Management Revue

*Manag. Rev.* **2025**; 36(1): 39414
https://doi.org/10.31083/MRev39414

*Article*

# Exploring Generative AI-User Interactions through Self-Programming and Structural Coupling in Luhmann's Systems Theory

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Academic Editor: Simon Jebsen
Submitted: 7 October 2024 Revised: 21 January 2025 Accepted: 27 January 2025 Published: 1 April 2025

**Abstract**

This paper explores the concepts of self-programming and structural coupling between generative AI (Gen AI) and users, grounded in Luhmann's systems theory. By tracing the evolution of generative AI from early models to advanced architectures such as foundation models, the paper shows how these systems approximate contextual understanding and respond dynamically to user inputs. The concept of self-programming is extended to users, who refine their engagement strategies through repeated interactions, developing prompt scripts and styles that enhance the relevance and utility of AI outputs. The study highlights the recursive feedback loop between AI and users, wherein both entities mutually influence and adapt each other's operations. It further investigates the structural coupling of these interactions, focusing on the paradoxical interplay between dependence and independence, as well as the shared textual medium that evolves through user inputs and AI responses. Additionally, the paper identifies excluded thirds (e.g., authenticity and engineer) and persistent paradoxes in AI-mediated interactions, particularly the tensions between specificity and generality, as well as novelty and familiarity. The research calls for further exploration of these paradoxes to promote more meaningful and adaptive forms of AI-user interactions.

**Keywords:** Luhmann; Gen AI; self-programming; structural coupling; style
**JEL:** B52, M15, D83

## 1. Introduction

In his book, *What Computers Still Can't Do*, Dreyfus (1992) critiques the excessive confidence displayed by AI researchers, whom he believes are overly optimistic about AI's capability to achieve human-like intelligence. He argues that much of the AI community operates under misguided assumptions that human intelligence can be fully modelled and simulated through algorithms and symbolic processing—the manipulation of symbols based on predefined rules. Dreyfus highlights AI's struggle to function effectively in unstructured environments or handle the *contextual understanding* that humans inherently possess. He further stresses that human intelligence is *embodied*—that is, deeply connected to physical interaction with the world through their bodies.

In the Chapter of Epistemological Assumption, Dreyfus points out the epistemological differences in contextual understanding between Wittgenstein's philosophy and the perspective held by computer theorists (Dreyfus, 1992, p. 204). While both Wittgenstein and computer theorists agree there can be a simple point where rules are applied directly without the need for additional rules to guide their application, they diverge significantly in their views on how this stopping point should be understood or described. For Wittgenstein, there is no fixed or absolute stopping point at which rules always apply in the same way. Instead, this stopping point is fluid and context-dependent, depending on the practical demands of the situation (infinite regress of rules). By contrast, in the eyes of Dreyfus, computer theorists typically aim for a fixed and absolute stopping point, where rules are applied in a precise and unchanging manner. For them, the infinite regress of rules comes to a halt at a level where the interpretation is self-evident and independent of situational demands.

The recent advancement of generative AI (Gen AI) poses a significant challenge to Dreyfus' assertion that AI is fundamentally rule-based and thereby lacked the ability to adapt flexibly to contexts in the way humans naturally do. Through structural coupling with users' experiences and demands, Gen AI seemingly approximates contextual understanding and embodied intelligence, producing responses that give the illusion of situational awareness. It remains questionable whether the development of Gen AI has bridged Dreyfus's epistemological gap. However, it is evident that the structural coupling of Gen AI and users would lead to new forms of interactions (e.g., prompt engineering). In this paper, the author relies on Luhmann's concepts of *self-programming*, *paradox*, and *structural coupling* to explore emerging patterns of users' interactions with Gen AI.

The paper is structured to explore the evolution and interaction dynamics of Gen AI and users. Section 2 traces the development of Gen AI, highlighting its progression from early models to advanced architectures like Transformers, and how these advancements shape AI-user interactions.

Section 3 applies Luhmann's concept of self-programming to AI and users, explaining how they adapt and influence each other's behaviours. Section 4 examines structural coupling, focusing on self-generated text as a medium for interaction. Section 5 explores how users and AI co-evolve stylistically, resulting in new forms of creative and interactive outputs.

## 2. Evolution of Generative AI: Emerging Form of Interaction

### *2.1 Artificial Intelligence Redefined: Bridging Symbolism, Interactionism, and Data-Centric Approaches*

The historical evolution of artificial intelligence (AI) reveals a dramatic shift from symbolic, rule-based systems to data-driven approaches that underpin today's generative AI (Gen AI) technologies. Early AI research often relied on explicitly encoded representations of the world. These systems used formal logic and structured rules to process information and solve problems, operating under the assumption that intelligence required an exact and comprehensive model of the environment. While this approach achieved notable successes in well-defined domains, it struggled with real-world complexity, ambiguity, and unpredictability.

Rodney Brooks' "Intelligence Without Representation" challenges traditional AI paradigms by rejecting the need for explicit representations and central control, arguing that intelligence emerges from direct interactions between perception and action in dynamic environments (Brooks, 1991). He introduces the subsumption architecture, a hierarchical, behaviour-driven system in which independent, parallel layers interact directly with the environment, advocating for an incremental development approach that starts with simple systems and gradually builds complexity, ensuring adaptability and robustness without reliance on abstract representations. Brooks critiques the reliance on abstraction and simplified environments in traditional AI, highlighting the limitations (e.g., scalability) of these methods in real-world applications.

This perspective proposes that intelligence is context-specific (situated) and emerges as complex behaviours develop from simple interactions. Brooks' work reflects a shift from cognitivism (thinking as central to intelligence) to interactionism (interaction as central to intelligence). His principles influenced both the development of modern behaviour-based robotics and ongoing debates in AI design. However, his critical comments on the failures of traditional AI research, including connectionism (e.g., neural networks), have prompted intriguing counter-arguments from critics, who suggest that Brooks dismisses the usefulness of symbolic representations too hastily (Jordanous, 2020). They argue that symbolic representations have significant strengths in structured problem-solving and are better suited for addressing higher-order cognitive processes, such as abstract reasoning and planning. In fact, Gen AI models, such as ChatGPT, align more closely with the concept of "intelligence with representation", as they rely on implicit, sub-symbolic representations within a neural network. These models operate based on pre-trained knowledge encoded in distributed patterns of weights and embeddings, enabling them to process and generate responses by leveraging statistical relationships learned from data.

The emergence of data-centric AI, exemplified by Gen AI models, underscores the critical role of harnessing extensive datasets and computational intelligence to address the limitations of earlier AI approaches. This transition toward data-driven AI has been propelled by two major developments in big data and Cyber–Physical Systems (CPS) (Iqbal et al, 2020). The first trend is the increasing adoption of scalable, distributed architectures, coupled with advances in cloud and edge computing, which facilitate the real-time collection, processing, and storage of vast datasets generated by CPS components such as Internet-of-Things (IoT) devices and user interactions. Another significant trend involves the integration of advanced computational intelligence techniques into CPS, including soft computing (e.g., fuzzy logic) and deep learning, which empower systems to handle high-dimensional, noisy, and unstructured data effectively. These advancements collectively establish robust frameworks that enhance the accuracy and efficiency of CPS across various domains, fostering innovation in data-centric applications.

### *2.2 Generative AI's Journey: From Early Models to Transformer*

Generative AI refers to systems that can produce new, original content by learning from existing data. Unlike traditional AI, which focuses primarily on tasks such as classification or analysis (for example, recognising objects in images), Gen AI creates something new that has not been explicitly observed before. Although it may seem like a recent advancement, Gen AI has been evolving for many years. A notable early example is Google Translate, which transforms text between languages by synthesising information from large language corpora. The key difference between early versions of Gen AI and more recent advancements lies in their ability to generalise. As Domingos (2012) highlights, the primary aim of any machine learning system is to *generalise* beyond the examples it was trained on. This means that recent Gen AI systems are much better at creating new and diverse outputs that are not limited to the specific examples within the training dataset.

The researchers (e.g., Sengar et al, 2024) attribute the breakthrough of more advanced Gen AI systems to the development of *Generative Adversarial Networks* (GANs) and *Transformer* models. In the introduction of their pioneering paper, Goodfellow et al (2014) made a key distinction between discriminative and generative models. While discriminative models that map input data directly to an output label (e.g., classifying whether an image contains a cat or a dog), generative models approximate the underlying data distribution by learning its joint probability distribution, allowing them to generate new data points. By combining two techniques—the generator, which produces new samples (e.g., generated images) to mimic real data, and the discriminator, which differentiates between real and generated data—into an adversarial training strategy, they proposed the GANs model, effectively addressing the challenges faced by earlier generative models. This shows that, from a technological perspective, Gen AI evolves by distinguishing itself from discriminative (or classifying) AI models.

The *Transformer* architecture, introduced by Vaswani et al (2017), marked a major advancement in Gen AI. Originally applied to natural language processing (NLP), this groundbreaking design is particularly effective in managing sequential data and are utilised in large language models (LLMs) such as GPT (Generative Pre-trained Transformer). In their seminal paper, "Attention Is All You Need", Vaswani et al (2017) introduced attention mechanisms (self-attention and multi-head), which enables AI models to focus on the most relevant parts of the input, capture long-range dependencies (or relationships), and process sequences in parallel (or simultaneously). For instance, self-attention allows each word in a sequence to focus on (or pay attention to) other words in the same sequence to calculate their relationships (e.g., subjects, objects and verbs) by giving them different weights of importance. Multi-head attention runs multiple self-attention mechanisms in parallel, capturing more diverse relationships between words (e.g., one focusing on the subject-verb relationship, another on the verb-object relationship, and another on syntactic structures like grammar). Thanks to its attention mechanisms and parallelisation, the Transformer requires significantly less time to train compared to traditional models.

### *2.3 Generative AI as Foundation Models*

Some researchers (e.g., Bommasani et al, 2021) refer to recent advanced Gen AI models as foundation models due to their distinctive societal influence and the paradigm shift they represent, making them more accessible to people beyond the machine learning community. Foundation models are characterised by their ability to generalise across different tasks through pretraining on vast amounts of unstructured datasets, often using self-supervised learning. Bommasani et al (2021) assert that foundation models have led to an unprecedented level of homogenisation, standardising around a dominant design (such as the Transformer architecture) and consolidating methods across different fields through multimodal models. Furthermore, foundation models have demonstrated surprising emergent capabilities, which arise from their scale, as seen in GPT-3's ability to perform tasks it wasn't specifically trained for, such as in-context learning.

Foundation models can also be seen as general-purpose technologies (GPTs), similar to the steam engine, electric motor, and semiconductors, as they are characterised by their pervasiveness, potential for continuous improvement, and ability to generate complementary innovations across diverse sectors (Bresnahan and Trajtenberg, 1995). Due to the generality of purpose and innovative complementarities, two distinct externalities may arise: a 'vertical' one between GPTs and each application sector, and a 'horizontal' one across different application sectors. For example, in terms of vertical externalities, GPT-3 (Generative Pre-trained Transformer 3) can be used to power virtual customer service agents, automating responses to customer inquiries, or to analyse legal contracts and assist in drafting legal reports. Regarding horizontal externalities, GPT-3 can enhance productivity in the software sector by helping developers generate code more efficiently. This, in turn, may lead to faster development of financial technology (fintech) solutions in the banking and insurance sectors.

Foundation models develop a wide range of general capabilities, some of which exhibit emergent (unexpected) properties. These capabilities span areas such as language, vision, robotics, reasoning, interaction, and philosophy (Bommasani et al, 2021). For instance, foundation models have the ability to operate in multiple languages, enabling them to handle cross-lingual tasks such as translation with minimal or no specific training data—a capability known as few-shot or zero-shot learning. In few-shot learning, the model is given a few examples of the task (e.g., sea otter → loutre de mer, peppermint → menthe poivrée) along with a task description (e.g., "Translate English to French"). In zero-shot learning, the model generates predictions based solely on the task description, without being provided with any examples (Brown et al, 2020). This learning capability is particularly powerful in situations where labelled data is limited or difficult to obtain. Additionally, a key strength of these models is their ability to combine multiple modalities, such as text, audio, and images. This capability allows them to generalise to new tasks that span across text, audio, and visual domains, such as automated video captioning, speech-to-image generation, text-to-video synthesis, or multimodal content analysis.

The generative and multimodal capabilities of foundation models have introduced *new forms of interaction* with AI-infused applications. For instance, users without expertise could input simple descriptions or text, and the Gen AI model can produce expert-level creative content, such as writing, music, or image creation. As a result, the distinction between developers and end-users may become less clear (Bommasani et al, 2021). In some cases, end-users may be able to co-create or even directly build their own AI applications by engaging with models through natural language interfaces. From the author's perspective, this emerging interaction between users and Gen AI has not yet fully addressed the paradoxical nature of interdependence and independence. Drawing on Luhmann's concepts, the author seeks to explain this duality, highlighting how increasingly contingent interactions between users and Gen

AI foster the self-programming of independent operations for both the AI and the user.

## 3. Self-Programming of Generative AI and User

*3.1 Luhmann's Concepts of System, Self-Programming and Code*

Luhmann introduces the idea that *systems* can be understood as *forms (or differences)*, where the primary characteristic of a form is its ability to distinguish between two sides: the system and the environment. "Systems can be called a form under the condition that the concept of form must always apply to the difference between system and environment" (Luhmann and Gilgen, 2013, p. 51). In this context, a system is a difference between itself and environment. Also, a system needs "one single type of operation in order to reproduce the difference between system and environment if the system is to continue to exist" (Luhmann and Gilgen, 2013, p. 54). "If an operation of a certain type has started and is capable of connectivity – that is, if further operations of the same type ensue from it – a system develops. […] The system creates itself as a chain of operations" (Luhmann and Gilgen, 2013, p. 52).

This idea underscores the importance of *conceptual abstraction*, which allows us to compare similar and different features (or functions) within a specific theoretical framework. This functional approach aims to understand how differences impact the processing of information within a system, thereby giving it a defined form. This is crucial for solving problems within that system. "Functional analysis uses relations to comprehend what is present as contingent and what is different as comparable. It relates to what is given, whether that be states or events, to perspectives on problems and seeks comprehensively to enable a problem to be solved in one way or another. […] It serves as a connecting thread to questions about other possibilities" (Luhmann and Bednarz Jr, 1995, p. 53).

In Luhmann's framework, *self-programming* refers to structuring (or conditioning) its own operations in a way to regulate its future operations. A self-programmed system sets its own internal rules (conditions) for how to *correctly* process information and make selections. Self-programming "does not mean that the individual work is an autopoietic, self-generating system. But one can say that the work constitutes the conditions of possibility for its own decisions […]. One must recognise how the rules that govern the work's own formal decisions are derived from these decisions." (Luhmann and Knodt, 2000b, p. 204). For example, the legal system demonstrates self-programming through the mechanism of developing and refining legal precedents. Courts often refer to precedents (past decisions) to guide present judgments.

*Memory* recalls or forgets the historical reference that is crucial for self-programming to occur, enabling *recursive feedback loops* to function. It ensures continuity within the self-programming process by providing a context for each operation, serving as the foundation for maintaining coherence over time. The memory is "a sort of consistency test for which it is typically not necessary to recall when something specific was or was not learned. […] There is a connection between, on the one hand, the theory of memory and, on the other, a pragmatic orientation towards the future. […] One might perhaps say that memory is nothing but a continuous consistency test of different information, always in light of certain expectations" (Luhmann and Gilgen, 2013, pp. 71–72). This perspective aligns with von Foerster's view (2003) that memory is not a static storage but a dynamic process involving self-referential evaluation and recursive adaptation. It is shaped by the ongoing interplay between recognition—classifying and identifying experiences by connecting them to past encounters—and recall—transforming previous experiences into organised representations (Von Foerster, 2003).

Self-programming requires a code (guiding distinction) to determine how a system will respond to various inputs or stimuli. Without codes, the system would lack a structured means of making selections. *Code* is a "binary schematism that knows only two values and that excludes third values […]" (Luhmann and Knodt, 2000b, p. 186). The key characteristics of a code include: (1) "the ability to translate the viewpoint of the function into a guiding difference"; (2) "openness to supplements (programmes) that offer (and modify) criteria to determine which of the two code values is to be considered in any given case"; (3) "being cast into the form of a preferential code, that is, into an asymmetrical form that requires a distinction between a positive and a negative value" (Luhmann and Knodt, 2000b, p. 186). For instance, in the legal system, the binary code is structured as legal/illegal, enabling the system to distinguish between actions that conform to the law and those that do not.

*3.2 Generative AI and User: Systems as Differences*

Luhmann defines technology as "evolutionary advances in terms of proving their worth under conditions of increasing complexity" (Luhmann and Barrett, 2012, p. 312). Through the concept of evolutionary achievement, he rejects the idea that society itself has become technical or that social interactions are now dominated by technology. For instance, in *The Technological Society*, Ellul (1964) argues that technique—the totality of methods rationally arrived at and having absolute efficiency—has become an autonomous force that dominates every aspect of human life. This "technological society" is characterised by the omnipresence of technique, which redefines human values and relationships, leading to a dehumanised society. Similarly, by introducing the concept of "Technopoly", Postman (1992) contends that society has moved beyond being merely influenced by technology to a state in which technology is deified, and all aspects of life are subordinated to its requirements and demands.

In Luhmann's view, the concept of technology has always been understood in relation to what it is not—its counter-concepts, such as nature and humanity (Luhmann and Barrett, 2012, p. 314). This framing reflects the role of the observer, whose viewpoint and interests shape how technology is defined and interpreted. This underscores the evolving nature of the concept of technology, prompting us to rethink its meaning in a complex society where traditional oppositions, such as technology versus humanity, are steadily losing relevance.

Contemporary Luhmannian scholars, unlike Luhmann himself, are not hesitant in conceptualising technology as a system. For instance, Reichel (2011) proposes viewing technology as a function system within society, where it communicates using binary codes (work/fail) and operates through the medium of operativeness. Within this system, subsystems like R&D teams and standardisation bodies emerge to support technological communication and decision-making. Reichel further introduces an alternative perspective, conceptualising technology as an autopoietic system—self-referential and distinct from society or individuals. Autopoiesis, or self-making, means that technology sustains and evolves itself through internal logic and operations, making it purely 'technological' rather than 'social'. Whereas the "internal logic" of an autopoietic system resonates with Vincenti's (1995) engineer-oriented perspective on "technical logic" shaping technology within real-world constraints, Reichel's conceptualisation diverges by focusing on technology as a self-producing system, distinct from social or individual contexts.

According to my understanding of Luhmann's theory, a system is defined by its boundary to distinguish itself from its environment and reproduce this difference through its operations. Building on this concept, both users and Gen AI can be conceptualised as systems with their own boundaries, operations, and mechanisms for maintaining their distinctiveness from their environments. Users, as cognitive or social systems, operate through processes such as perception, decision-making, and communication. Gen AI, as a technological system, operates through algorithms, prompting interfaces, data processing, and generative outputs. The interactions between these systems are facilitated by structural coupling, which paradoxically enhances both the dependence and independence of these two differentiated forms.

The distinction between *autopoietic* and *allopoietic* systems is useful for understanding the evolving nature of these systems. Autopoietic systems are self-referential, producing and reproducing their own operations to sustain their existence. For example, users, as social systems, process information based on social constructs, maintaining autonomy in decision-making and interaction. Similarly, Gen AI systems exhibit autopoietic tendencies in their ability to generate responses or outputs based on internal algorithms and self-referential operations within the constraints set by their programming. This self-referential process highlights both systems' abilities to sustain and reproduce their distinctiveness while interacting with their environments.

However, the relationship between users and Gen AI can also display characteristics of allopoiesis, particularly when one system becomes overly reliant on the operations of the other. For instance, users may enter an allopoietic dynamic if they become entirely dependent on AI-generated outputs for decision-making, thereby foregoing their cognitive autonomy. Similarly, a Gen AI system risks functioning as an allopoietic system if it is reengineered to produce outputs dictated by external factors (e.g., political power). For instance, Neves (2001) uses the concept of allopoiesis to describe how legal systems in peripheral countries frequently fail to maintain autonomy due to their over-integration with external environments (e.g., political or economic systems). He critiques the empirical applicability of Luhmann's theory of autopoietic (self-producing) legal systems in many global contexts, particularly in peripheral states. In these contexts, the binary code "legal/illegal", which is foundational to law's autopoietic reproduction, is often overridden by external codes like "power/no-power" or "wealth/no-wealth", further compromising the autonomy and integrity of the legal system. Consequently, the legal system becomes an instrument for external systems. This perspective suggests that the system may function as a pluralistic network of operations with inherent indeterminacy, leaving room for evolution and potential transformation.

### *3.3 Self-Programming of Generative AI*

Generative AI (Gen AI), such as ChatGPT, engage in *self-referential processes* where they use past selections to inform future operations. During training, Gen AI is exposed to vast amounts of data. The system learns by making predictions (e.g., predicting the next word in a sentence) and comparing those predictions to the actual data. Memory manifests as *the form of learned patterns*, allowing the system to build upon past data to guide future operations. This memory is encoded in the network's weights and biases, which are fine-tuned through prior training data.

The system's output is evaluated by the code of *coherent/incoherent (or correct/incorrect)*. Then, a loss function calculates how far off the system's prediction was from the expected outcome. This loss is then used to adjust the system's internal weights through *backpropagation*. In this context, the system "learns" by continuously updating its weights over many iterations to reduce the loss, effectively "self-programming" to improve its performance and coherence.

After the self-supervised training phase, some systems undergo an additional phase of fine-tuning using reinforcement learning, often referred to as Reinforcement Learning from Human Feedback (RLHF). In this stage, human evaluators rank the system's responses according to contextual coherence. Based on these rankings, the system's parameters are updated using an algorithm to increase the likelihood of producing contextually coherent responses in the future. This can be also considered a form of "self-programming" since the system is algorithmically optimising its operation based on feedback, albeit with human guidance.

Once trained, Gen AI relies on in-context learning to produce contextually coherent responses. The Transformer's self-attention mechanism represents a paradigm shift by allowing the system to dynamically focus on relevant parts of the input context without the need for internal memory states that carry information across time steps, as required in traditional mechanisms like RNNs (Recurrent Neural Networks) (Vaswani et al, 2017). The Transformer mechanism does not store explicit memories of past interactions. Instead, it leverages self-attention to dynamically reference relevant parts of the input text within the given context. This approach can be thought of as an implicit form of memory, where all relevant information is processed simultaneously to maintain coherence, rather than relying on sequential memory states.

### *3.4 Self-Programming of User*

Generative AI's coherent/incoherent code is structurally dependent on the user's evaluation of relevance. In other words, the *coherent/incoherent* code of the AI interacts dynamically with the *relevant/irrelevant* distinction that the user applies. This process is further refined by the user's *useful/useless* distinction, based on whether the AI's response meets their specific needs. For example, if the user inquiries about the weather in Dubrovnik, but the AI provides a *generally* relevant (on-topic) response about the weather in Glasgow, the user might deem the answer useless, as it fails to address their *specific* intention.

Through continuous engagements with Gen AI, the user observes the emerging patterns in their interaction with the AI, thereby programming themselves to produce useful outputs (e.g., applicable information) by preemptively filtering irrelevant aspects of their prompts. This is a self-referential process as the user draws on previous interactions to fine-tune future engagements.

Based on the recursive feedback loop, users gradually develop internal structures (e.g., prompt scripts and styles) to enhance the clarity and precision of their queries, thereby increasing the utility of the outputs. Over time, prompts are structured step-by-step, with each step building upon the previous one, generating scripts. Luhmann illustrates the broader principle of the sequential structuring as follows: "In the medium of sound, words are created by constricting the medium into condensable (reiterable) forms that can be employed in the medium of language to create utterances (for the purpose of communication)" (Luhmann and Knodt, 2000b, p. 106). *Script* represents a specific case of stereotyped temporal sequences. "The observation of causal relationships typically follows a script because it cuts out other, equally realistic possibilities for causal attribution" (Luhmann and Cross, 2000a, pp. 109–110).

Through repeated application across different contexts, specific scripts evolve into a style. *Style* emerges from habitual formal decisions, shaped by the demands of the work itself. Style is "a matter of applying prefabricated formal decisions that owe their emergence to a work-dependent sense of what is fitting. [...] A style presents itself as a synopsis stabilised by habit, while he is aware that this is the side-effect of a spontaneous, merely code-oriented practice that has abandoned itself to the self-programming of the work" (Luhmann and Knodt, 2000b, p. 209). That is to say, the process of stylisation emerges from the work's ingrained patterns of repetition, evolving without direct control. It becomes self-sustaining, shaping itself over time.

## 4. Structural Coupling in AI-Mediated Textual Interactions

### *4.1 Luhmann's Concept of Structural Coupling*

From Luhmann's perspective, structures are defined as expectations that guide the continuity and connection of operations, as conveyed in the statement, "structures are expectations in relation to the connectivity of operations" (Luhmann and Gilgen, 2013, p. 72). Structures and operations mutually dependent: structures serve as the framework or patterns that guide operations, while operations generate and reshape structures through their event-like nature. "All operations [...] establish the historical state of the system, the point of departure for the system in ensuing operations. [...] They form structures as selection schemata that make recognition and repetition possible, hence condensing identities, which they confirm in ever-new situations and thus generalise" (Luhmann and Barrett, 2012, p. 50).

Luhmann introduces the concept of operational closure, which highlights the self-referential feature of systems, distinguishing their internal operations from environmental influences. Operational closure means "the recursive enablement of a system's own operations through the outcomes of its [prior] operations" (Luhmann and Barrett, 2012, p. 51). Simply put, a system's memory matters. This recursive dynamic creates autonomy within the system, even as it interacts with its environment. This closure concept is directly linked to Luhmann's interpretation of Maturana's *autopoiesis*: "a system can generate its own operations only by means of the network of its own operations" (Luhmann and Gilgen, 2013, pp. 76–77).

Luhmann asserts that structural coupling is orthogonal to autopoiesis, emphasising their compatibility rather than a causal relationship between the two concepts. This suggests structural couplings do not dictate a system's operation but instead provide irritations (or stimuli) to it. These irritations, in turn, activate the system's *resonance* through the structural coupling (Luhmann and Gilgen, 2013, p. 88). The concept of structural *coupling* emphasises selectivity: "Something is included and something else is excluded.

[…] Structural coupling has, on the one hand, an exclusion effect – in this domain the system is indifferent – and, on the other hand, it brings about the canalisation of causalities that can be used by the system" (Luhmann and Gilgen, 2013, p. 85). As a metaphor, the canalisation of causalities implies that the system "channels" (or narrows down) the range of environmental influences while excluding others not directly pertinent to the system's operations. By canalising causal influences, the system does not become overwhelmed by the totality of the environment.

Luhmann illustrates structural coupling with examples such as the brain's connection to the external environment through the eyes and ears (Luhmann and Gilgen, 2013, p. 86). This coupling operates within a limited bandwidth of sensibilities, filtering what can be seen and heard to prevent the system from being overwhelmed by external stimuli. Another example is language and writing, where a small set of standardised pitches, sounds, and letters allows for the creation of highly complex combinations (Luhmann and Gilgen, 2013, p. 87). These combinatory potentials, in turn, influence both conscious and communicative processes.

Whereas language represents a relatively fixed structure, schemata (e.g., frames and scripts) provide more flexible frameworks for interpreting meaning, enabling systems to manage complexity. Examples of schemata include standardised ways of categorising something (e.g., a beverage as wine) and attribution schemata or scripts, which connect causes to effects and guide appropriate responses (Luhmann and Barrett, 2012, p. 61). Schemata like "true/false", "good/bad", or "beneficial/detrimental" are versatile and reusable across various contexts, offering interpretative frameworks that simplify cognitive processes and support decision-making.

### *4.2 Self-Generated Text as Structural Coupling and Multimodal Medium*

Structural coupling is characterised by orthogonality: total dependence on one another combined with operational autonomy (independence) (Luhmann and Gilgen, 2013, p. 200). Structural coupling is "simply the specific form in which the system presupposes specific states or changes in its environment and relies on them" (Luhmann, 1991, p. 1432). For instance, the economic and legal systems are distinct and function independently, each maintaining its own operational autonomy. However, they require specific dependence mechanisms (structural coupling), primarily through the concepts of property and contract, to interact effectively (Luhmann, 1991, p. 1435).

The relationship between generative AI (Gen AI) and the user is characterised by structural coupling: while Gen AI establishes the conditions for the user's engagement but does not dictate the meaning the user extracts from the output. Users maintain their autonomy to determine what is relevant or useful, relying on their interpretative frameworks and decision-making processes. Conversely, the user influences the outputs of Gen AI by crafting prompts and steering the interaction, while the AI independently generates responses guided by its own internal mechanisms.

Increased use of Gen AI, rooted in this reciprocal relationship, may amplify the paradoxical dynamic between dependence and independence, simultaneously reinforcing both the connection and the separation between them. While this dependence brings vulnerabilities and risks, it has unlocked unprecedented opportunities and a new level of independence, including personalised content generation tailored to individual needs and the democratisation of access to advanced tools and knowledge.

Drawing on Luhmann's hermeneutics, self-generated text produced through user prompts and AI responses can be interpreted as a medium that establishes structural coupling between users and Gen AI, serving as a common ground for the duality of self-programming. Through text, both the user and the AI generate and refine their interactions, creating a *shared space of possible forms* where each internal structure influence one another. "The imaginary space is construed from the inside out, as if breaking through the frame [of the text] or creating its own world behind the frame. The imagination is driven beyond the work [or text]. One must at once see and think away the frame in order to gain access to the work [or text]'s imaginary space. The guaranteed repeatability of observations might be of help in performing this operation" (Luhmann and Knodt, 2000b, p. 45).

Users and Gen AI collaboratively construct their own *reality* through interdependent operations, such as text generation. What stands out is that this reality is mediated by algorithms, which rely on sequential and iterative problem-solving processes. Consequently, reality is no longer perceived as a single, static entity but rather as the product of repeated and iterative procedures. In this sense, a *procedural understanding of reality* marks a shift from viewing it as fixed and unchanging to recognising it as dynamic, contingent, and shaped by ongoing processes and operations.

The effective use of the actual-potential structure (visible surface and invisible depth) demands specialised procedural knowledge and skills, such as prompting. Users must understand how to execute commands to interact with the AI and unlock its hidden capabilities. This process underpins the concept of "virtual reality", which depends on a presupposed ability (*virtus*) to distinguish virtuality from mere possibility and to actualise potential states (Luhmann and Barrett, 2012, p. 182).

Luhmann's concept of *medium* refers to "loosely coupled elements", which means "an open-ended multiplicity of possible connections that are still compatible with the unity of an element—such as the number of meaning sentences that can be built from a single semantically identical word" (Luhmann and Knodt, 2000b, p. 104). A medium is also understood as a "condition for transfers. In addition, there are close ties to the theory of memory, if memory is understood in terms of a delay in the reactualisation of meaning" (Luhmann and Knodt, 2000b, p. 104). In other words, it enables the movement of forms across different contexts and also introduces a temporal delay, allowing forms to be re-contextualised in a later interaction.

Self-generated text in the context of Gen AI operates as a flexible medium that is not limited to written or typed interactions. Instead, text can reenter other interfaces, such as voice commands and image generation. For instance, in ChatGPT, a user could use a spoken command ("Show me a picture of the forecast in Dubrovnik"), and the AI would process this input through the underlying textual medium. This is a "*reentry* of a distinction into what it has itself distinguished. The system/environment distinction occurs twice over: as difference produced through the system and as difference observed in the system" (Luhmann and Barrett, 2012, p. 19).

The emergence of a new medium paradoxically expands text-based operations into unforeseeable domains, facilitating seamless transitions between different modalities (e.g., audio-visual formats). This shift allows abstract, word-based concepts—such as double contingency—to be translated into concrete, intuitively graspable formats (e.g., an image illustrating mutual unpredictability). By bringing such conceptual complexities into visible and perceptual spaces, the new medium not only bridges the gap between abstract thought and sensory experience for a broader audience but also redefines the boundaries of how knowledge is communicated and understood. However, this development may accelerate the social decoupling of the medial substratum of communication and undermine the traditional unity of communication (information/utterance/understanding), along with concepts such as *authenticity* (cf. Luhmann and Barrett, 2012, pp. 185–186).

### *4.3 Excluded Thirds*

Structural coupling is fundamentally linked to selectivity. For such coupling to function, each system must selectively respond to inputs from the other based on its internal structures and needs. This selectivity inevitably introduces the issue of exclusion, as not all inputs or interactions are compatible or relevant. Such exclusion is not arbitrary but is dictated by the system's structural limitations and operational requirements. This implies that when dualistic self-programming occurs between users and Gen AI, certain elements are unavoidably excluded.

While the user's prompts are assumed to be *authentic* expressions of their intentions, Gen AI abstracts these prompts when producing text. This abstraction creates a distance between the user's authentic expression and the AI's output, similar to the gap between reality and its representation in language. This distance or exclusion effect can be framed as a form of latency observation, which displaces the unity of the distinction into unobservability (Luhmann and Knodt, 2000b, p. 84).

The concept of the excluded third refers to elements that exist both inside and outside the operational boundary of self-programming and cannot be fully integrated into the system's internal code-oriented structures. In structurally coupled interactions between users and Gen AI, authentic (unmediated) inputs, such as non-standardised dialects and context-specific subtleties, may be operatively excluded. For instance, when a user interacts with the AI using a non-standard dialect or a strong regional accent, the AI's processing may exclude some of the unique linguistic elements of the input because the system is primarily trained on standardised language patterns. These unique aspects of the dialect or accent could be processed as incoherent, thereby becoming the excluded third. Additionally, when users provide input that includes specific contextual details—such as local knowledge or events specific to a small community—the AI might exclude these elements if they are not recognisable within the system's pre-trained dataset. This introduces the paradox of specificity and generality into the AI-mediated interaction.

Moreover, the structural coupling between users and AI shifts attention to the immediate interaction, sidelining the mediating role of *engineers* and marginalising their contributions within the direct user-AI dynamic. In this context, engineers, as the excluded third, often receive less recognition for their work, as users tend to attribute the AI's outputs solely to the system itself rather than the human expertise behind it. When issues such as bias or misinformation arise in Gen AI outputs, the invisibility of engineers complicates accountability, as users may fail to understand or acknowledge the human decisions embedded in the AI's design and operation. The presence of engineers typically becomes apparent (surface) only when the Gen AI fails to function properly. Failures challenge the stability of complex systems, which are often treated as "black boxes", and compel users to re-engage with the underlying (depth) processes, thereby revealing the previously hidden contributions of otherwise invisible engineers (Latour, 1987).

### *4.4 Specific/General and Old/New as Sources of Paradox*

The tension between *specificity and generality* can be understood as a paradox within the framework of Luhmann's systems theory, especially when applied to the dualistic self-programming of users and Gen AI. In Luhmann's terminology, every operation generates forms that are included and, *paradoxically*, forms that are not excluded (Luhmann and Barrett, 2018, p. 101). Two seemingly contradictory elements are both required for a system to function, and yet they appear in tension. This paradox is particularly relevant when considering how users and Gen AI mutually self-program their interactions, as they are constantly balancing between specificity (the user's authentic, detailed, or context-specific inputs) and generality (the AI's generalised, standardised processing and responses).

The tension between old and new in the context of self-programmed interactions between the user and Gen AI introduces an additional layer of paradox. The paradox arises from how informational value is attributed to something novel or new, yet this value diminishes or even disappears once the new is reproduced, referenced, or processed again, transforming it into something familiar or "old". Luhmann's systems theory is grounded in the idea that systems operate by making distinctions—here, the distinction between old (familiar/reproduced) and new (novel/informational). The paradox is that while systems need new information to evolve, once that information is processed and becomes part of the system, it is no longer "new" and loses the very novelty that gave it value in the first place. For example, the user seeks novel outputs from ChatGPT, but once they receive a response that satisfies this novelty, it is no longer new. It becomes part of the user's knowledge, and its informational value diminishes as it transitions into the familiar. ChatGPT must then engage in a new interaction to reintroduce novelty, otherwise the user may disengage.

## 5. Stylistic Co-Evolution Between Generative AI and User

### *5.1 Genius/Taste in AI and User as a Creative Deviator*

The dualistic interaction between generative AI (Gen AI) and the user can be seen as a dynamic where the unexpected becomes paradoxically probable (*variation* and *selection*). The vast number of outputs generated by AI increases the chance that some will be innovative. These rare, exceptional cases contribute to the evolutionary process of innovation, supported by the statistical likelihood of their occurrence. "Genius" stands for the improbability of emergence (the source of unexpected variations), and "taste" for the likelihood that works prevail (the mechanism of selective preferences) (Luhmann and Knodt, 2000b, p. 224). The tension between genius and taste in this duality is comparable to the relationship between the AI's generative capacity (genius) and the user's preferences (taste). The AI generates vast amounts of content based on its programming (the "genius" aspect), while the user evaluates, curates, and refines the output (the "taste" aspect).

In the AI-user dynamic, the user plays the role of a creative deviator (or critic) who introduces stylistic deviations. By giving creative/critical prompts or changing preferences, users challenge the AI to step beyond its default programming and produce outputs that align with their unique creative goals, aiming to deviate from *stabilised* styles. For instance, a user might prompt the AI to generate a story that moves away from the typical beginning-to-end narrative, instead opting for a fragmented, non-chronological sequence, disrupting the typical flow of events (*breaking traditional narrative structures*). The output might be a mystery novel where the "detective" fails to solve the mystery, shifting the focus to character development rather than plot resolution (*subverting genre expectations*). By introducing *suspense*, the character's development may disrupt the connection between the past and future, allowing the narrative to follow a winding path filled with self-generated uncertainty. It is only near the narrative's end that the reasons behind the events become clear. Suspense functions as a form of narrative ornamentation, adding variety while maintaining coherence in the narrative (Luhmann and Knodt, 2000b, p. 221).

### *5.2 Deconstructing and Combining Forms as Stylistic Deviations*

Style as a programme operates like a set of standards or guidelines that a system follows to produce works that fit within the boundaries of a particular style. These standards encompass principles (e.g., form and composition), themes and techniques. "Choosing familiar styles as programmes in an easily recognisable manner amounts to making a rather cheap claim to belong to [a particular] system, and often the works end up not being very convincing" (Luhmann and Knodt, 2000b, p. 209). Creative departures from established standards, or stylistic deviations, propel the evolution of a system by suspending previous frame conditions. Instead, they dynamically challenge and restabilise their own boundaries. Dynamic stability and stylistic deviation serve as effective pathways for addressing the paradox of standards and innovation (Kim, 2024).

Stylistic deviation can involve deconstructing and combining forms. *Deconstructing a standardised style* involves breaking down the established scripts (preprogrammed patterns for structuring users' inputs to produce familiar outputs). This does not mean simply abandoning the script or style but rather analysing its components and identifying areas where novelty could be introduced if approached differently. For example, the problem-solution-success structure is a common script used in many forms of narrative, especially in business, marketing, and educational contexts. This script usually follows a straightforward path: first, a problem is identified; then, a solution is proposed or implemented; and finally, the success or outcome of applying that solution is described. From a deconstructive approach, instead of a singular problem and solution, the user can prompt for diverse interpretations of the problem and multiple competing solutions. These are just a few examples of deconstructive approaches, though the possibilities are far from exhaustive.

*Combining different forms* can be another way to challenge and restabilise the boundary of a standardised narrative structure. For instance, the user may prompt the AI to blend Luhmann's complex, analytical description with a more poetic, expressive form. In a Luhmannian analysis of social systems, one might deconstruct how organisations manage risk through binary distinctions, using precise theoretical terms. By incorporating a poetic style, the description could add a symbolic or emotional dimension. Consider the Luhmannian style: "*Organisations operate by reducing complexity through binary codes such as risk/security, which allow the system to make distinctions and control its environment.*" Poetry-infused layer: "*Like a sailor navigating through a storm, decisions made under the guise of security can never escape the shadows of* *risk—the sea is never truly calmed, only momentarily subdued*." In this way, the paradox of specificity and generality is managed: the Luhmann-style description provides the precision and specifics, while the poetic form introduces a broader symbolic or emotional layer that speaks to the human experience of coping with uncertainty, creating a richer or more general form of communication. For instance, the sea can serve as a symbol. "The symbol not only stands for what it excludes but also signifies the impossibility of signifying the excluded […]. In this sense, the symbol stands once again for the observation of an unobservable world" (Luhmann and Knodt, 2000b, p. 177).

### *5.3 Self-Generated Questions as a Tool to Navigate Complexity*

AI's self-generated questions can serve as a powerful mechanism for navigating the paradoxes that arise in interactions between users and Gen AI, such as the tension between old and new or specificity and generality. Firstly, by asking questions, the AI initiates a process of continuous exploration where each query opens up the potential for new, novel outputs. This addresses the tension between old and new by consistently refreshing the interaction with new dimensions. Additionally, AI's self-generated questions enable it to dynamically respond to the user's specific needs while remaining anchored in its general knowledge base. Consider a user who asks ChatGPT, "How can AI be used in education?" The AI might provide a general response. However, it could follow up with a self-generated question such as, "Are you interested in how AI can be used to personalise the learning of Niklas Luhmann's theory?" This question helps the AI balance specificity and generality, enabling the user to steer the conversation in a way that best meets their needs.

One of the main challenges in user-AI interaction is that novelty can quickly turn into familiarity. AI's self-generated questions help manage this by promoting recursive exploration—a process where the AI continually returns to earlier topics but reframes them in a new way. This helps keep the interaction fresh and prevents the old from fully taking over. Self-generated questions enable the AI to take a familiar topic and reframe it with a new focus or in a different context. This brings novelty even when the conversation seems to be revisiting old ground. In this way, the AI allows the user to use strategic prompts to shift the perspective, keeping the interaction relevant and avoiding repetition.

## 6. Conclusion

In Plato's *Phaedrus*, Thamus, an Egyptian king, hosts the god Theuth, the inventor of writing, who offers writing as a gift to enhance memory and wisdom (Postman, 1992). However, Thamus contends that writing will instead lead to forgetfulness, as people will depend on written records rather than their own memory, and it will create the illusion of wisdom without true understanding. This tale serves as a metaphor for how technological advancements bring both advantages and unintended consequences.

The evolution of generative AI marks a significant shift from rule-based algorithms towards systems capable of simulating contextual understanding, much like the introduction of writing in Plato's Phaedrus. While generative AI holds immense potential to enhance creativity, productivity, and problem-solving, it also carries the risk of fostering superficial understanding or overdependence on technology, potentially diminishing human cognitive skills and critical thinking.

As manifested in Finn's book title, *What Algorithms Want*, some argue that society evolves into an era where algorithms—defined as "procedural sets of steps to solve a problem"—function not merely as technical tools but also as cultural artefacts that appear to possess desires, shaping and being shaped by the environments in which they operate (Finn, 2017). Finn stresses the concept of 'algorithmic imagination', suggesting that algorithms have their own form of creative agency, influencing how people think, create, and imagine while fuelling the quest for self-knowledge.

While this pre-adaptive narrative often portrays the future of society in a dichotomous manner, presenting it as either a utopia or a dystopia, the author instead focuses on the evolving nature of systems, emphasising their inherent indeterminacy and the emergence of new forms of interaction. These interactions are characterised by self-programming and structural coupling, which encapsulates the paradoxical interplay between dependence and independence. The discussion also highlights that while generative AI has advanced significantly, it still operates within the paradoxes of specificity versus generality and old versus new. These paradoxes are navigated through user-stylised prompts and the AI's self-generated questions.

By applying Luhmann's systems theory to the novel context of generative AI-user interactions, this paper provides a unique lens to understand the recursive, co-evolutionary dynamics between users and AI. This perspective invites both theorists and practitioners to explore the evolving interdependence of systems, uncover new forms of interaction, and critically engage with paradoxes, such as the tension between specificity and generality, while reflecting on the role of the excluded third and formulating deeper, more critical questions.

As these AI systems become more integrated into everyday use, their impact on society and various industries will likely continue to expand. However, the question remains whether AI has truly bridged the epistemological gap highlighted by Dreyfus or if the apparent situational awareness is merely a sophisticated illusion. Further research into the co-evolution of generative AI and users is needed to explore how these technologies might develop to support richer, more authentic, and innovative forms of interaction while addressing the inherent paradoxes that govern their functionality.

## Availability of Data and Materials

Datasets used and/or analysed for this study are available from the corresponding author upon appropriate request.

## Author Contributions

The author confirms that I am solely responsible for the entirety of this work. The author conceptualised and designed the study, conducted the research, and prepared the manuscript, including drafting, revising, and finalising the content. The author has reviewed and approved the final version of the manuscript.


## Acknowledgment

I sincerely appreciate Professor Jin-chul Rho for his invaluable teaching on Luhmann's art system theory, which greatly contributed to the conceptual foundation of this study.

## Funding

This research received no external funding.


## Conflict of Interest

The author declares no conflict of interest.

## References


Bommasani R, Hudson DA, Adeli E, Altman R, Arora S, von Arx S, et al. On the Opportunities and Risks of Foundation Models. arXiv. 2021. (preprint) https://doi.org/10.48550/arXiv.2108.07258

Bresnahan TF, Trajtenberg M. General purpose technologies 'Engines of growth'? Journal of Econometrics. 1995; 65: 83–108. https://doi.org/10.1016/0304-4076(94)01598-T

Brooks RA. Intelligence without representation. Artificial Intelligence. 1991; 47: 139–159. https://doi.org/10.1016/0004-3702(91)90053-M

Brown T, Mann B, Ryder N, Subbiah M, Kaplan J, Dhariwal P, *et al*. Language models are few-shot learners. Advances in Neural Information Processing Systems. 2020; 33: 1877–1901.

Domingos P. A few useful things to know about machine learning. Communications of the ACM. 2012; 55: 78–87. https://doi.org/10.1145/2347736.2347755

Dreyfus H. What Computers Can't Do: A Critique of Artificial Reason. The MIT Press: Cambridge, MA. 1992.

Ellul J. The Technological Society. Vintage: New York. 1964.

Finn E. What Algorithms Want: Imagination in the Age of Computing. The MIT Press: Cambridge, MA. 2017.

Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, *et al*. Generative adversarial nets. Advances in Neural Information Processing Systems. 2014; 27.

Iqbal R, Doctor F, More B, Mahmud S, Yousuf U. Big Data analytics and Computational Intelligence for Cyber–Physical Systems: Recent trends and state of the art applications. Future Generation Computer Systems. 2020; 105: 766–778. https://doi.org/10.1016/j.future.2017.10.021

Jordanous A. Intelligence without representation: A historical perspective. Systems. 2020; 8: 31. https://doi.org/10.3390/systems8030031

Kim D. The paradox of standards and innovation: Reconceptualising standards and standardisation with the help of Niklas Luhmann. Systems Research and Behavioral Science. 2024. https://doi.org/10.1002/sres.3068

Latour B. Science in Action: How to Follow Scientists and Engineers through Society. Harvard University Press: Cambridge, MA. 1987.

Luhmann N, Barrett R. Theory of Society (Vol. 1). Stanford University Press: Stanford. 2012.

Luhmann N, Barrett R. Organization and Decision (D. Baecker, Ed.). Cambridge University Press: Cambridge, UK. 2018.

Luhmann N, Bednarz Jr. J. Social Systems. Stanford University Press: Stanford. 1995.

Luhmann N, Cross K. The Reality of the Mass Media. Stanford University Press: Stanford. 2000a.

Luhmann N, Gilgen P. Introduction to Systems Theory (D. Baecker, Ed.). Polity Press: Cambridge, UK. 2013.

Luhmann N, Knodt EM. Art as a Social System. Stanford University Press: Stanford. 2000b.

Luhmann N. Operational closure and structural coupling: the differentiation of the legal system. Cardozo Law Review. 1991; 13: 1419.

Neves M. From the autopoiesis to the allopoiesis of law. Journal of Law and Society. 2001; 28: 242–264. https://doi.org/10.1111/1467-6478.00188

Postman N. Technopoly: The Surrender of Culture to Technology. Vintage: New York. 1992.

Reichel A. Technology as system: towards an autopoietic theory of technology. International Journal of Innovation and Sustainable Development. 2011; 5: 105–118.

Sengar SS, Hasan AB, Kumar S, Carroll F. Generative artificial intelligence: a systematic review and applications. Multimedia Tools and Applications. 2024; https://doi.org/10.1007/s11042-024-20016-1

Vaswani A, Brain G, Shazeer N, Parmar N, Uszkoreit J, Jones L, et al. Attention is all you need. In 31st Conference on Neural Information Processing Systems (NIPS 2017). CA, USA. Long Beach. 2017.

Vincenti WG. The technical shaping of technology: Real-world constraints and technical logic in Edison's electrical lighting system. Social Studies of Science. 1995; 25: 553–574. https://doi.org/10.1177/030631295025003006

Von Foerster H. What is memory that it may have hindsight and foresight as well? In Von Foerster H (ed.) Understanding Understanding: Essays on Cybernetics and Cognition. Springer: New York. 2003. https://doi.org/10.1007/0-387-21722-3_3