MOVING TOWARDS CONSTRUCTIVIST AI ABOVE EPISTEMIC LIMITATIONS OF LLMS ENHANCING THE EFFICACY OF MIXED HUMAN-AI APPROACHES THROUGH SOCIO-TECHNICAL RESEARCH: AUTOPOIETIC STRUCTURAL COUPLING & CONSENSUS DOMAINS OF COMMUNITIES OF PRACTICE

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ABSTRACT

Current AI models, particularly large language models (LLMs), are predominantly grounded in positivist epistemology, treating knowledge as an external, objective entity derived from statistical patterns in data. However, this paradigm fails to capture "facts-in-the-conscience", the subjective, meaning-laden experiences central to human sciences. In contrast, phenomenology hermeneutics and constructivism, as fostered by socio-technical research (16), provide a more fitting foundation for AI development, recognizing knowledge as an intentional, co-constructed process shaped by human interaction and community consensus. Phenomenology highlights the lived experience and intentionality necessary for meaning-making, while constructivism emphasizes the social negotiation of knowledge within communities of practice. This paper argues for an AI paradigm shift integrating second-order cybernetics, enabling recursive interaction between AI and human cognition. Such a shift would make AI not merely a tool for knowledge retrieval but a co-participant in epistemic evolution, supporting more trustworthy, context-sensitive, and meaning-aware AI systems within socio-technical frameworks.

KEYWORDS

AI epistemology, Large Language Models(LLMs), Consensus Domain, Human-AI Interaction, Structural Coupling.

1. INTRODUCTION

The rapid advancement of artificial intelligence, particularly in the domain of large language models (LLMs), has sparked intense discussion regarding their cognitive capacities and epistemological foundations. While these models display impressive linguistic fluency and pattern recognition, their fundamental architecture is deeply rooted in a positivist epistemology that assumes knowledge as an objective, external entity to be extracted from data. However, such an approach stands in stark contrast to the way human cognition operates, particularly in the realm of social sciences, where meaning is not merely retrieved but actively constructed through lived experience and community consensus.

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This paper explores the limitations of contemporary AI approaches in light of epistemological perspectives in the human sciences, and highlights the importance of integrating insights from epistemology and socio-technical research. By engaging with the foundational work of Winograd and Flores [1] on structural coupling and consensus domains, as well as insights from the way socio-technical research in IS has appropriated these concepts, we argue for a paradigm shift in AI design. Rather than viewing AI as a neutral tool that processes objective data, we propose an approach that aligns with phenomenology and constructivism, recognizing the inherently social and interpretative nature of human knowledge.

On the way we provide theoretical foundation to recent initiatives of blending machine activity with human actions, illuminating the value of proposed best practices and suggesting approaches for improvement.

1.1. Framing the Article

Informatics is a science of the artificial [2]; it follows logical and rationalistic reasoning [1]. Artificial Intelligence (AI) is part of it. When applied to natural sciences, the empiricist philosophical approach to science is dominant and sufficient. Not so when applied to human sciences, and to the study of organisation. Here, the incredibly rich and diverse world of different subjective consciences play leapfrog with one another, calling for hermeneutic skills. Applying computers to human and social sciences, as we do today for example in the socio-technical domain of IS, and much more, we are brought to address the issue of the philosophical underpinning of our research activities.

Winograd and Flores attacked rather early in the digital revolution the issue of understanding computers and cognition, fostering a phenomenological orientation rather than a rationalistic one, and embracing philosophical researches and phenomenological scientists like Gadamer, Heidegger, Searle and Maturana. Their foundational book points to crucial concepts like autopoiesis of all living beings, structural coupling between individual biology and the world, and the peculiar twist of structural coupling in groups consensus domains, because of mutual interactions. Concepts that are centre stage today. Socio-Technical Research (STR), a special instance of human science, has appropriated crucial phenomenological concepts of Winograd and Flores.

Data production and data analysis establish the prerequisites for scientific rigour in all sciences, including human ones. STR, as the other human and social sciences, places paramount importance on data as "facts-in-the-conscience". Which is an inherently counter-intuitive expression, because 'fact' conventionally means 'a thing that is known or proved to be true'. Yet phenomenological philosophers consider facts in the conscience as real as facts in the real world.
Husserl's phenomenology [12, 13] presents itself as the fitting philosophical foundation for addressing “facts-in-the-conscience”, offering a descriptive phenomenological method to seek rigour. Empiricist and hermeneutic approaches are also available, however, with their methods, as another two legitimate philosophical foundations for the task.

Criteria for scientific rigour of methods for human based research descending from each of these three philosophical foundations are well known [3]. They are recalled in some detail in this paper, with the intent of making them readily available for application to AI approaches. We propose to employ them in reflecting on the epistemology of AI’s algorithms.

In doing so, we shall apply concepts of the Socio-Technical tradition in IS [16]: individual sedimentation of meaning and shared meaning in a community of practice. We shall explicitly consider the precise and different meanings that humans subjectively assign to real world facts,

like the work routines in a given organisation. We are prepared to accept the unavoidably subjective nature of these meanings: a situation at variance with natural sciences. More explicitly we consider the foundational theoretical distinction posed by Claudio Ciborra and Giovan Francesco Lanzara [35], but before them by Harold Garfinkel [27], Gregory Bateson [37], and Argyris and Shon [38], of these meanings from the underlying work routines considered as facts in the real world: in fact, meanings are not invariant, like the routines, but depend on personal knowledge [4, 5]. So that the same work routine, employing certain technology, is seen in one way by one person, and quite differently from another one – the fundamental obstacle towards enterprise innovation, when managers in a critical position just can't see it. Sometimes the same meanings are socially shared, and polished from individual subjective bias, by members of the same working group, which is then said to constitute a Community of Practice (CoP). [6,7] This is then the phenomenological path towards science in the social arena. The term 'scientific' is used in ways that seem to be at odds with the characteristics usually associated with science, such as auditability and repeatability. This property of CoP is the counter equivalent of auditability and repeatability in the natural sciences [Jacucci 2024].

We can expect that Deep Learning (DL) algorithms [8] trained with subjective data harvested in social studies of organisation, in most relevant areas on the domain like accountability or innovation, will have to deal with issues requiring – also when dealt with by humans - hermeneutic abilities and cybernetic second order reasoning; like the assignment of intentions to managers in action; or the consideration of different meanings of work routines, in a situation of change. A great challenge, eventually facilitated by dealing with CoP..

1.2. Plan of the Paper

PART I – Antecedents
PART II – The Need of Cognitive Capacities and Epistemological Foundations of AI approaches
PART III – Issues in Granting Cognitive Capacities and Epistemological Foundations of AI approaches

PART I – ANTECEDENTS

In Part I we introduce basic concepts.

2. WINOGRAD & FLORES 1986: UNDERSTANDING COMPUTERS AND COGNITION

We recall the fostering of a phenomenological orientation by Winograd and Flores [1] in *understanding computers and cognition*, and retain central concepts: the unconscious biological contribution to human cognition, by the *autopoietic structural coupling* [52] of individual biology with the world, and the consensus domain generated in human communities by structural coupling in a situation of concept sharing and "polishing".

In their highly influential book Understanding Computers and Cognition [1], Terry Winograd and Fernando Flores challenge the traditional rationalist philosophical framework that dominates Western approaches to studying computer applications. They advocate for a shift towards a phenomenological orientation, drawing on the insights of philosophers and phenomenological scientists such as Gadamer, Heidegger, Searle, and Maturana.
This shift involves recognising:

- The importance of action in language,[1, pages 56, 58-60]

- The role of subjectivity in interpretation,[ibid, pages 27-33, 35, 111-114]
- The significance of immediate intuition in understanding, [ibid, pages 27-33, 115-124]
- The impact of autopoietic structural coupling—the interaction between an individual's biological cognition and the external world [ibid, pages 45-49].

The implications of this perspective are far-reaching:

1. Two distinct modes of acquiring knowledge: [ibid, pages 38-53]

- Autopoiesis, an unconscious biological mechanism inherent to all living beings.
- Rational reasoning, a conscious process based on mental representations of the world.

2. The social dimension of cognition, which operates through a specific consensual domain [ibid, pages 48-52, 76] within human communities, such as communities of practice. [6, 7]

3. The need to examine and reveal the role of biological cognition in shaping human learning and evolution, particularly in the context of ontological design—the process of shaping our own being and becoming. [1, pages 163, 177-179]

2.1. The concept of Autopoiesis

All living organisms, individuals or groups, continually produce constituent processes useful to them, reflexive in nature, that interfere with their perception of the world. So that in fact, they construct their own vision of the world, beyond what would be given by non-biased senses.

2.2. The concept of Structural Coupling

The senses interaction between an individual's nervous system and the external world, generating adaptation and producing biological cognition by autopoiesis (including psychological prejudices).

2.3. The concept of Consensus Domain

The concept underscores how shared understanding arises through communicative acts. The psychological consensus domain of shared understanding is generated in human communities by structural coupling in a situation of sharing and "polishing" the sedimentation of previous reflections (in the form of cultural prejudices).

3. JACUCCI: PHENOMENOLOGICAL OBSERVATIONS ON HUMAN SENSE MAKING

We recall reflections on epistemology in the socio technical tradition of IS [16, 19, 20, 21], and elicit and briefly illustrate here the criteria for scientific rigour in human based research, following each of the three philosophical foundations; and present early reflections, indicating ways to link these criteria to some aspects of AI-based approaches. Our initial discussion delves into the fundamental criteria governing scientific rigour. Within this context, we elucidate the distinct attributes, merits, and susceptibilities inherent in the methods they engender. We direct to specific instances of ST literature where these methods have been applied. In this endeavour, we comprehensively introduce Giorgi's insight and writings.

3.1. The Subjective Path to the Meaning People attribute to World Things

Amedeo Giorgi's analyses the phenomenological enquiry into subjective acts, confronted to the objectivist enquiry of normal scientific analyses [3]. According to him, phenomenology is the only philosophical basis of science capable of taking into account " … the intricate and rich nuances of individual experiences and the meaning people attribute to their encounters with the world". [3] "The ultimate outcome of phenomenological analyses are eidetic expressions concerning the meaning of experiential events. What phenomenology adds to normal scientific analyses are the probing into subjective acts that are the correlates of worldly presentations." The term "correlates of worldly presentations" refers to "the inner experiences that correspond to, or are associated with, the external events or phenomena that we encounter in the world. Phenomenology recognises that our experiences are not just passive receptions of sensory inputs, but they involve active interpretation and consciousness. In mundane terms: the last statements emphasise how phenomenology contributes a unique perspective to scientific analyses, in contrast to more conventional scientific approaches. It focuses on understanding and exploring subjective experiences, particularly how individuals perceive and interpret the world around them. In "normal" scientific analyses, researchers often prioritise objective, measurable, and quantifiable data. They aim to uncover patterns, relationships, and general laws that apply to a broader population. This approach tends to overlook the intricate and rich nuances of individual experiences and the meaning people attribute to their encounters with the world". [3]

3.2. Reflection creates Sedimentation of Personal Knowledge

What is the origin of subjective experiences? Different individuals have different thoughts, and perceive and interpret differently the world around them. Reflection is one of the causes. To rethink and reflect is important, say Peter Bednar and Christine Welch [22]: "We … believe that it is both necessary and desirable to revisit and discuss again topics of significance. Only through reflection upon our own past work and that of others can we build productive learning spirals. Only in this way can we establish and extend a reflexive relationship to future practice."

The defining characteristic of human consciousness in engaging with the world is the intentional focus on a specific object – a foundational premise, see for example [14]. Reflecting on the object produces sedimentation of subjective thoughts. Let's go back to the very beginning of phenomenology, by recalling Schutz, as done, again, by Bednar and Welch [23]: "When elaborating upon 'meaningfulness' Schutz (in Wagner [24]) questions how it is possible for any mutual understanding or communication between people to take place … He reflects that such possibilities can only be approached via 'sedimentation' of pre-interpreted experiences built up through conscious life. Any justifiable methods for interpreting social interrelationship must then be based on careful description of underlying assumptions and their implications. He goes on to suggest that the methods of the social sciences cannot be regarded as adequate to this task. … They require a philosophical analysis. And phenomenology ... has not only opened up an avenue of approach for such an analysis but has in addition started the analysis itself (in Wagner [24, p.56]." Note that, at Schutz times, human sciences performed with the objectivist epistemology of natural sciences. Bednar and Welsh then go on: "This concept of a 'sedimentation' of pre-interpreted, lived experience comes about, for Alfred Schutz, through reflection. … Thus, meaningfulness can only be attributed in retrospect. … "

Reflection creates sedimentation in what we may call personal knowledge, that is, the individual tacit ability to read meaning in a situation, from details around a focus [4, 5]; sedimentation is personal, different individuals encompass different sedimentations; mutual understanding in

communication between people is complicated by their different sedimentations, hence different personal knowledge hence different assumptions hence different meanings in confronting the same situation: in one word, subjectivity. Contributions to any human science, that involve facts in the conscience of different people and their interrelations, cannot be safely made without explicitly considering subjectivity and the different sedimentations hence assumptions.

Conscious reflection is not the only source of sedimentation: humans are naturally equipped with autopoiesis [52, 25], i. e., the faculty of generating by evolution for better survival special mechanisms apt to tacitly create sedimentations directly from experience, without conscious reflection. Sedimentations are called, and act as, prejudices.

3.3. Sharing in a Community of Practice

As they come from different individual experience stories, different individuals unavoidably possess different sedimentations, hence different personal knowledge, and unavoidably assign different meanings to the same situation. Unless they undergo a communal cleansing process through sharing reflections on their different assumptions, in some community of practice. The authors Bednar and Welch [23] link Shutz's first thoughts on phenomenology to early thoughts on information systems, formed in a socio-technical perspective: "In considering Schutz's view, the authors are reminded of the work of Börje Langefors, in the mid Sixties, with the Infological Equation [26]. Reflecting on the nature of information systems, Langefors suggests that those people who are to interpret data in order to inform themselves must be viewed as part of the system. … Meaning (information or knowledge) is thus created by each individual. Pre-knowledge … is considered to be created through the entire lived experience of the individual concerned (cf Schutz's concept of 'sedimentation'). .. He observes that communication may be seen to approach success most closely where individuals interpreting the same data belong to a group, definable for example by …common professional interest, e.g. standardized accounting data among accountants." [28] Within a group, members engage in recurring exchanges of thoughts, facilitating the sharing and sedimentation of ideas. This phenomenon enhances communication efficacy among group members, setting them apart from others. Psychologist Daniel Stern calls this the power of Interpersonal Dialogue [29]. Consequently, communities of practice stand out as unique entities where shared historical sedimentations foster robust communication, nurturing collective thinking and reinforcing the social construction of novel ideas. Thus, each community of practice [6, 7]., represents a distinct social milieu following a bespoke intellectually constructed path. So, when considering facts-in-the-conscience of group members of a given community-of-practice regarding their professional subject matters, we are reassured by their personal professional knowledge that their conscience correspond to reality, by their consuetude with it, and their reiterated, shared, reflected upon, sedimented experience. See Ciborra & Lanzara's Formative Context. [35]

4. THREE QUALITATIVE APPROACHES

Qualitative methods find extensive acceptance and widespread use. A multitude of methodologies have been introduced over time. Yet, these methodologies are fundamentally underpinned by three distinct philosophies that provide the guiding principles for the scientific approaches stemming from them. To elucidate these philosophies we draw from Amedeo Giorgi's discourse on this subject [3].

4.1. Empiricism

Empiricism, the oldest philosophy of science dating back five centuries, originally designed to support scientific endeavours in the natural sciences, remains dominant across many fields of study. However, during the early 20th century, two other philosophies emerged: phenomenology and hermeneutics. At its core, empiricism asserts that all knowledge must stem from direct experience, with no reliance on a priori truths. Sensory modalities and tangible observations are given prominence. Subsequent verification, particularly by others, plays a crucial role in establishing robust knowledge, failing which information is provisional. One of the earliest qualitative methods rooted in empiricism is Grounded Theory (GT), originating within Sociology. GT employs a comparative analysis approach wherein data examination yields hypotheses that form tentative theories, subsequently subject to ongoing data scrutiny. This methodology generates theory from empirical data, dispelling speculative conjecture. Simultaneous involvement in data collection and analysis, coupled with the construction of analytical codes and categories derived directly from data, ensures the development of stringent data-dependent codes and categories. Thus, all formulated concepts and properties must be firmly rooted in the data. Subsequent comparisons and distinctions within the data, viewed from disciplinary lenses such as sociology or psychology, facilitate the potential generation of initial theoretical hypotheses. A note of caution is echoed by Giorgi: "…GT emphasises conceptualisation and not description, abstracting from time, place, and persons in a way that description does not… the researcher must transform the detected everyday meanings into disciplinary meanings, in order to build a theory. But this could be…" problematic, as the researcher, for example, "could interpret the everyday empirical meanings psychoanalytically, behaviourally, or cognitively and still be justified as a psychological interpreter" [3, p. 12]. Hence, GT is grounded in empirical foundations rather than being purely empirical. Nevertheless, in its practical application, it holds recognition as a scientific method.

4.2. Hermeneutics

To grasp the essence of "understanding," transcending mere methodical approaches for investigating human science phenomena, Heidegger [9] and Gadamer [10] established hermeneutics. At its core, hermeneutics asserts that comprehending human phenomena necessitates interpretation. Consequently, knowledge, at its best, embodies a plausible comprehension of a phenomenon, in contrast to the definitive, objective understanding typical of the natural sciences that permits no alternatives. The objective of such research lies in comprehending lived experiences through the meanings conveyed within them. However, texts are products of human creation, infused with perspectives and expressed through language marked by word ambiguity. Additionally, texts introduce context, giving rise to considerations of the author's intentions and the intended audience. The method guiding scientific research into human phenomena stands in stark contrast to that governing natural phenomena, governed by causes and effects. Hermeneutic thinkers contend that subjectivity exerts significant influence on human phenomena. Consequently, there is no independent starting point when dealing with human phenomena. To navigate this, hermeneutic researchers universally engage within the hermeneutic circle, a protocol suited to this situation. Hermeneutic reasoning is circular, though not a self-defeating cycle, as aptly expressed by Palmer [11]: "The whole receives its definition from the parts, and reciprocally, the parts can only be understood in reference to the whole". The hermeneutic method has two basic elements: "… 1) that the researcher produces the best interpreted meaning … not without other possible understandings… and 2) that the analysis requires the use of the hermeneutic circle with its fore-structure of understanding" [3, p. 14]. It tends, albeit with a different route than empiricism, also to detect and clarify everyday lived meanings, as expressed by humans, and turn them into precise disciplinary meanings. Given the assumptions, hermeneutic results are interpretations, theories with a degree of tentativeness. Constructivism is the phenomenology learning theory of hermeneutics. Constructivism is a learning theory that emphasizes the active role of learners in building their own understanding.

Rather than passively receiving information, learners reflect on their experiences, create mental representations, and incorporate new knowledge into their schemas. This promotes deeper learning and understanding.

Constructivism is 'an approach to learning that holds that people actively construct or make their own knowledge and that reality is determined by the experiences of the learner' [36, p. 256]. In elaborating on constructivists' ideas, Arends [39] states that constructivism believes in the personal construction of meaning by the learner through experience and that meaning is influenced by the interaction of prior knowledge and new events.

4.3. Phenomenology

Husserl [12, 13] phenomenology employs a descriptive approach. For him, intuition is the basis for knowledge acquisition, not interpretation. Intuition is "… how phenomena present themselves to acts of consciousness. The modes of appearance of all objects are meant to be described…" [3, p. 20]. "… the phenomenological philosophical method … consists of three basic steps: experience or imagine a concrete phenomenon and carefully describe it; second systematically but freely vary dimensions of the phenomenon in order to ascertain its essential features; and, third describe the essence that has been discovered, once the method of free imaginative variations has been completed. This is also known as the eidetic reduction of the concrete phenomenon… " [ibid, p. 20].

Some adjustments are necessary to transition from philosophy to the realm of science and a human-focused scientific discipline (psychology, sociology, or other). This extension of Husserl's phenomenological philosophy and method to a human focused scientific discipline is performed by Giorgi in Psychology with his Descriptive Phenomenological Method (DPM). "The ultimate outcome of phenomenological analyses are eidetic expressions concerning the meaning of experiential events. What phenomenology adds to normal scientific analyses are the probing into subjective acts that are the correlates of worldly presentations." And how does DPM really work? "Phenomenology … delves into the realm of subjective human consciousness. It seeks to understand the essence of human experiences, the way individuals make sense of their interactions with the world, and how they perceive and interpret phenomena. By examining the subjective acts (thoughts, feelings, perceptions, etc.) that accompany our encounters with the world, phenomenology adds depth and context to our understanding of reality" [14]. What are the specific results of the PDM method? "The result of the application of the scientific phenomenological method are eidetic descriptions that are general and based upon intuitions that are clarified with the help of the procedure of imaginative variations" [3, p. 22]. But the connection to the real world requires, in principle, further analysis. After solving this vulnerability, in the sequel we shall see how, again through consensus domains of Section 2.2 and the involvement of Community of Practice members, descriptive phenomenology can also lead to the establishment of scientific evidence.

4.4. Respective Approach Vulnerabilities *vis à vis* Scientific Rigour

"It should be noted that all three philosophies support methods that actually have an identical task and, while there is some overlap among them, ultimately, the approaches and methods are not identical. It turns out that they are parallel processes, the differences reflecting the different philosophies that support the methods. The identical task may be described as the attempt to come up with a precise disciplinary meaning of data expressed in the language of everyday life" [3, p. 27]. The scientific attitude towards phenomena is quite different from the "natural attitude" exhibited by common people in everyday life, populated by common sense and "horse sense".

Phenomenology has the same problem as empiricism, i.e., how to escape the "natural attitude". But "… the solution it tries out is the opposite of the theoretical and the objectifying, where the emotions are barred and the lived experience cleansed.

Phenomenology looks for an a-theoretical comportment and interpretation beyond the natural attitude …" [17, 18]. Their respective vulnerabilities are quite different as well. With respect to the theme of scientific rigour: empiricism contains a remnant of uncertainty in the choice of theory, hermeneutics in the choice of interpretation. Uncertainty can be reduced with objectivist criteria: by being methodical, systematic, general, critical, and by sharing and verification with others. These do not concern theorising or interpreting in particular, and those vulnerabilities remain in part. Descriptive phenomenology, conversely, can attain full scientific precision concerning facts-in-the-conscience, while its connection to the real world necessitates further scrutiny. Addressing, and responding to this vulnerability empowers descriptive phenomenology to establish scientific substantiation. This approach, aimed at objectivity within facts-in-the-conscience, represents the highest attainable standard of adherence to the world existing out there.

PART II – THE NEED OF COGNITIVE CAPACITIES AND EPISTEMOLOGICAL FOUNDATIONS OF AI APPROACHES

In Part II we elaborate reflections on cognition, with reference to AI approaches.

5. REFLECTIONS ON STRENGTHS AND WEAKNESSES OF AI-DL APPLICATIONS

The extended reflections reported above, about the complexity of human subjectivity and of human research approaches, and its consequences on the criteria for scientific rigour of the three qualitative research methods described, will allow to confront these criteria with the various forms introduced of DL, hoping to gain further understanding about machine learning from what is already known about human learning. For instance, that Interpreted AI may be seen as a hermeneutic approach, when based on a priori interpretations, while AI alone may be seen as a descriptive phenomenological one, when fed original and uncontaminated data. These reflections are intended to put down the roots and design the initial landscape of the subject.

We will prepare the terrain, by offering reflections on strengths and weaknesses of AI-DL applications that might profit from confrontation with the reflections of Section 4. We shall start with a case of a hindrance. We shall then mention a case of advantage.

5.1. Hinderance

A recent review of current legal applications of AI [43] shines light on its present use. It says: *"We break down AI's current legal applications into the following categories of applications:*

- *Helping lawyers perform due diligence and research*
- *Providing additional insights and "shortcuts" through analytics*
- *Automating creative processes (including some writing) in legal work*

Because of the breadth of our research (and hence the length of this article), we encourage readers to feel free to skip ahead to the applications areas of greatest interest for them." So, aspects of lawyering can be automated but AI cannot be the Judge and certainly cannot be the jury!

5.2. Illuminating Examples of AI Limitations in Contextual Make-Meaning

Because of their features, AI as well as other emerging digital technologies suffer of well-known issues of lack of accountability and transparency [42]. From the perspective constructed by the reflections in this paper, we question the ability of AI systems, when confronted with a given human socio cultural context, to account for the consequences of the human actions described therein.

Applying AI NLG tools to make sense of enterprise management, for example, is inadequate, especially in domains requiring accountability-driven performances. Relying on generic validation methods for AI systems proves insufficient. For further insights, refer to recent reviews on explainable AI systems (31), validation methods for AI systems (32), evaluating explainable AI (33), and NLG system evaluation (34).

Despite the exceptional performance of large language models (LLMs) on a wide range of tasks involving natural language processing and reasoning, there has been sharp disagreement as to whether their abilities extend to more creative human abilities. A core example is the interpretation of novel metaphors: "the metaphors an LLM might generate are limited to those that human writers have already formed and planted into texts, thereby making humanity's store of metaphors available to be mined by LLMs". [45]. More: in a recent study of behavioural differences between expert humans and language models in wargame simulations, the LLM simulations cannot account for human player characteristics, showing no significant difference even for extreme traits, such as "pacifist" or "aggressive sociopath." [46]

5.3. Opportunity, an Example: Helping Managers in the Dynamics of Innovation

We now point to a positive feature of AI integration into current management tools, which offers a great opportunity for helping managers in the dynamics of innovation.

In a foundational, often forgotten paper, entitled "Formative contexts and information technology: understanding the dynamics of innovation in organisations", Claudio Ciborra and Giovan Francesco Lanzara [35] take a theoretical step that they regard as crucial: "We must draw a distinction between the work routines as they are carried out daily in organizations and the 'formative context' within which those routines are 'formed' and receive their meaning and scope in an actual situation of action". This phenomenological distinction that goes back to Garfinkel, Bateson, and Argyris and Shon, is all important to understand the interaction between the use of technology and organisational awareness during change. Change produces a temporary dis-aligning of routines and meaning. Anticipating the new meaning may help foster the change of routines. When the change of routines has been fostered by the circumstances, the new meaning is often slow in surfacing. Hence, the importance of overcoming limitations in the formative context, to help foster change.

We maintain that the practice of machine learning, for instance by feeding neural networks information about most disparate organisational contexts and situations, with different routines and corresponding meanings attributed by the involved actors, can help present managers with illuminating new meanings.

6. HINDERANCE, IN DETAIL: REQUIREMENTS FOR UNDERSTANDING RELATIONAL SOCIAL ENVIRONMENTS, THE CASE OF ACCOUNTABILITY

An interesting case to address is the relation that might be construed between AI and Accountability: a certain AI and a certain Accountability.

Whatever their nature, AI routines can be either used stand alone, or be of support to human activity [40]. In trying to understand data they can be oriented by human knowledge and interpretation [41]. They can also be equipped with some explanatory ability about their functioning and results [47] Accountability of AI routines is normally intended as their eventual ability to account for the own results they generate.

We wish to address here a different kind of Accountability, with respect to AI systems: their eventual ability, when confronted with a given human socio cultural context, to account for the consequences of the human actions described therein.

6.1. Challenges in Integrating AI and Accountability in ST Contexts

Here, Accountability requires the availability of two necessary ingredients [48]: a) the availability of a certain kind of data - of cybernetic second order data like roles, responsibilities, intention, awareness, needed for accountability and second order governance [48] -; and, b) the availability of a certain ability – the ability of the hermeneutic interpretation of that data within the appropriate social culture, a basic commitment to mutual understanding in human communicative actions [15] -. Both availabilities are questionable for current AI systems operating on current ICT platforms.

Current institutional information infrastructures operate under the now four-decade-old information paradigm of Data Processing and Distribution (DPD). DPD is limited to cybernetic first order functional data. [30] Here, the type of Accountability that we wish to pursue in socio technical contexts is not within reach: second order data are missing. Therefore, applying AI routines here will not work. And it will not work also because AI routines do not possess, as yet, personal culture and hermeneutic interpretation abilities. [42, 45, 46]

Reference [68] explores the relationship between AI and Accountability in complex, multi-agency environments, such as healthcare systems and inter-organisational enterprise settings, involving relational rather than simply functional human interactions [50, 51]. Here, Accountability refers to the ability to hold human actions responsible during periods of change. Managing change effectively in these environments, which involve multiple stakeholders and diverse cultures, requires, above first order functional data about human actions, a higher-level framework of second-order concepts, like principles, objectives, intentions, and awareness, assigning roles and responsibilities to actors performing a change or communication act. These concepts – of basic relevance in relational social experiences - are essential for ensuring accountability of the actors, but go beyond the basic functional data typically handled by institutional ICT platforms.

Currently, individuals fill this gap by informally exchanging necessary information through informal tools like email and messaging apps. Without this additional second-order data, neither humans nor AI systems can adequately answer accountability questions in these complex settings. Present powerful Trained Generative (TG) AI systems are based on Deep Learning (DL) models [8] and/or Large Language Models (LLMs) [45], that can take raw data from institutional platforms and “learn” to generate statistically probable outputs when prompted. Obviously these

systems cannot invent and take into account cybernetic second order data, that has not been provided to them. Moreover, lacking both the personal subjective culture of human experience, as well as hermeneutic interpretation capabilities, they are ill-equipped to provide meaningful insights into human actions. For example, AI DL and LLMs systems, characterised by machine learning mechanisms based on the probabilistic evaluation of proposed massive data, extract meaning from facts of the world in a way that is completely different from human individual sedimentation, or socio cultural amalgamation and homogenisation. A way that does not guarantee the respect of the causal links specific of human sense making. Therefore, applying AI automation to extract accountability from institutional platform in these conditions, is wrong twice:

- Doing faster the wrong thing (no hermeneutic abilities),
- Garbage in garbage out (no cybernetic second order data).

The path to using AI for Accountability in relational enterprise is, therefore, fraught with challenges. These cautions are particularly relevant in the push to integrate AI with natural language generation (NLG). Blind reliance on AI can lead to expecting insightful responses about human behaviour without providing all the necessary input or considering the system's interpretive limitations.

6.2. Light at the End of the Tunnel, for Integrating AI and Accountability in Complex ST Contexts

A recently proposed, innovative, structured communications paradigm, called Information Communications (IC) paradigm [30], to be introduced in institutional information infrastructure, is described as capable of handling human conversations accessing and elaborating second order data, governance, and accountability.

At the same time, we should reason about which type of current AI routines are suited, if any, to pursue the performance of certain hermeneutic interpretation abilities.

To analyse the connection between AI and the kind of Accountability we are interested in, consider the types of questions that need to be answered:

- What happened, and what are the interpreted causal linkages?
- Who knew what, and what are the interpreted motivational linkages?
- Who informed whom, for what purpose, and with what consequences, and what are the conversational linkages?

The first part of each question is empirical, while the second requires judgment and interpretation. The system in which these processes occur must be socio-culturally aware. To provide a positive solution to the problem of addressing Accountability in relational enterprises with AI based tool, we should examine the connection between AI and Accountability and explore the requirements for integrating second-order data and hermeneutic interpretation abilities into AI systems. Unfortunately, the answer to the query is negative, we are not there yet. [21]

Recently, Augmented Intelligence offers a promising option. It focusses on the enhancement of human capabilities through the collaborative efforts of humans and AI systems [40]; it creates human-AI pairs in which both elements may contribute towards interpretation: the human element can provide the required hermeneutic abilities.

PART III - ISSUES IN GRANTING COGNITIVE CAPACITIES AND EPISTEMOLOGICAL FOUNDATIONS OF AI APPROACHES

In Part III, we shall draw useful conclusions - in terms of framework, classification, hints and a strong suggestion - from the concepts introduced, and the reflections elaborated, in Parts I and II

7. A FRAMEWORK FOR EVALUATING CONTEMPORARY AI BY THEIR EPISTEMOLOGY

7.1. Epistemology and the Limits of Contemporary AI

Within the human sciences, three primary epistemological traditions shape our understanding of knowledge: positivism, phenomenology, and constructivism. Positivism assumes that knowledge exists independently of the observer and can be discovered through empirical observation and measurement. AI models based on deep learning largely adhere to this paradigm, extracting statistical correlations from vast amounts of text without understanding meaning beyond surface-level associations. The result is a mechanistic reproduction of language that, while often coherent, lacks true comprehension, intentionality, or contextual sensitivity.

Phenomenology, by contrast, emphasizes the lived experience of individuals, focusing on how meaning emerges through intentional acts of consciousness. Constructivism extends this perspective by positing that knowledge is not passively received but actively co-constructed within communities of practice. These perspectives highlight the relational, interpretative, and dialogical nature of human cognition, aspects that are largely absent in current AI paradigms. Without incorporating mechanisms that allow for structural coupling—the dynamic, reciprocal interaction between AI and human agents—LLMs remain vulnerable to factual hallucinations, contextual insensitivity, and the inability to engage in genuine discourse.

7.2. The Role of the Socio-Technical IS Research Tradition

Socio-technical research provides a crucial framework for rethinking AI's epistemic role. Rooted in second-order cybernetics, this perspective acknowledges that knowledge is not merely an artifact but an evolving social process that emerges through interaction. Winograd and Flores' critique of early AI foresaw the pitfalls of treating cognition as an abstract computational process divorced from human experience. Their concept of the consensus domain underscores how shared understanding arises through communicative acts, a process that AI systems, as currently designed, do not engage in meaningfully.

More recent reflections from socio-technical research, particularly in the work of Jacucci and colleagues, further develop this argument by examining how sedimented knowledge within communities of practice influences both technological and epistemic evolution. In this light, the development of AI must not be confined to isolated algorithmic improvements but should be situated within the broader socio-cultural contexts in which it operates. An AI that truly supports human cognition must be designed to interact dynamically with these evolving knowledge structures, fostering engagement rather than merely retrieving data.

7.3. Towards an AI that Embodies Structural Coupling and Consensus Domain

Bringing these insights together, we argue that contemporary AI development must integrate the principles of phenomenology, constructivism, and socio-technical research to move beyond its

current limitations. One promising direction is the design of AI systems that can engage in dialogical interaction, adapting not just to the data they are trained on but to the evolving discourse of the communities they serve. This would entail embedding mechanisms that allow AI to recognize and participate in consensus-building processes, rather than merely predicting textual outputs based on statistical likelihood.

An illustrative example of this approach can be seen in the different ways users interact with ChatGPT. While some users treat it as a simple query-response system, others engage in more elaborate discussions, prompting the AI to refine its responses through iterative exchanges. This interactive potential hints at the possibility of AI as an epistemic partner rather than a mere retrieval tool. However, for this potential to be fully realized, AI must be equipped with frameworks that enable it to recognize shifts in discourse, account for contextual dependencies, and contribute to knowledge construction in meaningful ways.

8. CLASSIFYING CURRENT AI MODELS WITH EPISTEMOLOGY

Classifying current AI models according to the three epistemological approaches to human and social sciences—Positivism, Phenomenology, and Constructivism—helps illuminate their conceptual underpinnings and limitations.

8.1. AI Models Aligned with Positivism

(Objective, Mechanistic, and Rule-Based Knowledge Representation)
Characteristics of Positivist AI Models:

- Based on formal logic, statistical inference, and empirical validation
- Assume an objective reality that can be measured, predicted, and controlled
- Depend on data-driven learning without requiring subjective interpretation

Examples of AI Models:

- Symbolic AI / Expert Systems (GOFAI - "Good Old-Fashioned AI")
    - Rule-based reasoning systems (e.g., MYCIN, DENDRAL, Prolog-based AI)
    - Logic-driven and deterministic inferences (e.g., automated theorem provers)
- Machine Learning (ML) Models with a Strong Empirical Focus
    - Supervised learning models for classification and regression (e.g., Decision Trees, \Support Vector Machines)
    - Reinforcement learning (e.g., AlphaGo, OpenAI Five) in environments where the world is treated as a set of objective rules
- Large Language Models (LLMs) in Their Basic Form
    - GPT, BERT, LLaMA (before fine-tuning for human alignment)
    - Treat language as statistical patterns without intrinsic understanding

Limitations from an Epistemological Perspective:

- Reductionist: Does not account for subjective experience or social context

- Lacks interpretive depth: Cannot explain *why* a particular decision is made beyond data correlation
- Ignores the structural coupling between knowledge and human experience

8.2. AI Models Aligned with Phenomenology

(Experiential, Subjective, and Meaning-Oriented AI)
Characteristics of Phenomenology-Oriented AI Models:

- Emphasize subjective interpretation and meaning-making
- Attempt to capture lived experiences rather than just statistical correlations
- Engage with *contextual* rather than purely syntactic patterns

Examples of AI Models:

- AI for Affective Computing
    - Emotion recognition systems (e.g., Affectiva, Microsoft's Azure Emotion API)
    - AI-driven sentiment analysis (e.g., models designed to recognize moods from text or speech)
- Embodied AI & Robotics
    - Sophia the Robot (Hanson Robotics) – attempts to mimic social interactions
    - AI-driven prosthetics and assistive devices that adapt to user behaviour
- Fine-Tuned LLMs with Alignment for Human Interaction
    - ChatGPT (especially post-RLHF, where reinforcement learning from human feedback adds phenomenological alignment)
    - AI models engaging in *pragmatic meaning-making* rather than mere syntactic generation
- Interactive Narrative AI & Creativity-Focused AI
    - AI-driven storytelling tools that adapt based on user input (e.g., AI Dungeon, Character.AI)
    - AI-generated art and music that responds to emotional cues (e.g., OpenAI's MuseNet, DeepDream)

Limitations from an Epistemological Perspective:

- AI lacks true intentionality (does not *experience* meaning, only simulates it)
- Context sensitivity is still largely predefined rather than emergent
- Structural coupling is simulated rather than intrinsic (e.g., GPT-4 does not *experience* consensus, it statistically approximates likely responses)

8.3. AI Models Aligned with Constructivism

(Socially Constructed, Adaptive, and Situated Knowledge AI)
Characteristics of Constructivist AI Models:

- Learning emerges from interaction within social and contextual environments
- AI is treated as a participant in co-constructing knowledge, rather than just processing data
- Embeds meaning negotiation and adaptation through human-AI collaboration

Examples of AI Models:

- AI for Human-Centered Design & Community-Based Knowledge Construction
    - *Wikipedia's SuggestBot* – AI that learns from community edits to improve article recommendations
    - AI models supporting participatory democracy (e.g., Pol.is – a deliberative platform using AI for consensus-building)
- AI in Socio-Technical Systems & Hybrid Human-AI Networks
    - IBM's *Debater AI* – Engages in structured argumentation with humans
    - Open-ended AI collaboration platforms (e.g., *OpenAI's Codex* for interactive programming)
- AI in Conversational Agents that Facilitate Group Knowledge Sharing
    - Social bots designed for knowledge co-creation (e.g., AI-powered forums, AI-mediated dialogue systems)
    - GPT-4 when used as a co-pilot in community-driven knowledge processes (e.g., scientific discourse, collaborative writing)
- AI in Multi-Agent Systems & Swarm Intelligence
    - Distributed AI models that co-evolve through interactions (e.g., self-organizing traffic systems, robotic swarm AI)
    - AI facilitating collective intelligence (e.g., Stanford's *Hivemind AI* research)

Limitations from an Epistemological Perspective:

- AI still lacks true reflexivity – it does not *consciously* adapt its own epistemological framework
- The degree of human participation varies widely, making true co-construction difficult to scale
- Ethical risks: AI may reinforce biases rather than genuinely engage in dynamic knowledge negotiation

8.4. Comparison Summary

Epistemological Approach	Core AI Characteristics	Examples of AI Models	Key Limitations
Positivism (Objective, Empirical, Mechanistic)	Rule-based, Statistical, Data-driven	Expert Systems, Classical ML, Reinforcement Learning, Basic LLMs	Lacks interpretation, meaning-making, and contextual understanding
Phenomenology (Subjective, Meaning-Oriented)	Context-sensitive, Emotionally-responsive, Experiential AI	Affective Computing, Embodied AI, Fine-tuned LLMs, Creative AI	Lacks intentionality, meaning is simulated rather than experienced
Constructivism (Socially Constructed, Adaptive)	Co-constructive, Interactive, Situated AI	Human-AI collaborative systems, Knowledge-building AI, Swarm AI	Lacks reflexivity, participation varies, ethical risks in bias reinforcement

8.5. Thoughts Towards a Synthesis

While current AI models tend to fall primarily under Positivist and Phenomenological categories, a Constructivist AI paradigm is emerging in human-AI collaboration, consensus-building, and collective intelligence research. The challenge for AI research moving forward is to:

1. Integrate the strengths of all three epistemological approaches to create hybrid models that combine objective analysis, subjective experience, and social knowledge construction.
2. Design AI systems that engage in *structural coupling* with human communities—embedding meaning-making processes beyond statistical inference.
3. Move towards AI as a *co-evolutionary partner* rather than just a tool, enabling dynamic epistemic shifts rather than static knowledge retrieval.

9. EPISTEMOLOGICAL HINTS

We reflect on the possibility of straight extension to AI of our considerations about human qualitative research methods. We provide hints for directions of future work, in linking different AI architectural styles to the different methods of our three foundational philosophies.

9.1. Hints for Empiricism

Empiricism vulnerability: the arbitrary choice of the initial practice based theory, to let grow.
This is the slot for AI applied to natural science type cases, where “facts in consciousness” are not relevant. The AI literature is mostly filled with this type of cases. But we are interested in the life of organisations made up of people.

If we are keen to identify anyway empiric type cases where subjectivity is relevant, we should look to AI DL algorithms and architectures [46] and also other architectures, searching for analogies with an empiric method, e.g., the practice based theorising method of empiricist grounded theory, to point to eventual biases for a specific choice of initial theory to be built up on the go.

However, we cannot overlook the observation that the incremental learning of chatbots like ChatGPT that enrich their answers in the course of the conversation, building on what has been exchanged so far, is a clear reminder precisely of the practice-based theorising of empiricist grounded theory.

9.2. Hins for Phenomenology

Phenomenology vulnerability: Adherence to reality.

AI architectures not engaging in dialogical interaction with a human may, in any case, be considered to be closer to the unbiased, virgin intuition of descriptive phenomenology. Here, we note that we have to take care of three caveats, regarding the material used to train the GenAI routine:

1. The same language used by actors in managing affairs, should be the one used in accounting for them;
2. The subjective bias of the meanings people assign to real-world facts encountered, due to different individual sedimentations, can be mitigated by restricting the participants to members of the same CoP;
3. The verification of results must ensure invariance under free imaginative variations of contextual parameters.

9.3. Hints for Hermeneutics

Hermeneutics vulnerability: the arbitrary choice of the “correct” interpretation.

The situation is a rather complex one, however, for the hermeneutics item. A new trend of Augmented Intelligence focuses on the enhancement of human decision-making through the collaborative efforts of humans and AI systems. Not AI as a replacement for human intelligence, but a harmonious integration that amplifies human capabilities without supplanting them. According to Harfouche, Quinio, & Bugiotti [47], organisations are increasingly adopting collaborative decision-making frameworks that leverage the strengths of both humans and AI, leading to more informed and effective outcomes. This means that the comparison we are trying to perform is not limited to human and machine learning, but includes mixed situations.

Informed AI (IAI) [41] is example where humans provide additional information, allowing the AI to operate with a comprehensive awareness and integration of relevant data, context, and knowledge to make decisions or provide insights, i.e., with a specific interpretation. It resembles a hermeneutics approach, and it is biased by the choice of human interpretation.

Furthermore, we are moving towards a Human-Centric Explainable AI system architecture, where Explainable AI (X-AI) refers to AI systems designed to provide insights into how and why they arrived at a particular decision or output [40]. The goal is to make AI's decision-making process transparent, understandable, and interpretable for humans. Again, we are perfectly in the human hermeneutic domain.

We are even beginning to see progress in handling the concept of accountability, regarding the actions by the human actors involved in the situations considered.

9.4. Discussing the Hints

More often than not, it becomes a question of interpretation. But how can we humans be sure that we are choosing the "correct" interpretations of the phenomena we encounter? Is our intuition so close to the truth that it can legitimately become science? Maybe, if we commit to an hermeneutical, genuinely phenomenological attitude?

We close the Section with answers to these questions (already mentioned in Section 6), taken directly from Heidegger's notes [Heidegger 1993, 2001]:

"Understanding - as intuition - goes along with and into the fullness of a situation… The phenomenological understanding is nothing else than an intuitive going along the meaning. It must stay close and present to the total situation of the phenomenon… Capacity to accompany - being intimate, "love". Love as motivating ground of the phenomenological understanding - given necessarily in its sense of enactment." Heidegger is aware of the difficulty of carrying out this task with this method:

"The first task is therefore the appropriation of the situation in which understanding is rooted; the full, concrete appropriation is by itself a task that will perhaps exceed the powers of the present generation… Those who attempt something else mistake in principle precisely what should be their aim…*the pure cognition of the labyrinthine basic character of human existence*" (our emphasis). [23]

Those who attempt something else, may be successful in understanding natural phenomena, not human and social ones.

10. THE MUST: EMBODYING CONSENSUS DOMAINS IN LLMS, ENGAGING IN DIALOGICAL INTERACTION WITH COMMUNITY OF PRACTICE MEMBERS

As AI routines are far from affording something like even by far human's structural coupling, or consensus domains, they cannot access human experiential contextual make-meaning and cognition, let alone the establishment of scientific evidence.

The only path for AI to improve on this front is engaging in dialogical interaction with a human having these affordances. This road has already been undertaken recently in the field. Of course the human is being chosen to have expertise in the domain.

In force of the reflections presented in this paper, we further advocate for choosing a member of a community of practice in the domain of interest.

And, we have provided the conceptual framework to support both the path of engaging LLMs in dialogical interaction with a human having these affordances, in particular a member of a community of practice in the domain of interest: making use of the consensus domain, the unique element that can lead to the establishment of scientific evidence when treating consciousness of people. Or at least that can get as close to reality as possible, in this world.

11. CONCLUSIONS

The epistemological challenges facing AI today are not merely technical but fundamentally philosophical. By adhering too rigidly to a positivist framework, contemporary AI models risk misrepresenting the very nature of human knowledge. Phenomenology and constructivism offer

an alternative foundation that acknowledges the deeply social and interpretative dimensions of cognition. The concept of structural coupling provides a pathway for AI to evolve beyond static data processing and engage in a more dynamic, reciprocal relationship with human users.

By drawing on insights from socio-technical research, particularly the role of consensus domains and community-driven knowledge formation, this paper envisions a future where AI serves not as an isolated computational system but as an integral participant in human epistemic practices. This requires a shift towards designing AI that prioritizes meaning-making, contextual awareness, and participatory engagement, ensuring that its integration into human society aligns with the way knowledge is actually produced and sustained.

Our key conclusion is that the future of AI must not only be measured by its technical sophistication but by its ability to support and enhance the fundamental human prerogative of constructing and sharing meaning. By embracing phenomenology, constructivism, and socio-technical insights, we can move towards an AI that is not only computationally advanced but epistemically and socially attuned to the realities of human cognition and collaboration.

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