018] Hupkes, E., Jelisavcic, M., and Eiben, A. E. (2018). Revolve: A Versatile Simulator for Online Robot Evolution. In *Applications of Evolutionary Computation. LNCS 10784*, pages 687–702. Springer.

[Ijspeert, 2008] Ijspeert, A. J. (2008). Central Pattern Generators for Locomotion Control in Animals and Robots: A Review. *Neural Networks*, 21(4):642–653.

[Jelisavcic and et al., 2017] Jelisavcic, M. and et al. (2017). Real-World Evolution of Robot Morphologies: A Proof of Concept. *Artificial Life*, 23(2):206–235.

[Koos et al., 2013] Koos, S., Mouret, J.-B., and Doncieux, S. (2013). The Transferability Approach: Crossing the Reality Gap in Evolutionary Robotics. *IEEE Transactions on Evolutionary Computation*, 17:122–145.

[Kriegman et al., 2020] Kriegman, S., Blackiston, D., Levin, M., and Bongard, J. (2020). A Scalable Pipeline for Designing Reconfigurable Organisms. *PNAS*, 117(4):1853–1859.

[Kriegman et al., 2018] Kriegman, S., Cheney, N., and Bongard, J. (2018). How Morphological Development can Guide Evolution. *Scientific Reports*, 8(13934):doi.org/10.1038/s41598–018–31868–7.

[Lipson and Pollack, 2000] Lipson, H. and Pollack, J. (2000). Automatic Design and Manufacture of Robotic Life Forms. *Nature*, 406(1):974–978.

[Marshall, 2006] Marshall, C. (2006). Explaining the Cambrian "Explosion" of Animals. *Annual Review of Earth and Planetary Sciences*, 84(1):355–384.

[Miras, 2021] Miras, K. (2021). Constrained by Design: Influence of Genetic Encodings on Evolved Traits of Robots. *Frontiers in Robotics and AI*, 8:177.

[Miras et al., 2020a] Miras, K., De Carlo, M., Akhatou, S., and Eiben, A. (2020a). Evolving-Controllers Versus Learning-Controllers for Morphologically Evolvable Robots. In *International Conference on the Applications of Evolutionary Computation*, pages 86–99. Springer.

[Miras et al., 2020b] Miras, K., Ferrante, E., and Eiben, A. (2020b). Environmental Influences on Evolvable Robots. *PLoS ONE*, 15(5):e0233848.

[Nitschke and Howard, 2022] Nitschke, G. and Howard, D. (2022). AutoFac: The Perpetual Robot Machine. *IEEE Transactions on Artificial Intelligence*, 3(1):2–10.

[Nordmoen et al., 2021] Nordmoen, J., Veenstra, F., Ellefsen, K., and Glette, K. (2021). MAP-Elites Enables Powerful Stepping Stones and Diversity for Modular Robotics. *Frontiers in Robotics and AI*, 8:56.

[Pfeifer and Bongard, 2007] Pfeifer, R. and Bongard, J. (2007). *How the Body Shapes the Way We Think: A New View of Intelligence.* MIT press.

[Pfeifer et al., 2007] Pfeifer, R., Lungarella, M., and Iida, F. (2007). Self-Organization, Embodiment, and Biologically Inspired Robotics. *Science*, 318(5853):1088–1093.

[Pfeifer et al., 2012] Pfeifer, R., Lungarella, M., and Iida, F. (2012). The Challenges Ahead for Bio-Inspired 'Soft' Robotics. *Communications of the ACM*, 55(1):76–87.

[Pugh et al., 2021] Pugh, J., Soros, L., and Stanley, K. (2021). Quality Diversity: A New Frontier for Evolutionary Computation. *Frontiers in Robotics and AI*, 3(40):doi: 10.3389/frobt.2016.00040.

[Rahwan et al., 2019] Rahwan, I., Cebrian, M., Obradovich, N., and et al. (2019). Machine Behaviour. *Nature*, 568(1):477–486.

[Rothschild and Mancinelli, 2001] Rothschild, L. and Mancinelli, R. (2001). Life in Extreme Environments. *Nature*, 409(1):1092–1101.

[Shah et al., 2021] Shah, D., Powers, J., Tilton, L., and et al. (2021). A Soft Robot that Adapts to Environments through Shape Change. *Nature Machine Intelligence*, 3(1):51–59.

[Shah et al., 2020] Shah, D., Yang, B., Kriegman, S., Levin, M., Bongard, J., and Kramer-Bottiglio, R. (2020). Shape Changing Robots: Bioinspiration, Simulation, and Physical Realization. *Advanced Materials*, 2002882(1):1–12.

[Silva and et al., 2016] Silva, F. and et al. (2016). Open Issues in Evolutionary Robotics. *Evolutionary Computation*, 24(2):205–236.

[Sims, 1994] Sims, K. (1994). Evolving 3D Morphology and Behavior by Competition. *Artificial Life*, 1(4):353–372.

[Spanellis et al., 2021] Spanellis, C., Stewart, B., and Nitschke, G. (2021). The Environment and Body-Brain Complexity. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 138–145. ACM, Lille, France.

[Trianni, 2014] Trianni, V. (2014). Evolutionary Robotics: Model or Design? *Frontiers in Robotics and AI*, 1(13):doi: 10.3389/frobt.2014.00013.

[van Diggelen et al., 2021] van Diggelen, F., Ferrante, E., Harrak, N., Luo, J., Zeeuwe, D., and Eiben, A. (2021). The influence of robot traits and evolutionary dynamics on the reality gap. *IEEE Transactions on Cognitive and Developmental Systems*, 1(1):1–10.

[Weel et al., 2014] Weel, B., Crosato, E., Heinerman, J., Haasdijk, E., and Eiben, A. E. (2014). A Robotic Ecosystem with Evolvable Minds and Bodies. In *Proceedings of the International Conference on Evolvable Systems*, pages 165–172. IEEE Press, Piscataway, USA.

[Zardini et al., 2021] Zardini, E., Zappetti, D., Zambrano, D., Iacca, G., and Floreano, D. (2021). Seeking Quality Diversity in Evolutionary Co-design of Morphology and Control of Soft Tensegrity Modular Robots. In *Proceedings of the Proceedings of the Genetic and Evolutionary Computation Conference*, pages 189–197. ACM.