The Individual Semiotic Process, Collective Patterns, and AI Applications

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Abstract

This essay redefines semiotics through a "sensory input" framework, leveraging artificial intelligence (AI) to analyze individual and collective reactions to signs, transforming semiotics into a practical, data-driven discipline. By reframing signs as quantifiable perceptual entities—spanning human senses, animal behaviors, and technological inputs—this approach enhances the sender-message-receiver model with systems, chaos, and complexity theory, enabling applications in marketing, healthcare, education, construction, environmental monitoring, urban planning, virtual environments, and microbial research. The semiotic process, the interaction between sensory inputs and reactions, drives semiotic ergonomics, optimizing intuitive designs for products, services, and machines to enhance user satisfaction and efficiency. AI's rapid analysis, visualized in Figures 1–3, reveals collective patterns, with Figure 3 showing how semiotic dimensions (encoding aim/intention, communication/anticipation, context creation), embedding the Price, Convenience, and Connection (PCC) framework, shape reactions ethically. Addressing ethical concerns like privacy and manipulation, market-driven transparency fosters win-win outcomes, outperforming bureaucratic regulations. Future research should explore AI's integration with complexity theory for cross-cultural and microbial advancements, positioning semiotics as an interdisciplinary field.

Keywords: Applied Semiotics, Sensory Input, AI-Driven Predictions, Semiotic Ergonomics, Semiotic Process, Semiotic Dimensions, PCC Framework, Complexity Theory, Systems Theory, Chaos Theory, Sender-Message-Receiver Model, Cross-Cultural Applications, Market-Driven Ethics

1. Introduction

Semiotics, the study of signs and their interpretation, traces its roots to ancient Greece, yet its practical impact has often been limited by an emphasis on theoretical abstraction (Chandler, 2015). This essay argues that artificial intelligence (AI) revolutionizes semiotics by leveraging its unprecedented capacity to analyze vast, dynamic datasets of individual and collective reactions in real time, enabling transformative applications across diverse domains, from marketing to microbial research. Central to this argument is a redefinition of signs as **sensory inputs**, a paradigm shift in semiotic scholarship that prioritizes practical applicability. Unlike Sebeok's broad "stimuli," which excels in non-human biosemiotics (e.g., bacterial quorum sensing or animal communication), "sensory input" emphasizes quantifiable perceptual responses, making it uniquely suited for human and animal semiotics on Earth (Sebeok, 2001; Deacon, 1997). In contrast to Eco's sign-function, which focuses on cultural codes, "sensory input" targets perception, enabling AI-driven analysis across human senses—sight (e.g., a vibrant billboard), sound (e.g., a catchy melody), touch (e.g., a soft fabric), taste (e.g., a savory dish), and smell (e.g., the scent of rain)—animal senses (e.g., bats' echolocation, dogs' pheromone detection), and technological inputs like Geiger counters for radiation or ultrasound imaging (Eco, 1976; Kayser, 2025a).

The **semiotic process**, defined as the interaction between sensory inputs and the reactions they elicit, optimizes not only traditional communication (e.g., advertisements) but also products, services, machines, and environments through **semiotic ergonomics**—an intuitive design approach that enhances **how, how much, how long, how often, and with how much satisfaction** humans interact with them (Norman, 2013). For example, in marketing, sensory inputs like verbal tactics (e.g., "limited time offer"), soothing background music, or aromatized air function as signs but can introduce polysemy, where multiple interpretations complicate perception (Lindstrom, 2005; Barthes, 1977). A store's bright lighting may enhance focus for one shopper (positive reaction) but induce discomfort for another (negative reaction), shaped by individual cognitive biases or cultural contexts, such as preferences for bright vs. subdued lighting in different regions (Kahneman, 2011; Hall, 1976; Lotman, 1990). The "sensory input" definition clarifies the critical link between signs and perception, as signs must be processed—consciously (e.g., responding to a jingle's call to action) or subconsciously (e.g., mood shaped by ambient scents)—to elicit reactions. Beyond communication, semiotic ergonomics transforms product design, as seen in Apple's intuitive iPhone interfaces or Tesla's streamlined car controls, which contrast with complex premium car systems (e.g., BMW 7 Series, Mercedes S-Class) that require training due to poor intuitive design (Norman, 2013).

This approach extends to diverse fields, demonstrating semiotics' interdisciplinary potential. In education, gamified sensory inputs, such as interactive learning apps with vibrant visuals, motivate efficient studying, countering smartphone overuse by channeling engagement into productive behaviors (Selwyn, 2022; Csikszentmihalyi, 1990). In construction, intuitive controls for heavy machinery like excavators or cranes enhance operator alertness, reducing accidents and fatigue while fostering flow during long shifts (Norman, 2013; Csikszentmihalyi, 1990). In healthcare, calming sensory inputs, such as soft lighting or gentle sounds, reduce patient stress, improving recovery outcomes (Topol, 2019). In environmental monitoring, AI analyzes wildlife reactions to sensory inputs (e.g., noise pollution) to inform conservation strategies (Kull, 2000; Karban, 2015). In urban planning, city aesthetics, such as green spaces or harmonious architecture, improve livability by eliciting positive resident reactions, varying by cultural context (e.g., preference for minimalist vs. ornate designs) (Batty, 2018; Hall, 1976). In virtual environments, immersive graphics drive engagement in metaverse platforms, with AI optimizing sensory inputs for user satisfaction (Kayser, 2025a). In microbial semiotics, bacterial responses to chemical signals (e.g., quorum sensing) aid medical research into antibiotic resistance (Wheeler, 2006; Hoffmeyer, 2008). In retail, intuitive store layouts guide customer navigation, enhancing purchasing experiences (Batty, 2018).

Manipulating sensory inputs raises ethical concerns, such as privacy invasion or overuse (e.g., smartphone addiction). The **Price, Convenience, and Connection (PCC) framework**, embedded within the semiotic dimensions (e.g., encoding profit-driven intentions, establishing persuasive communication, creating hard to resist contexts), addresses these through market-driven transparency, fostering win-win scenarios that enhance profitability, user satisfaction, and societal well-being (Kayser, 2025b; Zuboff, 2019). Unlike bureaucratic regulations, which often stifle innovation, create inefficiencies and facilitate corruption, market solutions incentivize transparency and align offerings with human needs, reducing unethical practices like deceptive advertising or exploitative pricing through competitive pressures and consumer feedback (Pine & Gilmore, 1999; Kotler & Keller, 2016). However, regulated market approaches increase the risk of profit-driven biases, requiring careful design to ensure ethical outcomes, such as transparent data use in AI-driven personalization (Zuboff, 2019).

Table 1 compares traditional sign theories with “sensory input,” highlighting its novelty and practical applicability:

Theory/ Definition	Key Concept	Fortes	Applicability Areas	Limitations Compared to “Sensory Input”	Novelty
Peirce’s Triad (1931)	Representamen, interpretant, object.	Comprehensive, flexible for icons, indices, symbols.	Philosophy, linguistics, cultural studies.	Abstract, less quantifiable for AI (Kayser, 2025a).	Foundational but theoretical.
Saussure’s Dyad (1916)	Signifier and signified.	Foundational for structuralism.	Linguistics, literary analysis.	Limited to symbolic signs (Eco, 1976).	Language-centric, less practical.
Eco’s Sign-Function (1976)	Cultural codes.	Inclusive of social contexts, polysemy.	Cultural studies, media analysis.	Less perception-focused (Nöth, 1990).	Broad but not quantifiable.
Sebeok’s Stimuli (2001)	Stimuli in biosemiotics.	Universal, covers non-human semiotics.	Zoosemiotics, biosemiotics.	Broad term confuses in human contexts (Kayser, 2025a).	Universal but less precise.
Sensory Input (Kayser, 2025a)	Perceived sensory inputs.	Perception-centric, quantifiable, AI-integrated; enables semiotic ergonomics.	Marketing, healthcare, education, construction, environmental monitoring, microbial research, urban planning, virtual environments.	Less applicable to non-perceptual biosemiotics.	Novel for applied, AI-driven semiotics.

Building on foundational theories (Peirce, 1931; Saussure, 1916; Eco, 1976; Sebeok, 2001; Shannon & Weaver, 1949), the “sensory input” definition reframes signs as quantifiable perceptual entities, complementing existing scholarship. The semiotic process, driven by **systems, chaos, and complexity theory** (Lorenz, 1963; Gleick, 1987; Strogatz, 2018; Luhmann, 1995; Bateson, 1972), quantifies reactions to reveal collective patterns, with AI enabling rapid analysis for precise predictions, as visualized in Figures 1, 2, and 3 (Goodfellow et al., 2016). The PCC framework, embedded within semiotic dimensions as a particular successful strategy for creating signs, guides ethical, market-driven applications, fostering intuitive designs and societal benefits through transparency (Kayser, 2025b; Pine & Gilmore, 1999).

2. The Individual Semiotic Process

A sign is any sensory input perceived through human senses—sight (e.g., a glowing traffic light), sound (e.g., a piercing siren), touch (e.g., a cold metal surface), taste (e.g., bitter medicine), smell (e.g., fresh-brewed coffee)—animal senses (e.g., dogs' pheromone detection, bats' echolocation), or technological aids like ultrasound imaging or infrared sensors (Kayser, 2025a). Unlike symbolic sign theories prioritizing linguistic or cultural symbols (Eco, 1976; Saussure, 1916), this approach posits that signs exist inherently, whether consciously noticed or not, and can be—and already are—utilized by technological entities like AI for optimization. For instance, a faint background hum in a room may subconsciously influence mood, functioning as a sign without explicit awareness, shaped by cognitive biases or cultural conditioning (Cobley & Semetsky, 2017; Kahneman, 2011; Lotman, 1990). This universality expands semiotics to encompass human communication, animal behaviors, and technological systems, addressing limitations in frameworks like Peirce's triad, which focuses on interpretive relationships rather than quantifiable perception (Peirce, 1931; Sebeok, 2001; Deacon, 1997).

The **semiotic process**, the interaction between a sensory input and the reaction to it, centers on the message/receiver dynamic, distinct yet related (Figure 3) to **semiotic dimensions** (sender/message functions, e.g., encoding aim/intention, communication/anticipation, context creation), which incorporate methodologies like PCC for reaching receivers (Kayser, 2025b; Jakobson, 1960). For example, a supermarket's promotional signage (sender/message) or a politician's candidacy announcement involves semiotic dimensions, while the receiver's reaction (e.g., purchase intent) defines the semiotic process. Figure 3 illustrates this interplay, showing how semiotic dimensions enhance the sender-message-receiver model for practical applications through chaotic interactions (Jakobson, 1960; Strogatz, 2018). Reactions are highly individualized, as unique as fingerprints or DNA, shaped by instinct, emotion, rationality, biological factors (e.g., genetics, microbiomes), and cultural influences (e.g., regional norms, social values) (Nöth, 1990; Hoffmeyer, 2008; Hall, 1976). For instance, a thunderstorm's sound may prompt fear (negative reaction) in one individual or curiosity (positive reaction) in another, influenced by personal histories or cultural associations (e.g., storms symbolizing renewal in some cultures, danger in others) (Lotman, 1990).

Quantified as A-values on a Likert scale (-5 for strongly negative to +5 for strongly positive), individual reactions exhibit wide ranges (e.g., 2.5–3.2 for liking a song), driven by chaotic variability described in complexity theory (Lorenz, 1963; Strogatz, 2018; Bateson, 1972). Aggregating reactions across groups narrows these ranges, enabling predictability—a task AI performs rapidly, processing millions of data points in seconds using neural networks or clustering algorithms (Goodfellow et al., 2016; Russell & Norvig, 2021). For example, analyzing a song's sensory inputs (e.g., melody, rhythm) across 4 groups, measuring factors A (melody), B (rhythm), C (mood enhancement), and D (sing-along appeal), yields a summed average of A–D factors ranging from -3 to +5, with 60% of values between 2 and 5, justifying percentages for small-sample trend analysis. Percentages highlight early patterns, such as positive reception trends. After evaluating 389 groups, 90% of data falls within 3.9–4.2, reducing outlier impact (e.g., extreme negative reactions). After analyzing 859 groups, the range narrows to ~3.9–4.1, converging to an average of 4, demonstrating AI's efficiency in processing large datasets for near-certain predictions in seconds (Goodfellow et al., 2016). Starting with 4 groups for initial trends, scaling to 389 for broader patterns, and reaching 859 for high confidence, AI showcases rapid range narrowing.

For vast datasets, ranges become so narrowed that human users can focus on averages, as shown in

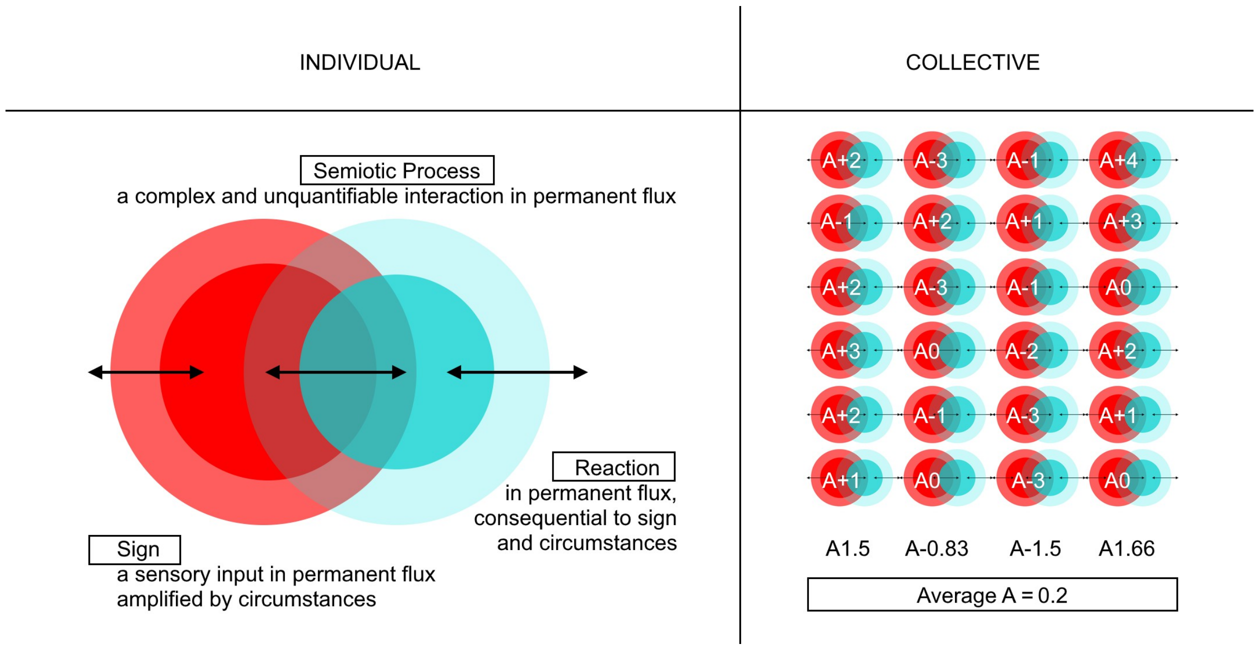
Figure 1: 24 A-values sum to 5, divided by 24, yielding an average of 0.2. In Figure 2, Group 1's average of A–G factors is 0.6 (e.g., A=0.2, B=0.4, etc., summed to ~4.2, rounded, averaged over 7 factors). The grand total ($583 \div 729 \approx 0.799$, rounded to 0.8) reflects 729 groups' averages, with all numbers rounded for simplification. This demonstrates how increased data narrows ranges, enabling entrepreneurial decisions, such as selecting a song for an advertisement or movie soundtrack to maximize audience appeal. AI personalizes experiences by substituting songs for outliers (e.g., negative reactions) with alternatives, enhancing satisfaction (Russell & Norvig, 2021). This multi-factor approach, rooted in complexity theory's emergent order, supports **semiotic ergonomics**, optimizing interactions with products, services, and machines (Strogatz, 2018; Norman, 2013). For example, song analysis optimizes music streaming interfaces (e.g., intuitive playlist navigation), enhancing user engagement and flow (Csikszentmihalyi, 1990). AI analyzes factors across cultures (e.g., rhythm preferences vary by region), optimizing global music platforms (Hall, 1976). Such predictions align songs with listener preferences, reducing manipulative marketing through transparency, fostering ethical outcomes (Zuboff, 2019). This approach applies to countless industries and areas, such as education (e.g., gamified visuals), healthcare (e.g., calming sounds), and retail (e.g., intuitive store layouts) (Selwyn, 2022; Topol, 2019; Batty, 2018).

Semiotic ergonomics enhances interactions across industries. In education, gamified sensory inputs in learning apps motivate efficient studying, countering smartphone overuse (Selwyn, 2022). In construction, intuitive excavator controls enhance operator alertness, reducing accidents (Norman, 2013). In premium cars, Tesla's intuitive interfaces outperform complex systems like BMW's 7 Series, which require training (Kayser, 2025a). In augmented reality, seamless interfaces optimize user interaction, fostering immersion (Kayser, 2025a). AI calculates efficient semiotic designs, enhancing satisfaction and motivating positive behaviors, such as diligent studying or safe machine operation (Russell & Norvig, 2021). These reactions are shaped by semiotic dimensions, incorporating PCC methodologies (e.g., cost-driven intentions, accessible platforms, socially resonant contexts), advocating market-based solutions to ethical concerns like manipulation or privacy invasion (Kayser, 2025b; Pine & Gilmore, 1999). This study counters critiques of profitability as greed-driven by showing that AI-driven semiotic ergonomics reduces entrepreneurial risk. For example, intuitive excavator controls lower production costs by minimizing design flaws, creating better products and ethical outcomes (Zuboff, 2019; Kotler & Keller, 2016).

3. Collective Patterns in Semiotics

Individual reactions, exhibiting wide ranges (-5 to +5), interconnect to form collective patterns, termed a **reactional total**, visualized in Figure 1 (Kayser, 2025a). Driven by systems, chaos, and complexity theory, these patterns emerge from dynamic interactions where small variations—akin to the butterfly effect—yield unpredictable trends (Lorenz, 1963; Gleick, 1987; Strogatz, 2018; Luhmann, 1995; Bateson, 1972). For example, reactions to a viral advertisement (e.g., sharing or ignoring) aggregate into trends like increased brand engagement, reflecting self-organizing systems (Luhmann, 1995). These patterns are shaped by cognitive biases, cultural contexts, and social dynamics, making them chaotic yet emergent (Kahneman, 2011; Hall, 1976; Lotman, 1990). Figure 3 visualizes how semiotic dimensions (encoding aim/intention, communication/anticipation, context creation) shape these patterns, extending the sender-message-receiver model with complexity theory for practical applications like optimizing marketing campaigns or urban designs (Jakobson, 1960; Kayser, 2025a).

Figure 1: Individual vs. Collective Semiotic Process



Description: On the left, a simplified model illustrates the semiotic process, where a red circle (Sign: A sensory input in constant flux) interacts with a blue circle (Reaction: In constant flux), visualized as overlapping circles in a Venn diagram style. Both circles are surrounded by transparent extensions, like concentric halos, representing situational influences (e.g., culture, environment, cognitive biases). Three black double-sided arrows indicate flux in all directions: one over the red sign circle and its extension, one over the blue reaction circle and its extension, and one on top of the overlap of the circles and their extensions (semiotic process flux). On the right, a table arranges 24 of these processes, each assigned an A-value (-5 to +5 Likert scale). The total sum of all 24 is 5, while the individual A-values for this sample range from -3 to +4, reflecting chaotic interactions (Lorenz, 1963). For example, 24 people reacting to a song yield an average A=0.2 (sum divided by samples, so 5 divided by 24), indicating slightly positive reception.

The semiotic dimensions, embedding PCC methodologies (e.g., cost-driven intentions, accessible platforms, socially resonant contexts), explain collective patterns by shaping reactions. For instance, a low-cost product on a user-friendly platform endorsed by a trusted community generates positive reactions, driving trends like sales spikes or social media engagement (Kayser, 2025b; Pine & Gilmore, 1999; Bennett & Segerberg, 2012). AI's rapid analysis narrows ranges for large groups, enabling precise predictions across applications, from marketing to construction safety, rooted in emergent dynamics (Luhmann, 1995; Strogatz, 2018).

4. Challenges in Traditional Semiotic Research

Traditional semiotic research faces a scientific dilemma: isolating phenomena distorts the holistic interplay of sensory inputs, encompassing all signs and their dynamic reactions (Saussure, 1916; Shannon & Weaver, 1949). Reductionist approaches fragment this interplay, limiting validity and applicability (Cobley & Semetsky, 2017). For example, Peirce's triad (representamen, interpretant, object) offers insight into interpretive processes but prioritizes abstraction over practical applications, struggling to quantify wide individual reaction ranges or narrower collective patterns (Peirce, 1931; Kayser, 2025a). Subfields like semiology or economic semiotics focus on generalized systems—language, symbols, or market signals—often overlooking chaotic variability shaped by biology, psychology, or culture (Barthes, 1977; Danesi, 2018; Kahneman, 2011; Hall, 1976).

The expansive scope of semiotics, covering human communication, animal behaviors, technological systems, and microbial signaling, complicates systematic study (Sebeok, 2001; Hoffmeyer, 2008; Wheeler, 2006). Traditional methods, reliant on small-scale qualitative analyses, cannot handle vast, fluctuating datasets required to model the semiotic process across millions of reactions, where variability gives way to emergent order (Nöth, 1990; Strogatz, 2018). The semiotic dimensions, incorporating PCC methodologies, highlight these limitations, as traditional approaches cannot quantify how for example cost, accessibility, or social resonance influence reactions (Kayser, 2025b; Pine & Gilmore, 1999). This study offers a model embracing complexity, utilizing AI to enable reliable forecasting, transcending traditional limitations (Luhmann, 1995; Goodfellow et al., 2016).

5. AI Applications in Semiotics

AI transforms semiotics by analyzing millions of semiotic processes in real time, delivering actionable insights (Kayser, 2025a). Machine learning models (e.g., neural networks, decision trees) leverage complexity theory's emergent order for applications across consumer behavior, ecological monitoring, and more (Strogatz, 2018; Goodfellow et al., 2016; Russell & Norvig, 2021).

Table 2 illustrates sensory input diversity:

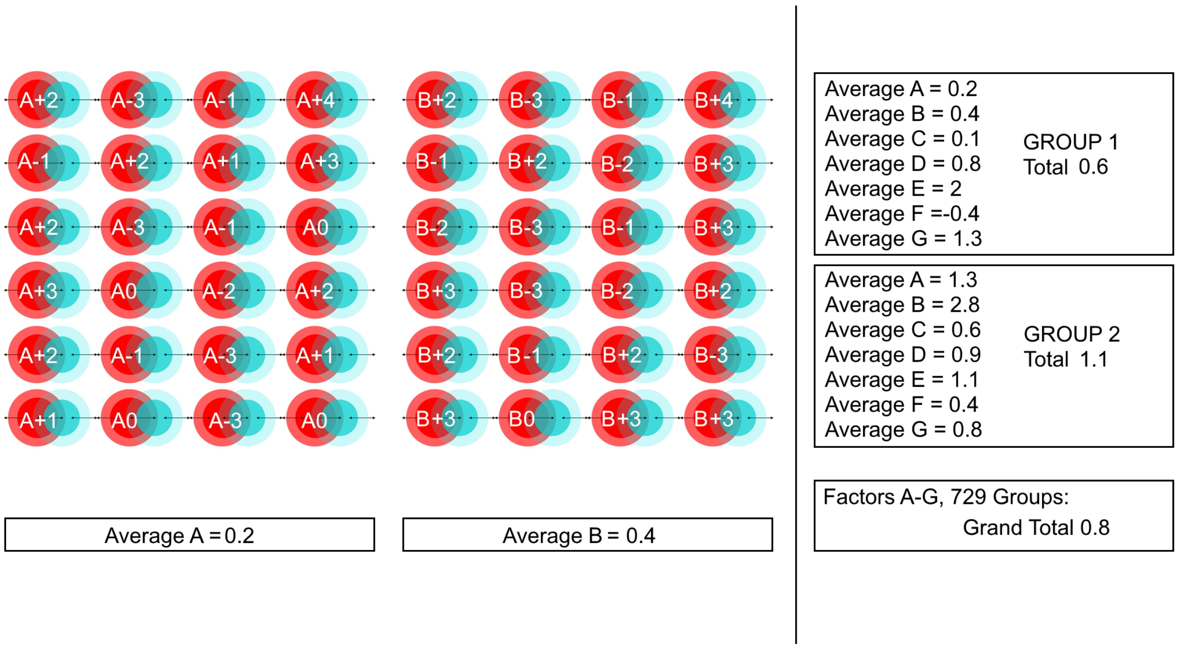
Entity/System	Sensory Input Examples	How They Work	Users	Applications
Humans	Words, sounds, written codes, body language, visuals, scents.	Perceived via senses; elicit conscious/subconscious reactions.	Individuals, AI systems.	Marketing, education, healthcare, construction, retail (Lindstrom, 2005; Norman, 2013).

Mammals	Sounds (e.g., barking), pheromones, visual cues.	Sensory organs trigger behavioral responses.	Dogs, whales, primates.	Animal training, conservation (Sebeok, 2001; Kull, 2000).
Fish	Chemicals, water vibrations, light patterns.	Lateral lines, chemoreceptors guide navigation, mating.	Salmon, tuna.	Aquaculture, environmental monitoring (Hoffmeyer, 2008).
Birds	Songs, visual displays, wind patterns.	Auditory/visual systems influence mating, defense.	Sparrows, parrots.	Ornithology, conservation (Sebeok, 2001; Kull, 2000).
Bees	Pheromones, waggle dance, ultraviolet light.	Antennae, eyes guide foraging, hive coordination.	Honeybees.	Pollination studies, AI-driven hive management (Hoffmeyer, 2008).
Ants	Pheromones, tactile signals, chemicals.	Antennae coordinate colony tasks.	Ant colonies.	Swarm intelligence, robotics (Strogatz, 2018).
Plants	Light, chemicals, mechanical touch (e.g., thigmotropism).	Photoreceptors, chemical sensors guide growth, defense.	Trees, vines.	Agriculture, ecological monitoring (Karban, 2015).
Bacteria	Chemical signals (e.g., quorum sensing).	Receptors trigger collective behaviors (e.g., biofilm formation).	Bacterial colonies.	Microbiology, medical research (Hoffmeyer, 2008; Wheeler, 2006).
Quantum Particles	Speculative quantum states.	Hypothetical; limited to quantum information theory.	Theoretical systems.	Emerging quantum semiotics (Brier, 2008).

- **Marketing**: AI predicts sales trends from sensory input reactions, optimizing campaigns cross-culturally by analyzing regional variations (e.g., packaging colors) (Hall, 1976; Russell & Norvig, 2021).
- **Healthcare**: AI optimizes treatment plans by analyzing reactions to sensory inputs (e.g., calming lighting), reducing stress (Topol, 2019).
- **Education**: Gamified sensory inputs enhance learning efficiency, countering smartphone overuse (Selwyn, 2022; Csikszentmihalyi, 1990).
- **Construction**: Intuitive controls for excavators reduce accidents, optimizing operator flow (Norman, 2013).

- **Environmental Monitoring**: AI tracks wildlife reactions to noise pollution, informing conservation (Kull, 2000; Karban, 2015).
- **Urban Planning**: AI assesses reactions to city aesthetics, optimizing livability (Batty, 2018).
- **Virtual Environments**: AI predicts engagement in the metaverse, enhancing user experiences (Kayser, 2025a).
- **Microbial Semiotics**: AI analyzes bacterial responses, aiding antibiotic research (Wheeler, 2006).
- **Retail**: AI optimizes store layouts for intuitive navigation, enhancing customer satisfaction (Batty, 2018).

Figure 2: Averages, Multiple Averages, Groups

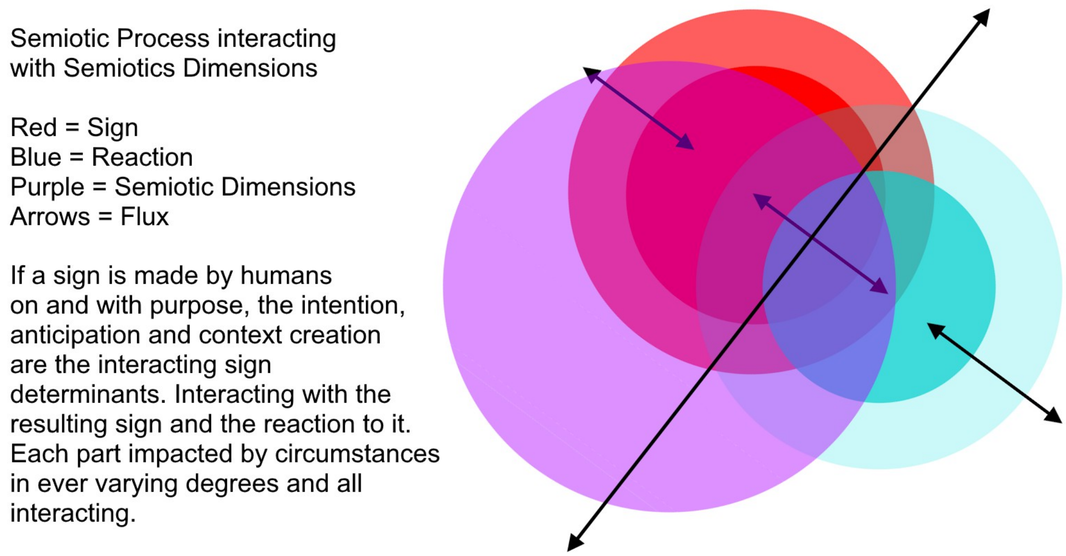


Description: On the left, the 24 semiotic processes from Figure 1 are repeated, alongside a similar arrangement with B-values. The average of all A-values is 0.2 (5 divided by 24), and of all B-values is 0.4. To the right, a table lists A–G factor averages for Group 1 (e.g., housewives, 40–50, average 0.6, sum ~4.2, rounded, divided by 7) and Group 2 (e.g., employed men, 35–45, average 1.1). Indicating how AI can use this system to evaluate large data amounts to pinpoint outcomes, enabling AI to make predictions with increasing accuracy. While small data would require utilizing percentages (see chapter 2, p. 4) to yield half-way usable results, the example given in Figure 3 is 729 groups, a sample so big that it would take humans a lot of effort to calculate the results but enables AI within seconds to not only evaluate complex decision processes with stunning precision, leading to vastly improved corporate decision making. AI can further avoid catering the evaluated subject to those who disliked it (giving scores of -5 and -4), choosing a suitable substitution instead.

Figure 2 illustrates the use of large data amounts, to result in a grand total average of 0.8 (583 ÷ 729 ≈ 0.799, rounded), which AI would achieve in seconds.
For example, evaluating ice cream involves A (taste), B (fruitiness), C (texture), D (color), E (packaging size), F (packaging color), G (pricing), adapting the song analysis from Section 2. AI analyzes factors across cultures (e.g., packaging color preferences), optimizing global R&D (Hall,

1976). This method applies to many industries, from online universities, hospitals, to retail, potentially enhancing both profitability and quality via semiotic ergonomics, thereby reducing the financial risk and its consequential resorting to unethical practices. AI applied semiotic measures allow for ethical business practices through transparency (Kayser, 2025a; Norman, 2013; Zuboff, 2019; Selwyn, 2022; Topol, 2019).

Figure 3: Semiotic Process and Semiotic Dimensions Interacting



Description: The red (sign) and blue (reaction) circles with their transparent extensions and flux-arrows from Figure 1's Semiotic Process are now extensively overlapped by a transparent purple ellipse, larger than the circles, enveloping over 70% of their overlap, symbolizing the three Semiotic Dimensions (encoding aim/intention, establishing communication/anticipation, creating and improving context) impacting both the sign and reaction significantly. The purple ellipse is in flux, indicated by a double-sided black arrow over the ellipse, representing non-directional flux in all directions. All arrows indicate flux in all directions, with angles irrelevant, reflecting chaotic interactions (Lorenz, 1963; Strogatz, 2018). The interactions illustrate highly complex and unpredictable actions and reactions between components, including personal associations (e.g., cognitive biases, regional cultural norms, social influences), noises (e.g., environmental sounds), technical glitches (e.g., system errors), and many more (Kahneman, 2011; Hall, 1976). This model enhances the traditional sender-message-receiver model for practical application, as AI's rapid optimization of sign creation (human or AI-generated) vastly increases the speed of the semiotic process and dimensions, enabling applications like marketing (e.g., resonant ad messaging), healthcare (e.g., calming hospital contexts), and virtual environments (e.g., immersive feedback) (Jakobson, 1960; Bateson, 1972; Kayser, 2025a). AI's analysis ensures transparency in encoding aim/intention, reducing manipulative practices for ethical outcomes (Zuboff, 2019; Goodfellow et al., 2016).

Semiotic ergonomics, enabled by AI, optimizes interactions, countering downsides like smartphone overuse by motivating positive behaviors (e.g., efficient studying, safe machinery operation). The semiotic dimensions, incorporating PCC methodologies, enhance predictive accuracy, aligning products with consumer needs and reducing unethical practices through transparency, unlike bureaucratic regulations (Kayser, 2025b; Zuboff, 2019; Kotler & Keller, 2016; Pine & Gilmore, 1999).

6. Conclusion

The semiotic process, driven by individualized reactions to sensory inputs, forms collective patterns through systems, chaos, and complexity theory (Lorenz, 1963; Gleick, 1987; Strogatz, 2018; Luhmann, 1995; Bateson, 1972). Wide individual reaction ranges narrow with larger datasets, enabling AI's precise predictions in real time, transforming semiotics into a practical, data-driven discipline (Kayser, 2025a). The "sensory input" definition unifies human, animal, and technological semiotics, complementing traditional theories (Peirce, 1931; Saussure, 1916; Eco, 1976; Sebeok, 2001; Deacon, 1997; Shannon & Weaver, 1949). **Semiotic ergonomics** optimizes products, services, and machines, fostering flow and satisfaction (Norman, 2013; Csikszentmihalyi, 1990). The semiotic dimensions, embedding PCC methodologies, guide market-driven solutions, reducing unethical practices through transparency (Kayser, 2025b; Zuboff, 2019; Pine & Gilmore, 1999). Future research should deepen AI's integration with complexity theory, exploring real-time reaction shifts, cross-cultural variations, and microbial semiotics for advancements in work, life, and consumption (Hall, 1976; Hoffmeyer, 2008; Wheeler, 2006; Strogatz, 2018).

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