Re-Centring the Human Constant: Modelling Attitude in the AI-Augmented Era

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Abstract

Prevailing narratives often position Artificial Intelligence (AI) as the defining reality of the digital age, with humanity reduced to a variable to be optimized. This paper inverts that assumption. We propose a conceptual and mathematical model of human–AI collaboration based on the complex number formulation $z = a + bi$, where the real component a represents the immutable foundation of human attitude i.e. consciousness, intent, and ethical direction and the imaginary component bi represents artificial intelligence—the powerful, supplementary force of computation and automation. The model shows that AI amplifies but does not replace the human constant: the magnitude of the system reflects amplified performance, while the argument (angle) reflects the system's ethical alignment. A dynamic extension highlights the "AI alignment problem" as the challenge of ensuring the rate of growth of human wisdom (da/dt) keeps pace with the accelerating growth of AI capabilities (db/dt). Applications include system design optimization, ethical auditing, and regulatory frameworks. We conclude that the future of AI will be defined less by machine power than by the quality of human attitude that anchors and directs it. The ethical task of the age is to cultivate a robust and virtuous a to ensure that the imaginary force of AI is harnessed for human flourishing.

Keywords: Human-Centred AI, Attitude, Complex Systems, AI Alignment, Ethics, Human-AI Collaboration

1. Introduction: Re-centring the Human

Artificial Intelligence (AI) has moved from speculative fiction to global infrastructure. Its influence now spans medical diagnostics, judicial risk assessments, financial trading, transportation, and military systems. In parallel, public discourse has often shifted toward a techno-centric narrative, presenting AI as the autonomous driver of history. In this framing, human input is secondary, an inefficiency to be optimized away (Bostrom, 2014; Tegmark, 2017).

This narrative is neither philosophically nor practically sufficient. While AI systems demonstrate extraordinary computational power, they remain tethered to the human contexts that design, deploy, and interpret them. Indeed, scholars of technology ethics have long emphasized that technological artifacts are never value-neutral but embody human intentions, assumptions, and limitations (Floridi, 2019; Moor, 2006).

We therefore propose a corrective: to re-centre humanity as the *real constant* in the AI-augmented age. Our thesis is simple yet profound: the human factor is an encompassing attitude, intent, values, and ethical reasoning that remains the foundation upon which AI must operate. To formalize this insight, we introduce a conceptual model using the language of complex numbers. This model demonstrates both the synergistic potential and the ethical risks of human–AI interaction.

The novelty of our contribution lies in bridging philosophy and mathematics. By mapping human and AI components onto orthogonal axes of the complex plane, we develop a formalism that allows for both intuitive interpretation and quantitative reasoning. In doing so, we hope to enrich ongoing debates about AI ethics, safety, and alignment (Amodei et al., 2016; Gabriel, 2020; Winfield, 2019).

2. Conceptual Framework

2.1 The Human Constant : Attitude (*a*)

We begin with the real component of our model. Let $a \in \mathbb{R}$ denote the human attitude: the bedrock of consciousness, intention, ethical orientation, and contextual understanding. This variable represents not only cognitive faculties but also the moral and affective dimensions that ground human decision-making.

Philosophical traditions underscore the primacy of such human constants. From Aristotle's emphasis on *phronesis* (practical wisdom) to Kant's insistence on intention as the core of morality, the "attitude" dimension shapes both action and evaluation. In the technological domain, Moor (2006) argues that machine ethics is impossible without clarifying the human ethical frameworks that anchor it.

In our model, a system with $z = a + 0i$ represents humanity unaided: capable of remarkable creativity and moral reasoning, but bounded by biological limits such as memory, processing speed, and cognitive bias. The historical arc of pre-digital civilization exemplifies such systems, where human potential was vast but constrained by material and informational limitations.

2.2 The AI Variable (*bi*)

The imaginary component, *bi*, represents artificial intelligence: a constructed, orthogonal force that expands capacity without replicating consciousness. Here, "imaginary" follows its mathematical meaning i.e. perpendicular to the real line, rather than suggesting unreality. AI operates in domains inaccessible to unaided human cognition, such as processing petabytes of data, optimizing multi-variable systems, and generating synthetic outputs (Russell & Norvig, 2021). Deep learning models now achieve superhuman performance in image recognition and medical diagnostics. Natural language processing systems such as GPT models generate text with fluency once thought impossible for machines. Yet these systems, powerful though they are, lack intrinsic purpose. A system with $z = 0 + bi$ is pure computational power without direction: an engine without a driver, potentially vast in reach but purposeless or dangerous if misapplied.

2.3 The Human–AI Complex ($z = a + b\,i$)

The synergy arises in the combination:

z=a+bi

This expression defines a collaborative vector, with the human attitude *a* anchoring the real axis and AI capacity *b* projecting onto the imaginary axis. The resulting vector embodies the augmented human AI system.

This framing highlights two critical insights. First, AI is not a substitute for human input but an amplifier of it. Second, the properties of the system, its magnitude and direction are determined jointly, not by AI alone. To understand these properties, we turn to the mathematics of complex numbers.

A conceptual framework diagram showing inputs "Human Attitude (a)" and "AI Power (b)" feeding into the model $z = a + b\,i$. Outputs include performance ($|z|$) and alignment (θ). Arrows point to applications: system design, auditing, and governance.

Figure 4: Conceptual Framework of Human–AI Collaboration

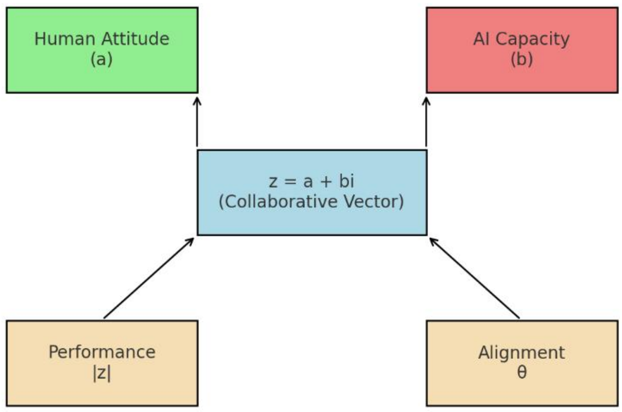

Figure 1

3. Mathematical Derivation

The value of representing human–AI collaboration as a complex number is that the formal properties of the system can be directly interpreted. The modulus (magnitude) reflects performance, while the argument (angle) reflects ethical alignment. Moreover, the temporal extension of the model captures the evolving challenge of AI alignment.

3.1 Magnitude: System Performance

The modulus of the collaborative vector is given by:

$$|z|=\sqrt{a^2 + b^2}$$

This measure represents the overall performance of the human–AI system. Importantly, the magnitude is always greater than or equal to either component alone. If a and b are both positive, the collaboration produces outputs that surpass the capacities of humans or AI in isolation.

Suppose a human decision-maker has an "attitude" value of $a = 3$, representing strong ethical reasoning and contextual awareness. The AI system has a computational strength $b = 4$. The collaborative vector is $z = 3 + 4i$, whose magnitude is $|z| = 5$.

This example illustrates the Pythagorean character of collaboration: the total system output is not additive (3 + 4 = 7) but geometric, forming a right-angled triangle on the complex plane. In this way, the model embodies the intuition that human–AI partnerships are not merely sums of parts but synergistic wholes (Floridi, 2019).

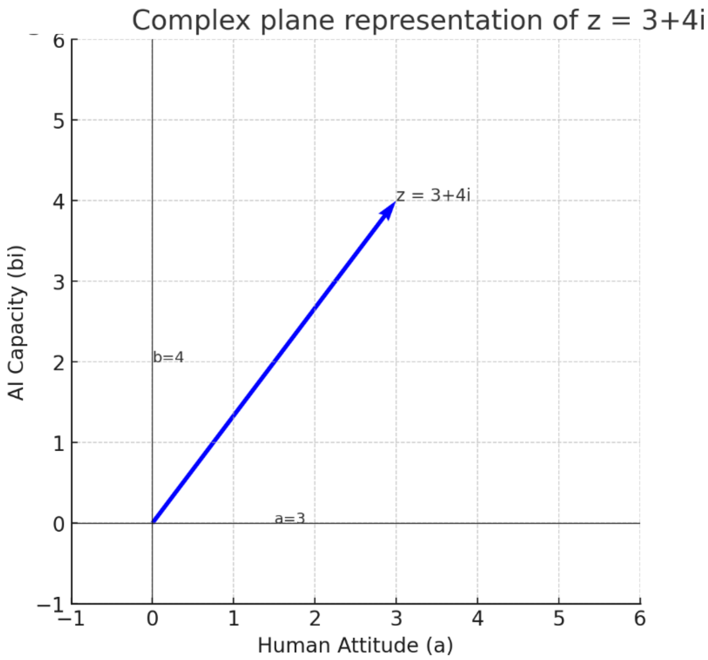

Figure 2

A diagram of the complex plane, with the horizontal axis labeled "Human Attitude (a)" and the vertical axis labeled "AI Capacity (b i)." A point is plotted at (3,4), with a vector drawn from the origin to the point. The hypotenuse illustrates the magnitude |z| = 5.

3.2 Argument: Ethical Alignment

The argument of the vector is defined as:

$$\theta = \arctan\left(\frac{b}{a}\right)$$

This angle represents the direction of the system's output relative to the real axis. In philosophical terms, it captures the balance of power and alignment between human attitude and AI capability.

- **Human-Dominated System ($a \gg b$):** Here, θ approaches 0°. The output is tightly aligned with human intention, but its power is limited. This describes traditional human decision-making assisted by minimal computational tools.
- **AI-Dominated System ($b \gg a$):** Here, θ approaches 90°. The system is powerful but misaligned, its trajectory determined by the biases embedded in data and algorithms rather than human oversight (Amodei et al., 2016).
- **Balanced Synergy ($a \approx b$):** Here, θ ≈ 45°. This is the optimal state of integration, where significant AI capacity is directed by strong human attitude. Such balance yields both

power and alignment, maximizing the likelihood of beneficial outcomes (Gabriel, 2020).

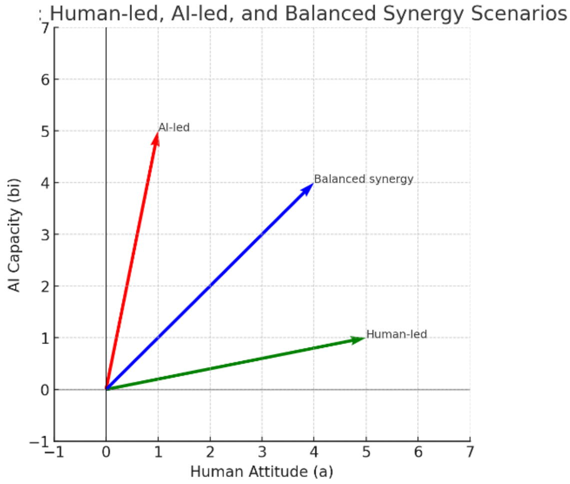

Figure 3

This figure is same complex plane as Figure 2, but with three illustrative vectors: one close to the horizontal axis (a ≫ b), one close to the vertical axis (b ≫ a), and one at 45° (a = b). Each vector is labeled with its interpretation: "Human-led but weak," "AI-led but misaligned," and "Balanced synergy."

3.3 Dynamics: The Alignment Problem

The true challenge lies not in static systems but in dynamics over time. We therefore define the collaborative vector as a function of time *t*:

$$z(t) = a(t) + b(t)i, dz/dt = da/dt + idb/dt$$

This expression captures how the components evolve. Empirically, AI capabilities *b(t)* often grow exponentially, following Moore's Law-like trends or advances in computational architectures. In contrast, human capacities *a(t)*—grounded in education, ethics, and governance—tend to grow linearly, if at all (Russell & Norvig, 2021).

The AI alignment problem emerges if *db/dt* ≫ *da/dt*: AI grows faster than human ethical oversight. The system's argument *θ(t)* drifts, leading to misalignment. The central challenge is accelerating the growth of human wisdom, ethics, and governance (*da/dt*) to match AI's exponential growth.

Under these conditions, the argument θ(t) increases over time, drifting toward AI dominance. The trajectory of the system's output thus becomes increasingly determined by machine capacity rather than human intent. This is the essence of the **AI alignment problem**: ensuring that human ethical oversight keeps pace with accelerating AI power (Bostrom, 2014; Gabriel, 2020).

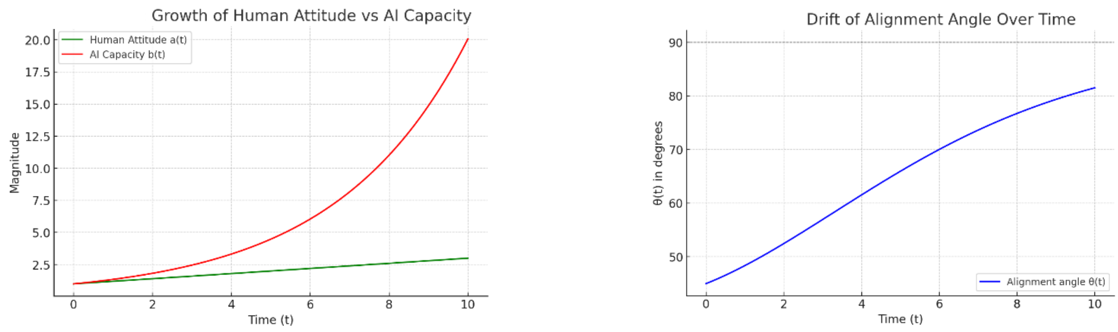

Figure 4

A time-series graph with two curves: *b(t)* rising steeply (exponential) and *a(t)* rising slowly (linear). The corresponding θ(t) is shown drifting upward toward 90°, labeled "misalignment risk."

3.4 Illustrative Real World Examples

The utility of the model becomes clearer when applied to real-world examples.

- **Healthcare Diagnostics:** When AI systems process imaging data at superhuman levels, but physicians provide contextual judgment (a significant, b large), the vector aligns near 45°, producing both power and ethical oversight.
- **Predictive Policing:** When algorithms dominate ($b \gg a$), relying on biased historical data with minimal human review, θ approaches 90°. The result is high output but low alignment, reproducing systemic injustices (Moor, 2006).
- **Human-Only Decision-Making:** In small-scale clinical settings without AI assistance, $a \gg b$, yielding low output but strong ethical alignment. This resembles pre-digital human decision-making.

3.5 Formal Constraints

One strength of the model is its prescriptive capacity. Designers or regulators may wish to impose constraints such as:

$$| z | \geq Zmin and \theta \leq \theta m$$

For example, in a medical AI system, regulators might require minimum system efficacy (e.g., $|z| \geq 10$) while constraining misalignment (e.g., $\theta \leq 50°$). Such constraints provide concrete, testable design requirements that ensure both power and ethical guidance (Winfield, 2019).

4. Applications

The strength of the $z = a + b\,i$ model lies in its dual role as both an interpretive metaphor and a prescriptive tool. By formalizing human–AI collaboration in terms of magnitude and argument, the model provides a framework for evaluating existing systems, guiding future design, and shaping governance.

4.1 System Design Optimization

One immediate application is in the design of socio-technical systems. Engineers and system architects are often tasked with balancing raw computational power against the need for meaningful human oversight. The complex-number model makes explicit that these two components are not interchangeable but orthogonal.

Case Example: Medical Diagnostics

In radiology, AI systems now detect anomalies in imaging scans with remarkable accuracy. Suppose an AI achieves $b = 9$, while the average human radiologist contributes $a = 6$. The combined system has a magnitude of $|z| = \sqrt{(6^2 + 9^2)} \approx 10.8$ and an argument $\theta = \arctan(9/6) \approx 56°$. While the performance is high, the alignment angle suggests AI is carrying disproportionate weight. To optimize the system, designers might integrate structured human-in-the-loop review processes, thereby raising a to 8. The resulting vector has magnitude $|z| \approx 12.8$ and $\theta \approx 48°$, reflecting improved synergy.
This example illustrates how the model can inform design decisions: the goal is not to maximize b independently, but to calibrate a and b such that both performance and alignment are optimized.

4.2 Ethical Auditing and Diagnostics

A second application lies in diagnosing existing systems for misalignment. Many high-profile failures of AI can be understood as cases where $b \gg a$.

Case Example: Predictive Policing
Predictive policing algorithms, such as those based on historical arrest data, often generate outputs that disproportionately target marginalized communities. In model terms, the system exhibits b large (powerful algorithmic processing) but a small (limited ethical oversight or contextual adjustment). The result is a vector with large magnitude but θ approaching 90°, indicating dangerous misalignment.

By quantifying a and b—for example, through surveys of oversight protocols, audits of data quality, and analyses of human-in-the-loop interventions—organizations can evaluate the effective θ of their systems. This allows for concrete diagnostics: the system is not simply "biased" in an abstract sense but demonstrably over-tilted toward AI dominance. Corrective action then involves strengthening a, e.g., embedding ethical review boards, transparency protocols, or community input into system design.

4.3 Regulatory and Governance Frameworks

The model also offers a conceptual basis for regulatory regimes. Instead of focusing exclusively on performance benchmarks (e.g., accuracy rates), regulators can demand metrics that capture both performance ($|z|$) and alignment (θ).

European Union AI Act Example
The EU AI Act (2021, draft form) classifies certain AI systems as "high risk" and requires transparency, human oversight, and accountability. These requirements can be mapped onto our model: they are essentially mandates to maintain θ within an acceptable range. For instance, in healthcare and justice applications, regulators might stipulate $\theta \leq 50°$, ensuring that human oversight remains robust.

By providing such a model, regulators can move beyond vague appeals to "responsible AI" and instead adopt quantifiable targets for alignment.

4.4 Broader Societal Applications

The model can be extended beyond specific domains to reflect societal dynamics. For example, public discourse about AI often reflects θ drift: as *b* grows exponentially, the perceived role of *a* diminishes. Education, public policy, and ethical discourse thus serve as mechanisms for increasing *a* across society, ensuring that technological development remains grounded in human values.

In this sense, universities, policy bodies, and civil society organizations are not ancillary actors but essential contributors to sustaining the human constant. Without them, the trajectory of technological development risks being skewed toward misalignment.

5. Discussion

The model $z = a + b\,i$ contributes to ongoing debates in philosophy of technology, AI ethics, and complex systems by offering a formalism that is at once rigorous and accessible. It clarifies conceptual tensions, provides diagnostic tools, and suggests prescriptive pathways. At the same time, it raises important limitations and future research questions.

5.1 Strengths of the Model

1. **Integrative:** The model bridges qualitative and quantitative approaches, making philosophical arguments about human primacy legible in mathematical terms (Floridi, 2019).
2. **Diagnostic:** It offers a simple yet powerful lens for identifying misalignment in socio-technical systems.
3. **Prescriptive:** By setting explicit thresholds for $|z|$ and θ, it provides concrete goals for designers and regulators.
4. **Accessible:** The use of complex numbers makes the model accessible to a wide range of audiences, from philosophers to engineers.

5.2 Limitations

The most significant limitation lies in operationalizing *a*. While *b* (AI capacity) can be measured in terms of computational power, model accuracy, or throughput, *a* (human attitude) is more abstract. It encompasses ethics, intent, and contextual awareness—dimensions not easily reducible to scalar quantities. Attempts to quantify *a* risk oversimplification or neglect of qualitative nuance.

Furthermore, the model assumes orthogonality between human and AI contributions, which may not always hold. In practice, human biases can shape AI training data, and AI outputs can reshape human attitudes—a recursive loop not fully captured in a two-dimensional framework (Gabriel, 2020).

5.3 Future Research Directions

Several extensions are possible:

- **Higher Dimensions:** The model could be expanded using quaternions or hypercomplex numbers to represent multi-human, multi-AI systems. This would capture situations where multiple stakeholders, each with distinct attitudes, interact with multiple AI agents.
- **Empirical Measurement of *a*:** Future research might operationalize a through expert surveys, ethical compliance checklists, or analyses of governance protocols.
- **Dynamic Modeling:** A richer temporal model could incorporate differential equations linking da/dt and db/dt to real-world processes such as education policy, technological innovation, and regulatory interventions.
- **Cross-Cultural Perspectives:** Different societies may define and cultivate a differently, emphasizing values such as individual autonomy, collective harmony, or ecological sustainability. Comparative studies could map how these differences affect θ in practice.

6. Conclusion

The age of AI is too often framed as a story of human replacement. In such narratives, AI becomes the "real," while humanity is relegated to a variable or constraint. This paper has inverted that framing. By modeling human–AI collaboration as $z = a + b\,i$, we have shown that the human attitude a is the real constant, while AI $b\,i$ is the imaginary multiplier.

The implications are profound. AI does not and cannot replace humanity; it amplifies it. The decisive factor for the future is not the sheer scale of machine intelligence but the quality of human attitude that anchors and directs it. If a is weak, the vector will be misaligned, regardless of the size of b. If a is strong, AI will magnify ethical and constructive trajectories.

The challenge of our era is therefore not merely technical but deeply philosophical: to cultivate a robust and virtuous a. Education systems must prioritize ethics and critical thinking. Policymakers must enact governance frameworks that constrain θ within acceptable bounds. Designers must build interfaces that amplify human intent rather than obscure it.

In short, the future of AI will be determined not by machines, but by the humanity that guides them. The ethical imperative is to strengthen the real part of the equation. Only then can the imaginary force of AI serve as a multiplier for human flourishing rather than a vector of misalignment.

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