

Maturity model for biointelligent systems

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Abstract: Society is in the midst of a transformation process that can be attributed to climate change and rapid technological progress. It is anticipated that a new technological leap will be made toward biointelligent value creation. This increasing integration of biological components into technical systems is fundamentally changing development practices and creating new challenges, particularly in product development. Therefore, this paper proposes a theoretical framework for the classification of biointelligent systems based on a maturity model to determine the current state of development.

Keywords: bioinspired design, sustainability, maturity model, biointelligent, meta analysis

1 Introduction

Society is in the midst of a transformation process that can be attributed to climate change, political pressure to achieve sustainability targets, and rapid technological progress. It is anticipated by studies that a new technological leap will be made toward biointelligent value creation, with the potential for a more sustainable subsistence strategy. This has been coined as the biological transformation (Baumgarten et al., 2024). The development of new technologies, processes, and organizations is imperative for the successful execution of the biological transformation (Miehe et al., 2019). Within this context, the notion of "biointelligence" is increasingly pivotal for the formulation of future innovation strategies and represents a novel approach both to production systems and products themselves (Miehe et al., 2019). The term "biointelligence" denotes the convergence of biological principles, technical artefacts, and data-driven information technology (Simon et al., 2025). This integration yields systems characterized by enhanced resource efficiency, robustness, and power (Hauf et al., 2024). In addition, political and technological initiatives including the European Green Deal, New Food, and strategies within international innovation ecosystems (e.g., BioMADE, BIOTRAIN) underscore the relevance of biointelligent systems. Biointelligent systems are characterized by the interaction of technology, information technology, and biology, as well as by their capacity to respond to external stimuli in an adaptive, self-organizing, and efficient manner (Emer et al., 2025; Luo et al., 2018). A representative example of such systems is the fully automated cultivation of human stem cells in robotic laboratory environments, where biological growth processes are continuously monitored and controlled through sensor systems and deep learning algorithms, enabling autonomous decision-making within the production process (Ochs et al., 2021). Biointelligent systems can incorporate both physical-biological forms of intelligence (e.g., living cells, microbiota, neural networks) and bioinspired concepts such as modular adaptability, swarm behavior, or stochastic decision logic (Bakhouya & Gaber, 2014; Wu et al., 2013).

2 Problem clarification and goal

Despite growing interest in biologically inspired and biohybrid technologies, the development of biointelligent systems remains conceptually fragmented and methodologically inconsistent. Existing research frequently uses terms such as bioinspired, biomimetic, biointegrated, and biointelligent interchangeably, without clearly distinguishing the level and role of biological involvement (Engbers et al., 2024; Miehe et al., 2023). This lack of conceptual precision makes it difficult to systematically classify systems, compare developments, or support design decision-making (Simon et al., 2025). The increasing integration of biological components into technical systems is fundamentally changing development practices and creating new challenges, particularly in product development (Sonnenberg et al., 2025). This is because biology is an additional discipline with different development procedures that must be systematically integrated into the development process of technical systems (Castle et al., 2024). The mere emulation of natural strategies has been demonstrated to be an ineffective approach (Teti et al., 2024), given the fundamental disparity regarding the different material compositions and lifecycles of biological and technical systems. Against this backdrop, a structured analysis of biointelligent systems and the identification of their key characteristics is necessary in order to reliably determine the design scope and limitations (Miehe et al., 2021; Simon et al., 2025). Concurrently, there is a necessity to identify further application scenarios and validate them through case studies or laboratory studies, thereby facilitating the transfer of research findings into operational applications (Emer et al., 2025). Furthermore, while numerous examples of biologically influenced systems exist, there is currently no structured framework that enables designers and researchers to assess the developmental maturity of such systems. As a result, the progression from inspiration to integration and ultimately to biointelligent functionality is not well understood, and the implications for product development remain unclear (Simon et al., 2025).

In practical terms, this lack of structured assessment leads to significant challenges in development processes, such as the inability to systematically benchmark system capabilities, identify development gaps, or make informed design decisions regarding the integration of biological and technical components. As a consequence, the development of biointelligent systems remains largely experience-driven and case-specific, limiting both comparability and reproducibility across applications. Another limitation in existing work is the absence of transparent and reproducible classification approaches. Many studies describe biologically influenced systems qualitatively, but do not provide explicit criteria or evaluation procedures that allow different researchers or practitioners to arrive at consistent conclusions. To address these gaps, this research develops a taxonomy and maturity-based classification framework for biointelligent systems grounded in a systematic literature analysis. The framework aims to clarify the defining characteristics of biointelligent systems, distinguish different levels of biological integration, and provide a structured method that supports analysis and design of such systems. By enabling a more systematic assessment of biointelligent technologies, the proposed approach contributes to improving conceptual clarity, comparability, and design-oriented application in this emerging field.

Maturity models provide a suitable methodological basis for gaining a better understanding of the development level of biointelligent systems, as they condense complex issues while enabling model-based analysis and design with greater accessibility (Akkasoglu, 2014). Furthermore, the utilization of stage theory is especially advantageous in the context of complex systems, as it facilitates the documentation of system maturity levels across distinct stages. This in turn enables a simplified analysis and classification of the analyzed use cases by means of comparison (Akkasoglu, 2014). Given the novelty of biointelligent systems, a maturity model can help achieve a quantifiable metric regarding the current state of development of the different use cases and system components. Additionally, it can also be used specifically to determine the degree of biointelligence of existing systems and new technology concepts (Miehe et al., 2020). In order to address this gap in the existing body of knowledge, this paper aims to answer the following research questions: *RQ1 – Which characteristic elements constitute biointelligent systems?* *RQ2 – What stages of maturity can biointelligent systems be divided into?* To achieve this objective, a thorough literature review was conducted. This review encompassed the current state of the art as well as relevant best practices and use cases in related subject areas. Furthermore, a maturity model for biointelligent systems was developed with the objective of structurally capturing their properties and facilitating their comparison. An assessment scheme has also been developed to facilitate the classification concepts within the model. The implementation of the maturity model is achieved through the establishment of a systematized collection of relevant use cases, thereby establishing a reference framework that supports the perception and development of biointelligent systems.

3 Methodology

In order to answer the research questions, a multi-stage, qualitative-analytical approach is pursued that integrates both theory- and practice-based findings. The initial step consisted of contextual research with the goal of gaining broad insight into the topic of biointelligent systems and determining the important keywords and synonyms. In the second step, described in chapter 3.1, a systematic literature review (SLR) was conducted with the objective of ascertaining the current state of research into biointelligent systems. The objective of this study is to extract key terms, conceptualizations, system-related findings, and use cases, then transfer them into a comprehensive classification system. To answer the second research question, the definitions and use cases found with the help of the SLR were analyzed to extract characteristic features of biointelligent systems.

3.1 Initial data collection

The systematic literature review was conducted in May 2025 using the method described by Biedermann et al. (2012). The search encompasses specialist articles, papers, and reports from pertinent fields such as biology, engineering, and medical technology. The four scientific databases Scopus, IEEE, Science Direct, and Web of Science were selected to ensure that as much of the available literature as possible is reviewed. The search parameters utilized are delineated in Table 1. The selection of search parameters is based on a preliminary contextual research of the subject area and subsequent iterative optimization of the search string based on the quality of the respective results.

Table 1. Parameters of the systematic literature review

Guiding question	Which characteristic elements constitute biointelligent systems?		
Publication	Monographs, anthologies, book and conference contributions, journal articles		
Keywords and synonyms	biointelligent biointelligence bioinformatics bioinspired biologicalization biologically-inspired	intelligent intelligence smart agile adaptive	system product design
Search string	TITLE (bioi* OR biolo*) AND ABS (smart OR intelligen* OR agile OR adaptive) AND ABS (system OR product OR design)		

The objective of the multi-stage research is to ascertain the fundamental characteristics of biointelligent systems, thus providing a uniform understanding of biointelligent systems and the unique features that distinguish them from non-biological deterministic systems. The preliminary search yielded 3,742 results across the four databases, which were subsequently analyzed using a fixed screening procedure. In order to ensure methodological rigor and reproducibility, explicit inclusion and exclusion criteria were applied. Publications were included if they addressed biointelligent systems or closely related concepts such as bioinspired or biointegrated systems and contained conceptual, methodological, or application-oriented insights relevant to system characteristics. Publications were excluded if they lacked relevance to the research question, focused purely on biological or purely technical systems, or did not provide sufficient conceptual contribution. This screening started with an initial review of the titles and keywords, after which the number of articles was reduced to 812 due to the others' lack of relevance to the research question. The remaining publications were then reviewed based on their abstracts and conclusions, with 554 hits advancing to the next stage of analysis. Of the remaining publications, 49 results were classified as highly relevant to the question of the definition of biointelligent systems. These texts were already analyzed in full using qualitative analysis methods as part of the study.

In this way, the thorough review yielded industrial and academic applications of biointelligent and related systems that were duly collected and analyzed. This provides the foundation for the contextualization and validation of insights from theoretical frameworks via the application of specific best practices.

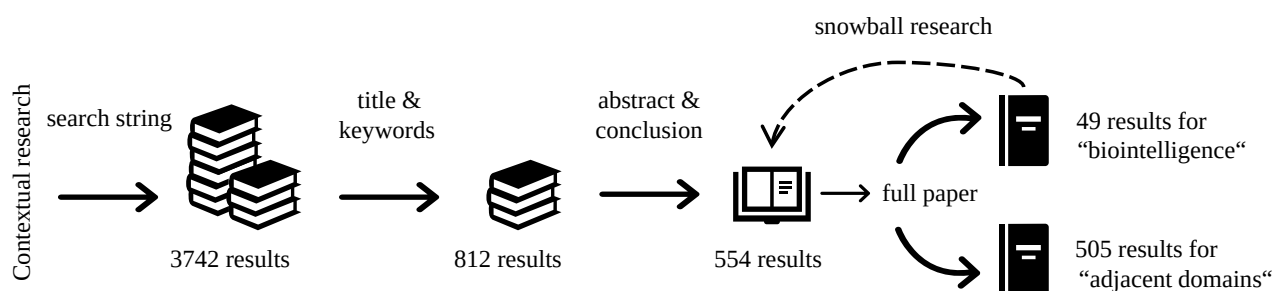


Figure 1. Schematic representation of the systematic literature review

Given the already analysed literature about the definitions of biointelligent systems by Simon et al. 2025, this contribution is an extension of this analysis and focuses on the 505 remaining results for the second part of the review. These contributions that do not always deal directly with biointelligence concept, but by featuring related topics they contribute a valuable context for the various characteristics of bioinspired or biointegrated and thereby provide conceptual differentiation in the development of the maturity model. The meta-analysis of the 49 results screened for definitions was performed by Simon et al. (2025) and generated four characteristic features of biointelligent systems.

1. Integration of biological elements (e.g., biomaterials, living organisms, biosensor structures) (Emer et al., 2025; Full et al., 2019; Konfo et al., 2024; Mächtlen et al., 2024)
2. Technical and digital components (e.g., AI, sensor technology, automation systems) (Hauf et al., 2024; Mächtlen et al., 2024; Miehe et al., 2023)
3. Bilateral interfaces for interaction between biological and technical systems (exchange of signals, energy, or materials) (Byrne et al., 2021; Miehe et al., 2019)
4. Intelligent system behavior (e.g., self-regulation, self-optimization, learning ability) (Byrne et al., 2021; Emer et al., 2025; Miehe et al., 2023; Shoshi et al., 2024)

To operationalize the individual key components mentioned in the definitions of biointelligent systems the characteristics were systematically extracted and summarized as described in section 4.1. In this work, these four characteristics are not independently derived but adopted as a conceptual foundation and systematically operationalized into measurable indicators within the proposed maturity model. Following that the remaining 505 results from the review were screened to determine use cases for bioinspired, biointegrated and biointelligent systems. A prerequisite for considering a given use case was a detailed description of the individual key components enabling an assessment of its maturity level.

3.2 Composition of the maturity model

The maturity model is constructed iteratively in a process that starts with defining the goals. It then moves on to building the model by deriving dimensions and indicators, performing validation, and finally applying the model. The four relevant dimensions were derived from the features found in the SLR, which were each divided into three indicators and operationalized with appropriate measurement scales. The establishment of defined scales is important to ensure reproducibility and comparability (Becker et al., 2009). Because maturity assessments can involve subjective judgements, the approach emphasizes validation with industrial use cases to mitigate ambiguity and bias (Akkasoglu, 2014).

Characteristic use cases for bioinspired, biointegrated, and biointelligent systems were therefore assessed based on the maturity model and then compared to the maturity level claimed by the authors. In addition to this, the model was assessed by multiple researchers from relevant domains like systems engineering and smart product-service design. For practical use, the model enables simple, transparent, and reproducible self-assessment with unambiguous scoring logic and adheres to principles of sound modelling including correctness, relevance, comparability, and systematic structure. The results can thus inform continuous improvement and strategic road mapping (Becker et al., 2012).

The goal of the maturity model is to exclusively evaluate biointelligent systems on the basis of the final system or product, making use cases quantitatively comparable with defined criteria. This enables the derivation of recommendations for action and development needs, including identifying research gaps and targeting the transformation of bioinspired or biointegrated systems into biointelligent systems. Unlike five-stage approaches such as CMMI (Altuntas & Uhl, 2016; Yamfashije, 2017) the model focuses on three stages based on the established terminology of the biological transformation: bioinspired, biointegrated, and biointelligent. Since additional intermediate stages are not clearly defined in the literature, this would make it difficult to distinguish between stages of development. The objective is to dissect and evaluate biointelligent systems by assessing their components and characteristics, with a focus on the biotechnical system or product rather than the development process. Predefined criteria enable classification across multiple dimensions, rated on a scale to create comparability, which facilitates consistent benchmarking and the derivation of targeted actions for improvement. The model offers a methodical and data-driven framework that facilitates the discernment of the performance and developmental potential of bioinspired and biointegrated systems, guiding their evolution towards fully biointelligent ones.

4 Maturity model for biointelligent systems

Due to the multifaceted architecture of biointelligent systems, the model is characterized by its multidimensional nature and is able to capture various characteristics and focal points of the system without losing practical relevance. The balance between differentiation and comprehensibility is crucial here (Altuntas & Uhl, 2016; Becker et al., 2009). Overall, this results in a phase-oriented, multidimensional, and validated instrument that addresses uncertainties and presents the performance and development capabilities of biointelligent systems transparently and comparably.

Biointelligent systems are assessed on the basis of four derived dimensions that cover the most important components. The dimensions consist of the characteristic features of biointelligent systems as mentioned above, namely the integration of biological elements, technical and digital components, bilateral exchange between the biological and technical system, and intelligent system behavior. The dimensions were then validated with the help of existing use cases. Furthermore, the dimensions were divided into three further indicators that reflect specific functions and aspects of the systems under consideration. Figure 2 shows the structure of the maturity model. Linking the characteristic property to the respective dimensions enables a differentiated evaluation, on the basis of which development needs for the respective discipline can be derived. This also facilitates the applicability of the model, as the complex interaction of the disciplines is reduced to the individual components. Each dimension is also subdivided into additional sub-indicators so as to distinguish between different types of biointelligent systems. This should also enable an assessment of the respective degree of biointelligence.

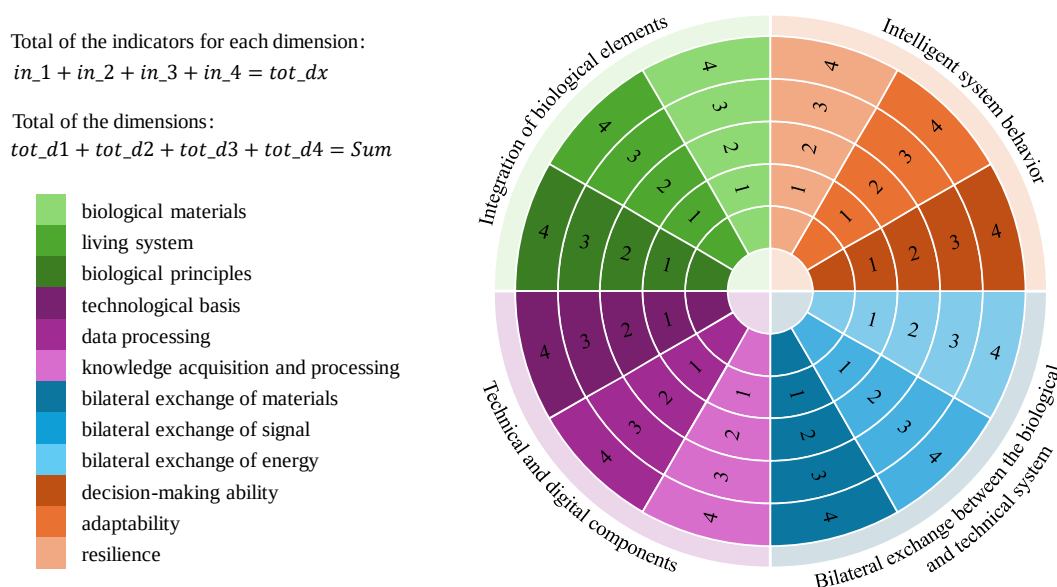


Figure 2. Maturity model for biointelligent systems

4.1 Dimensions of the maturity model

In accordance with the preceding definition of biointelligent systems, the properties mentioned therein are now to be extracted and summarised. The subsequent step will be to derive the characteristic properties of biointelligent systems. In order to create a structured overview, the 43 properties mentioned were compared with each other and reduced to 20 properties after removing duplicates. The goal is to identify components that can be described in generic terms, based on the individual definitions and characteristics that have been mentioned.

In order to achieve this objective, analogous components of the definitions have been summarised and grouped in table 2 and overarching characteristics have been derived from them. The higher-level characteristics on the right-hand side of the table are based on the properties with increased relevance that were derived from the definitions. The utilisation of biological materials, a concept delineated in four distinct definitions (Emer et al., 2025; Konfo et al., 2024; Mieke et al., 2019; Mieke et al., 2023) is characterised by the "integration of biological elements." The integration or combination of technology and biology is mentioned in seven definitions (Hauf et al., 2024; Mieke et al., 2018; Mieke et al., 2021; Mieke et al., 2023; Panagiotopoulou and Stavropoulos 2023; Shoshi et al., 2023; Shoshi et al., 2024) and related to the characteristic already mentioned and is therefore expanded by the use of "technical and digital components." The interaction of system components was outlined in six definitions (Full et al., 2019; Mächtlen et al., 2024; Mieke et al., 2020a; Mieke et al., 2020b; Mieke et al., 2020c; Mieke et al., 2023) and is represented by the characteristic "Bilateral exchange between the biological and technical system." The final overarching characteristic, "intelligent system behaviour," is primarily a consequence of the presence of the other components, but is nevertheless an important component in terms of distinguishing it from purely biointegrated systems. Consequently, it is imperative to incorporate this as a distinctive attribute of biointelligent systems.

Table 2. Grouping of the properties of biointelligent systems

Properties of biointelligent systems	Overarching characteristics (Simon et al. 2025)
merging intelligent paradigms and biology integration bio- and technology expanding CPS with biology bio materials designed according to living beings merging/fusion of bio, techno and info	Integration of biological elements
sensors and actuators data processing system artificial intelligence information channels	Technical and digital components
interaction of bio- and technology controlled information transfer bilateral information exchange	Bilateral exchange between the biological and technical system
enhanced intelligence create intelligent solutions local production scalable self-sufficient production increased efficiency	Intelligent system behavior

The dimensions for the maturity model were based on the characteristics of biointelligent systems derived from a systematic literature review, the results of which were mirrored with use cases. In this way, the dimensions are thus derived on the basis of theory and empirically validated. The model under discussion comprises four dimensions with a total of twelve indicators, each of which is rated on a five-point scale (0-4) with precise anchor criteria. The individual results can be aggregated per dimension and across dimensions, thereby enabling both profile creation and overall assessments.

The first dimension addresses the integration of biological elements and operationalizes the extent to which biology is functionally anchored in the system. The evaluation encompasses the occurrence and relevance of biological materials (Full et al., 2019), the relationship to properties of living systems (Mieke et al., 2018), and the utilization of biological principles for technical functions (Emer et al., 2025). These indicators are very important for distinguishing purely technical systems for bioinspired and biointegrated solutions.

The second dimension delineates the technical and digital basis as an enabler of biointelligent behavior. The technological maturity of the system is based on the technology readiness level (TRL) (Mankins, 1995), which is divided into five stages from conceptual idea to qualified operation. The expansion of data processing is from unorganized raw data to integrated, system-wide data storage. Knowledge acquisition and processing along a knowledge ladder results in the independent,

knowledge-based action of the system. The ladder is based on the concept introduced by North, which describes the transformation of signals and data into knowledge (North, 2016). The concept of biointelligent coupling revolves around a bilaterally functioning interface between the biosphere and the technosphere, the quality of which is differentiated in the third dimension. This covers the exchange of materials, signals, and energy, ranging from "non-existent" to unregulated forms and fully controlled interaction. Regulation can be implemented in a technical, control-based, or AI-supported manner (Miehe et al., 2020). Both the depth and controllability of the interaction are therefore represented as quality criteria. Finally, the fourth dimension examines intelligent system behavior (Miehe et al., 2023) independently of its implementation domain and distinguishes between decision-making ability, adaptability, and resilience. The highest level of maturity is achieved when the system is capable of making independent decisions depending on the context and learning from them, adapting in a flexible and self-organizing manner to changing environments, and restoring full functionality after abrupt disruptions.

4.2 Classification scheme for biointelligent systems

The assessment scheme of the maturity model is predicated on the systematic upstream identification of the characteristics that constitute the system under consideration. The assessment is conducted in two stages: Initially, all indicators are assessed on a five-point scale (0-4) and aggregated into dimension totals as shown in Figure 2. Subsequently, the four dimension totals are added to provide the overall score (maximal value of 48). Though, the total score is utilized to differentiate between degrees of expression and focal points, it does not serve as the determining factor for the allocation to maturity levels. This is because a pure point threshold has the potential to distort systems that exhibit qualitatively distinct profiles. The number of maturity levels was set at three, with a view to applicability and selectivity, bioinspiration, biointegration, and biointelligence, in order to ensure sufficient precision while keeping the complexity of the characteristic value matrix manageable. While the inclusion of additional levels might enhance the granularity of the system, it would result in a disproportionate increase in the complexity of the requirements for sub-indicators and their delimitation. The three levels of the classification system are based on the established stages of biological transformation, thereby increasing its practical relevance.

Levels are assigned on the basis of minimal requirements for each dimension, rather than on the total number of points. The requirements for each indicator were either based on the literature from which they were derived or the level of fulfillment was evaluated by Likert items. The lowest level of *bioinspiration* is attained once a minimum of one point is accumulated across the designated dimensions, and the model does not seek to achieve further differentiation within this level. The concept of *biointegration* necessitates the integration of biological elements with technical and digital components, resulting in the formation of a unified entity. The initial phases of material, signal, or energy exchange may be observed during this process. The degree of integration can be estimated using the "biological materials" indicator and, for fine differentiation within the level, using the total number of points. The concept of *biointelligence* necessitates the presence of minimal levels in all four dimensions. In the context of integrating biological elements, it is imperative that the indicator "biological materials" attains a minimal level of 2, classified as "partially fulfilled." Level 1 "not fulfilled" is deemed inadequate for ensuring biological anchoring as a feature of biointelligent systems. To represent one of the four key characteristics being "intelligent system behavior", at least one indicator (e.g., decision-making ability, adaptability, or resilience) must be rated at "partially fulfilled" (level 2). With regard to technical and digital components, a functional technological proof ("technological basis" indicator, level 1) and basic data processing ("data processing" indicator, level 1) are required as a minimum requirement. This means the system must possess at least an architecture that processes data streams (e.g., from sensors or at the biotech interface). It is notable that no minimum requirement is specified for "knowledge acquisition and processing": this is to ensure representation of systems in which information processing is primarily carried out in the biological part. In the context of a bilaterally functioning interface between technical and biological systems, the demonstration of at least one form of exchange (signal, energy, or material) at level 1 is essential. Active regulation is not yet required for this demonstration.

The scheme combines a finely grained performance assessment (0-4 per indicator, up to 48 total points) with clear, dimension-specific minimum criteria for maturity classification. This facilitates profile comparisons across dimensions and robust level assignment: The total score supports the classification of the characteristic within a level, while the minimal requirements for each dimension determine the level to which it belongs and avoid misclassifications through point-based thresholds.

4.3 Demonstration of the maturity model via application in use cases

The following section aims to demonstrate the applicability, utility, and quality of the maturity model. The model is therefore utilized in order to assess two existing use cases that exhibit the typical characteristics of bioinspired, biointegrated, or biointelligent systems.

Assessment of a bioinspired use case

The MARCBot is a rock-climbing robot designed for multimodal locomotion in complex terrains. It integrates a hybrid spiny gripper mechanism and an optimized control strategy to achieve both stable vertical climbing and efficient ground locomotion. It demonstrates enhanced adaptability, performance, and energy-efficient operation in extreme environments. The MARCBot is characterized by its developers as a bioinspired system, serving as a case study for validating a maturity model across defined dimensions and minimal requirements (Zi et al., 2024). Figure 3 shows the assessment of its maturity level based on the developed model. With regard to biointegration, it is evident that neither living organisms nor biological materials are incorporated into the technical structure; the corresponding indicators "biological materials" and "living system" therefore remain at level 0. In contrast, the mode of operation is evidently founded on biological principles, encompassing mechanical hooking onto rough surfaces, opposing clamping kinematics, and hoof-like support, derived from beetle tarsi, bird claws, and hooves, among other elements. Consequently, it attains level 4. These findings provide robust support for the classification of the subject as bioinspired rather than biointegrated.

The technical-digital dimension is advanced, since systematic climbing and running experiments have been conducted and the results have been benchmarked against those of other climbing robots. The prototype of the MARCBot was tested in a controlled environment ("technological basis" indicator, level 3). The data processing encompasses an on-board computing unit, inertial measurement data, state estimation employing an extended Kalman filter, model-based trajectory planning, and a control system for optimal force/torque distribution ("data processing" indicator, level 3). As the article does not explicitly address the concept of "knowledge acquisition and processing," it is reasonable to assume that a conservative level 1 is appropriate. When considered in isolation, this dimension would meet the minimal requirements for biointelligence. However, the complete absence of a bilateral interface between the technical and biological systems means there is no exchange of matter, signals, or energy with biological components. All three interface indicators remain at level 0, falling significantly short of the minimum requirement.

With regard to the intelligent system's behavioral characteristics, the MARCBot implements model-based decision-making and control functions (gait arrangement, path planning, optimization of contact and reaction forces). It is evident that a proportion of the information pertinent to the experiments presented was manually specified, thereby resulting in a certain degree of autonomy. This is further evidenced by the indicator "decision-making ability," which is set at level 2. The capacity for adaptability is the result of a combination of factors, including morphological intelligence (manifesting as passive compliance, beetle-inspired microspine modules, opposing clamping, and hoof-like support) and control-side adjustments during the swing phase. This enables robust adaptation to variations in roughness and contact geometries ("adaptability" indicator, level 2). Indications of stabilization during periods of state transition are evidenced by weight adjustment and the decoupling of body and leg movement. However, there is an absence of evidence indicative of self-healing or functional recovery, as indicated by the resilience indicator at level 1.

In the overall assessment, the maturity level designated "biointelligent" is found to be deficient primarily due to the absence of biological components: This maturity level would require at least level 2 for "biological materials" and at least level 1 in at least one interface indicator. However, neither of these conditions is met. The MARCBot can thus be categorically classified as a bioinspired system, due to the utilization of biological principles in the gripper and drive system.

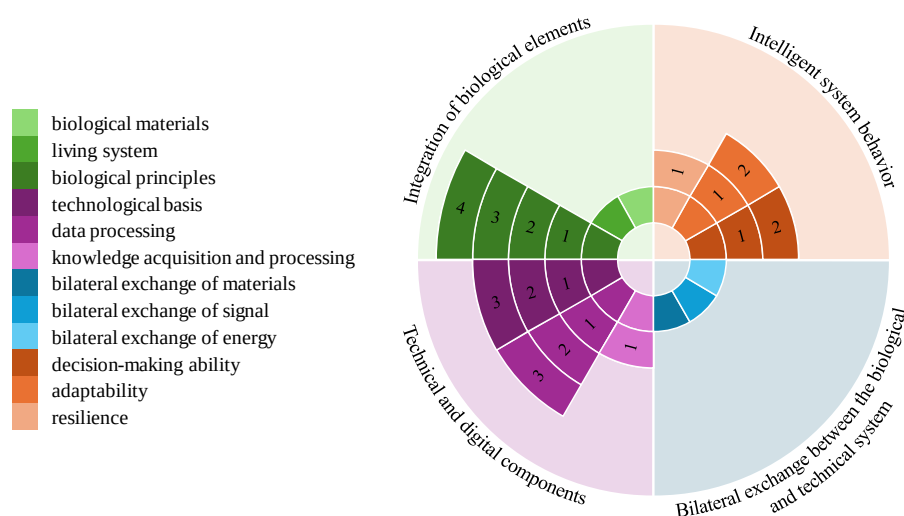


Figure 3. Maturity assessment of the bioinspired MARCBot based on the maturity model

Assessment of a biointelligent use case

The neuro-robot presented by (Li et al., 2016) integrates a living rat neural culture on a multi-electrode array (MEA) as a biological controller in a closed control loop with a technical platform. The neurons function as a decision-making center, with their action potentials being recorded in real time and decoded as motor commands (left/right/stop) in order to steer the robot. Conversely, robotic status information is fed back into the culture as electrical stimulation patterns. Figure 4 shows the maturity level of the neuro-robot. With regard to biointegration, biological materials are present and integrated in a system-relevant manner (level 4); the overall system itself is not a living organism but contains living components (level 1). Subfunctions are predicated on biological principles, including neural information processing and short-term plasticity. Consequently, this indicator can be assessed as partially fulfilled (level 2).

From a technological standpoint, a robust prototype with repeatable tests for object search behavior, a stimulator developed in-house, and modular software is available. This goes beyond a mere proof of concept (technological basis level 3). Data processing encompasses real-time signal recording, spike counting within designated time windows, threshold-based decoding, and the encoding of position data into stimulation patterns (level 2). It should be noted that explicit machine learning does not occur within the technical component (level 0). The biotechnical interface is bidirectional and signal-driven: spikes from defined electrode areas are read out (decoding), while stimulation patterns stimulate the culture (coding). It is evident that, given the absence of substantiated evidence demonstrating active, two-way interface regulation, the validation undertaken is conservative (signal level 1; material/energy exchange level 0).

With regard to intelligent system behavior, the overall system evinces rule-based decision-making capabilities in a closed loop (level 3) and empirically proven adaptability, as performance improves over trial runs, a plausible outcome due to short-term synaptic plasticity of the culture (level 2). No explicit resilience strategies are identified; given the adaptive properties, a conservative classification is appropriate (level 1). Besides the dimension of bilateral exchange, the indicators are clearly pronounced, meaning that the minimal requirements are met and the use case can be classified as biointelligent.

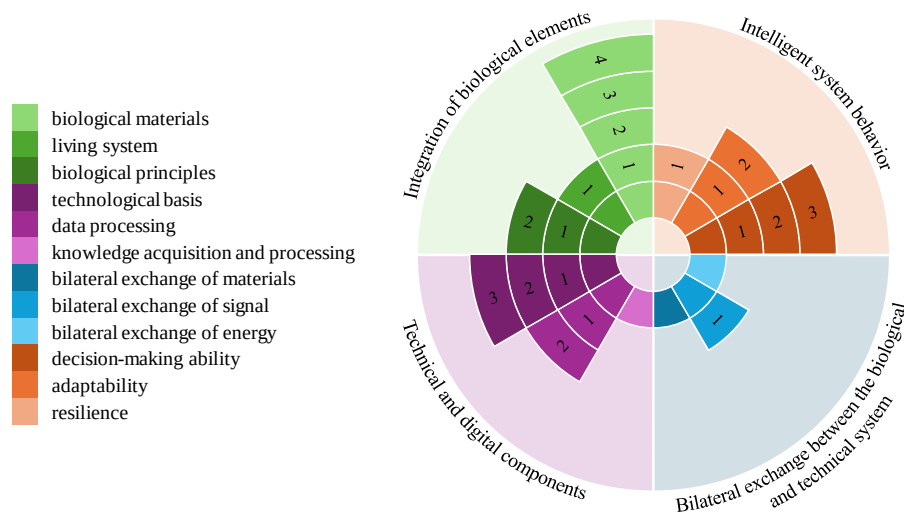


Figure 4. Assessment of the maturity level of a neuro-robot

5 Discussion and outlook

This paper proposes a theoretical framework for the classification of systems according to a maturity model for biointelligent systems. It comprises four dimensions: the integration of biological elements, technical and digital components, bilateral exchange between biological and technical subsystems, and intelligent system behavior. The model is organized into three categories: bioinspired, biointegrated, and biointelligent. The design is predicated on explicit minimal requirements ("gates") per dimension. It is imperative to note that a system cannot be considered biointelligent unless it exhibits at least one bidirectional signal interface and demonstrable intelligent behavior. Moreover, the technological basis and data processing must meet defined thresholds. The gates in question have been demonstrated to enhance discriminative power, thereby ensuring that technically sophisticated or biologically elaborate systems do not receive an undue label of biointelligent. The findings of the analyzed case studies show that the model produces consistent and transparent judgements. While the MARCBot does exhibit strong use of biological principles and robust technical performance, it does not integrate biological materials or support bilateral exchange and was therefore classified as bioinspired. Conversely, a neuro-robotic system that bidirectionally couples a mobile robot and a rat neuron culture on a multi-electrode array has been developed to demonstrate decision-making and learning-driven adaptivity, thereby satisfying all minimal requirements for biointelligent systems. In general, the classifications correspond to the primary

sources' self-descriptions which supports the model's internal logic. Despite the successful classification of the use cases, a number of areas require refinement with the help of further investigation of a variety of use cases. Firstly, the anchors per indicator and per stage require greater precision and operationalization in order to capture incremental progress. Secondly, uncertainty handling must be made explicit, perhaps with the help of fuzzy set theory (Akkasoglu, 2014), in order to improve robustness and reproducibility. Thirdly, an optional overall index for communication and monitoring must be developed that does not replace the profile view; this is in order to avoid compensatory effects like a "strong" rating in technology masking a "weak" one in intelligence. It is recommended that complementary coupling with established maturity frameworks like the technology readiness model be considered, as these address significant aspects (but not the biointelligence-specific triad of biological integration, bidirectional coupling, and intelligent behavior).

The conclusions that can be deduced from this analysis are threefold. Firstly, the concept of biointelligence necessitates the simultaneous realization of biological integration, regulated bidirectional interfaces, and observable intelligent behavior. In practice, the transition from biointegrated to biointelligent systems typically encounters failure at the interface or due to the lack of genuine adaptivity beyond threshold logic. Secondly, the contemporary landscape is dominated by bioinspired/biointegrated clusters, while authentic biointelligence is predominantly observed in laboratory demonstrators utilizing neural cultures. Thirdly, it is evident that there are clear leverage points. One of these is the advancements made in interface technologies regarding standardization, reduction in noise, and real-time closed loops; another is the strengthening of on-board intelligence, whether algorithmically or via explicit biological learning mechanisms.

From a methodological perspective, the model's strength lies in its multidimensional profile, which exposes both strengths and weaknesses without collapsing them into a single score. This facilitates benchmarking, prioritization of development actions, and roadmap design. To illustrate this point, consider a system that, while technologically sophisticated, may still fall short of the biointelligence threshold due to deficiencies in its interfaces or a lack of adaptivity. This scenario highlights the necessity for clear guidance on investment priorities. The four dimensions containing three indicators each are communicable and sufficiently discriminative at this early field stage. The framework remains modular and extensible for domain-specific additions. The model has the capacity to function as a self-assessment checklist, a framework for inter-organizational benchmarking, and a tool for strategic roadmaps. It is recommended that teams prioritize investments in areas of weakness, for example standardizing interfaces and control when sensing is mature, or developing adaptive algorithms or embedding biological learning when interfaces exist but intelligent behavior is absent.

In conclusion, the shown case studies provide a first demonstration of the model's utility and discriminative power. The model was able to distinguish between bioinspired, biointegrated, and biointelligent systems, reveals the critical paths for maturation, and offers concrete guidance for research, development, and strategy. A proper validation still needs to be done in future work, by analysing a variety of use cases across different fields of application. Furthermore, the reliability across independent reviewers and the sensitivity of the gate logic needs to be evaluated. The incorporation of higher granularity, uncertainty treatment, and domain-specific enrichments has the potential to enhance the model's functionality as a compass for developing biointelligent systems.

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