AI-DUCTION FOR ORGANIZATIONAL THEORY BUILDING: (HOW) CAN WE OVERCOME ONTOLOGICAL NEGLECT WITH AI?

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ABSTRACT

The field of management and organizational research is experiencing a significant transformation fueled by the integration of artificial intelligence (AI) technologies and the abundant data generated from diverse sources. While AI deployment presents opportunities for systematic and rigorous scholarly inquiry, it also poses an ontological challenge for theory building in understanding the organizational world. This paper addresses the need for actionable methodological guidance by exploring the intersection of AI and qualitative research in management and organizational studies. First, we review the utilization of natural language AI (NL-AI) techniques, focusing on three main forms: assistive AI, interpretive AI, and generative AI, and their role in research, intervention level and explorative quality. Second, we propose an AI-ductive model that integrates human interpretation with the capabilities of AI facilitating holistic data exploration for theory building and moving beyond the understanding of AI as a toolbox. This paper contributes to advancing the debate on how to foster knowledge generation in qualitative management and organizational research by leveraging AI attending to the hermeneutical circle and the intersection between AI and the researcher as co-producers of knowledge.

Keywords: artificial intelligence, hermeneutic circle, theory building, natural language AI

AI-DUCTION FOR ORGANIZATIONAL THEORY BUILDING: (HOW) CAN WE OVERCOME ONTOLOGICAL NEGLECT WITH AI?

Artificial intelligence (AI) technologies (including the utilization of machine learning methods and the development of natural language tools such as ChatGPT) is significantly transforming research (Antons, Breidbach, Joshi, & Salge, 2021; Tonidandel et al., 2018). The immense volume of data generated by human subjects through various sources such as devices, sensors, databases, and social media platforms (Tonidandel, King, & Cortina, 2018) are being used in diverse ways by researchers (Lee, Inceoglu, Hauser, & Greene, 2022; Sheng, Amankwah-Amoah, & Wang, 2017), highlighting their increasing significance in ensuring systematic, replicable, and rigorous scholarly inquiry. Moreover, the deployment of AI is also shedding light on the limitations of human researchers' capabilities (Leavitt, Schabram, Hariharan & Barnes, 2021). As a result, scholars are now contemplating the value of AI in supporting human researchers (Leavitt et al., 2021; Lindebaum & Ashraf, 2021). However, there is currently a lack of actionable methodological guidance on how to design, conduct, and interpret studies where AI technology can complement or work alongside researchers. While scholars continue to apply new AI techniques to organizational data, there is concern that they are doing so without adequately addressing ontological considerations that are important to organizational scholarship (Lindebaum & Ashraf, 2021).

Nowhere is this more so than with management and organizational research (Bhakoo et al., 2019), especially given the perennial debate between those that define science as prediction and claim for the centrality of replicability in the field (Aguinis & Solarino, 2019), and those researchers putting the focus on the importance of understanding (Gioia, Corley, & Hamilton, 2013) and research as bricolage (Pratt, Sonenshein & Feldman, 2022). The latest argue that different methods generate different knowledge about different aspects of that world, emphasizing that rigor and transparency should not be conflated with replicability (Pratt, Kaplan & Whittington, 2020; Sousa & Hendriks, 2006). Within this debate, it is acknowledged that AI methods can be used to generate information to construct theories about the world. However, this information may condition our experience of the world, which poses a significant challenge for theory building (Gioia, Corley, & Hamilton, 2013). Increasing voices claim that AI supported research only addresses a positivist or realist position (Lindebaum and Ashraf, 2021), focusing on science's task for prediction. This, they state, disregards the quests to explain social phenomena using interpretive approaches, incurring an ontological neglect (Lindebaum and Ashraf, 2021). Further, they postulate that the promises of AI to properly 'explain' and 'understand' social phenomena will require technological progress that – at this point in time – remains infeasible (Lindebaum & Ashraf, 2021).

As scholars continue to debate from different ontological perspectives, AI approaches - such as the use of natural language processing methods (NL-AI) -as seen in studies by Doldor, Wyatt and Silvester (2019) and Tonidandel et al. (2022) that refers to a more specific AI system that can understand and process human language - have emerged as a supplement to qualitative research processes, highlighting the ongoing disagreements. Adopting these approaches comes with the promise that delving deeply into the rich qualitative data, a bigger reach and more rigor can be guaranteed (Pandey & Pandey, 2019). However, there remains a lingering doubt whether, specifically, NL-AI is an appropriate approach that can be put to work for qualitative organizational studies (Langley & Simon, 1995; Lindebaum & Ashraf, 2021; Speer, 2021). In particular, regarding research in organizational settings, one of the main concerns raised about AI supported qualitative studies is the potential impact on theory building. In theory building, even though interpretation can be based on qualitative data that can be digitally produced or synthesized, and AI approaches can discern patterns and insights, a researcher's ontological assumptions often shape their analytical process (Gill, 2014).

Thus, at heart of this debate is the importance of interpretation of social phenomena in management and organizational settings (Laasch, Lindebaum & Caza, 2022; Pratt et al., 2020; Pratt et al. 2022), mostly referred to as hermeneutics. We argue that a careful examination of the concept of hermeneutics will enlighten this discussion (Gill, 2014). The principal idea underlying hermeneutics is the focus on the researcher's choices and judgement as interpretive moves. Indeed, interpretative scholars view the hermeneutical circle as the foundation of their analytical reasoning (Barrett, Powley, & Pearce, 2011). Although at the heart of the underlying debate, this perspective has not received sufficient attention in relation to AI use for research and theory development (Lindebaum & Ashraf, 2021). The worry is that without paying attention to hermeneutics, the claims of what AI can achieve for management and organizational theory building will continue to trivialize the complementary roles of AI and researchers. An increasing debate outside of management and organizational research, discusses the challenges of incorporating AI in research going as far as to consider whether AI tools qualify as co-authors (Walker, 2023). But, to date, there is a need to further our understanding of how AI, and in particular NL-AI, can support theory building, adopting perspectives rooted in hermeneutics including, inductive (Leavitt et al, 2021) and abductive traditions (e.g., Timmermans, 2012; Torasso, 1995).

Our paper, therefore, contributes to this discussion by creating a more nuanced view of an ongoing debate (which "forces" AI to the fore). We first, add to the growing number of contributions that explain how NL-AI is supporting qualitative organization and management research processes, by specifying three main forms of NL-AI: assistive AI, interpretive AI and generative AI and providing illustrative examples. We group the NL-AI by their explorative quality, intervention level and role in research, presenting a clear demarcation of NL-AI for use in organization and management research. Second, we contribute to the debate on the ontology of AI in organization and management research (Laasch, Lindebaum & Caza, 2022; Leavitt et al., 2021; Lindebaum & Ashraf, 2021). We address the criticism that AI approaches oversimplify research by solely emphasizing prediction and explanation (Lindebaum & Ashfrat, 2022). Third, we provide a map to show how NL-AI can become intertwined as coproducer of knowledge with qualitative researchers. With this map we show how to overcome some of the impediments for building theory based on the understanding of science as prediction. By focusing on induction and abduction processes (Agar, 2010; Mantere & Ketokivi, 2013), we demonstrate there is potential for theorizing with AI following what we call an AI-ductive process. AI-duction considers the "hermeneutics in the process" proposing a series of steps that can facilitate the exploration process for theory building in organization studies. We thus, develop a process model that provides the abilities to interpret data holistically provided by humans but incorporating the assistive, interpretative and generative possibilities of NL- AI. Overall, by situating the AI-duction model in the hermeneutic circle and maintaining a broader logic of research and theory generation, we aim to nuancing the understanding of NL-AI to prediction and explanation (Lindebaum & Ashfrat, 2022) and explore the role of NL-AI and researchers as intertwined and co-producers of knowledge.

ARTIFICIAL INTELLIGENCE FORMS IN MANAGEMENT AND ORGANIZATIONAL RESEARCH

This section reviews how AI and in particular, Natural Language AI (NL-AI) has been used in management and organizational research and why current development in NL-AI can help theory building. We refer to AI, in general, as the capability of machines in performing cognitive tasks and exhibiting intelligent behavior commonly associated with human intelligence and reasoning (Russell & Norvig, 2016). Indeed, AI is heralded as a new and revolutionary technology that will transform research practices, autonomously performing tasks and roles commonly thought to be the domain of human intelligence (Agrawal, Gans & Goldfarg, 2018). The claim is that AI has the potential to dramatically improve our ability to analyze, manipulate and understand complex data (Hannigan et al., 2019). When it comes to recognizing patterns in data, these technologies have been shown to achieve a significantly higher level of accuracy than its alternatives and is increasingly reshaping management and organizational research by operating, in the main, at the task level supplementing activities such as searches, detection, data collection and augmenting research (Leavitt et al, 2021).

NL-AI is a subfield of AI that involves using computers to understand and analyze human language. AI is often used as a general term for systems that exhibit human intelligence (Huang & Rust, 2020) while NL-AI refers to a more specific system that can understand and process human language. These systems can be used for translation and responses to queries. AI systems including NL-AI uses machine learning (ML) approaches. NL-AI uses ML to understand and process human language. Thus we refer to NL-AI throughout.

NL-AI can be distinguished from other AI approaches in that they are computational tools, methods, and techniques for analyzing, interpreting, and increasingly generating natural language (Manning & Schütze, 1999). Perhaps, most significantly, current NL-AI tools, such as ChatGPT, are now penetrating activities previously thought to be the preserve of humanly tasks such as creative written output and the evaluation of human-generated input (Christodoulou, 2023; Berg et al. 2023). Therefore, it is unsurprising scholars anticipate that researchers will eventually delegate reasoning authority to AI methods (von Krogh, 2018).

The diffusion of NL-AI technologies into management and organizational research is inspiring a range of new conversations exploring theoretical and methodological issues. Indeed, we are witnessing a gradual adoption of NL-AI-based research tools that are already engaging scholars in a constructive debate on how to leverage NL-AI-based tools for the benefit of the research field (Leavitt et al, 2021) such as Topic Modeling and ChatGPT. In particular, the concept of AI is raising intriguing questions related to research that requires intricate knowledge of methodologies and epistemology (Johnson et al., 2019). As such, scholars are examining what new opportunities there are for building and enhancing management and organizational theories at the intersection of NL-AI and organizational research. But even with these advances, it is still unclear whether [and how?] NL-AI can play a role in theory development and in theory-driven research (Leavitt et al, 2021).

In terms of qualitative research, NL-AI is playing an increasingly important role (Kobayashi, Mol, Berkers, Kismihók, & Den Hartog, 2018; Panday & Panday, 2019). NL-AI originated in the 1950s at the intersection of AI and linguistics and has since drawn from a variety of fields (Jurafsky & Martin; 2014; Kobayashi et al., 2018; Jurafsky & Martin; 2014). Today NL-AI sub field has advanced in an unprecedented way. For example, novel natural language models such as ChatGPT (OpenAI, 2022) have been developed to be analytically applied to tasks beyond abstract reasoning (Chatterjee & Dethlets, 2022) to interact in a humanly manner, for instance, having humanly conversations. The broad application of ChatGPT has been leveraged in a multitude of ways. Examples of such applications include generating descriptive or creative written output (Noy & Zhang, 2023), evaluating human-generated input (Christodoulou, 2023), aiding in ideation or creative problem solving (Mollick, 2022), and assisting with programming or coding tasks (Peng et al., 2023).

To classify different types of NL-AI, we borrow from the management and organizational research literature and studies investigating the use of NL-AI in qualitative research. We map them into the three main forms of NL-AI (i.e., assistive, interpretive, and generative), highlighting their purpose, their role in reasoning, their intervention level, explorative quality and their applications to qualitative research. Table 1 provides an overview and summary of three forms of AIs outlined above.

Insert Table 1 about here

Forms of NL-AI

Assistive AI. With the increasing computational power and efficiency of NL-AI, researchers have incorporated it into management and organizational research to handle tasks such as text analysis for large amounts of unstructured data (Kobayashi et al., 2018; Hickman et al., 2020). Particularly, Computer-Aided Text Analysis (CATA) has long been utilized in automating the quantification and coding of unstructured text data (Short et al., 2018; Short & Palmer, 2008). However, several basic forms of NL-AI employing natural language processing (NLP) to identify meaningful text segments, utilizing either a "bag-of-words" or a "bag-of-phrases" model (Ullah et al., 2016; Speer, 2021) are replacing many CATA systems and have been employed for computerized content analysis (e.g., McKenny, Short, & Payne, 2013; Short et al., 2010). These techniques enable automatic assignment of text strings or categories, facilitating fast and reliable classification, thereby offering potential for text and document analysis (Kobayashi et al., 2018). Despite the interest for qualitative exploration, these methods cannot discern the various meanings of a word or phrase based on its context in the text.

Another noteworthy form is topic modeling, a specific NL-AI technique. Topic modeling was developed to differentiate meanings by analyzing word usage in relation to other words. Topic modeling has gained popularity in management and organizational research, such as in the examination of organizational culture (Schmiedel et al., 2019; Doldor et al., 2019) and other applications (Pandey & Pandey, 2019). Finally, sentiment analysis techniques are now commonly used for exploration, classifying words based on their emotional tone (positive, negative, or neutral). This analysis provides a comprehensive understanding of elements such as the emotional nature of online conversations or the presence of hate speech (Castello et al., 2016).

CATA systems, topic modeling and sentiment analysis are used to observe a phenomenon in which constructs are already known and defined. The purpose of these forms of AI is therefore to further explore relationships and line of causations in the data. Applying these tools require human researchers to act on and react to the findings relaying on strong human intervention. Because the AI tools need to be assisted by human intervention, these tools are typically called assistive AI or supervised learning methods (Leavitt et al, 2021). Indeed, scholars, in general, say that assistive AI forms provide more substantial or grounded perspectives on the data and thus improve the quality of the concepts and categories used in the analysis. Assistive AI is used to analyze large amounts of unstructured text which do not scale (Bail 2014). They provide fixity to the process of finding analytical categories and help the researcher to finding convergence in the concepts, which is the process of identifying common themes, patterns, or agreements across different data points or sources.

In sum, assistive AI are explorative tools used to discover patterns in texts and to confirm trends. These patterns can then be used for further exploratory research. The example studies using assistive AI show the NL_AI is only used to automate the process of mining texts using probability and logics, humans are the ones defining the parameters and carrying it out the study and acting on the discovery by engaging in deductive reasoning (Puranam, Shrestha, He, & von Krogh, 2020).

Interpretive AI. Developments in NL-AI, beyond text mining, use statistical and probability models to analyze large datasets of text, allowing the system to learn patterns and associations between words and phrases. The rise in statistical language processing does not just involve data analysis (as shown above), but also involves the application of statistical methods to NL-AI (e.g., probabilistic parsing) (Klavans, J. L., & Resnik, P., 1996). The two are combined for learning from a corpus of data by deriving both syntactic rules and their probabilities (Chater, & Manning, 2006). This form of NL-AI is distinct from assistive AI in that it involves advanced methods and technologies that can connect, adapt and translate text (Putka et al., 2018). This form of AI uses algorithms to learn iteratively from text to find insightful information without being programmed where to look for a particular piece of information, suggesting some level of machine agency (Murray et al., 2021). This development saw serious work on speech and visual recognition. For example, NI-AI is used for translation, for tools such as Google Translate which can interpret and translate text from one language into another. We ascribe this as interpretive AI since AI is used to interpret a phenomenon. With interpretative AI the construct of the research are partially defined by AI through unsupervised learning. Interpretative NL-AI understands and learns from the data as phrases as though a human is reading a text. Whereas assistive AI relies on given inputs and desired outputs to construct a mapping between these, in the case of interpretive AI models are fit to observations with little prior knowledge of the output. This gives rise to the idea that novel interpretation autonomously emerges from the data (Janasik et al 2009, Putka et al., 2018), creating relative fixity in the constructs proposed by the AI-NL. In this way the human intervention is lower than in assistive AI and the researchers can use these forms of AI to explore new connections between existing questions and categories. For instance, Janasek (2009) argues that unsupervised learning methods, to some extent, can be seen as ‘‘research assistants,’’ tirelessly processing even large collections of data and creating meaningful generalized representations (Janasik, et al, 2009: 457). However, unsupervised learning is generally difficult and necessitates some form of indirect human feedback such as assuming that all sentences encountered in texts are positive examples of grammatical sentences in the language.

A key characteristic of interpretive AI is that, while the data passed to learning algorithms is extremely rich in internal structure (e.g., images, videos and text), the targets and rewards used for training are typically very sparse (e.g., the label ‘business’ referring to that particularly construct, or one or zero to denote success or failure in innovation). This implies that the learning process must consist of a deep understanding of the data itself and the underlying relationships. There are no clear-cut ways of avoiding misclassifications, which in turn leads to researchers often assuming interpretive AI generate output that cannot be explained (Somers et al, 2009).

Increasingly scholars are using this form of NL-AI in organizational research (e.g., Castelló & Lopez-Berzosa, 2023; Illia et al, 2023). For instance, interpretive AI has been applied to identify beliefs and emotions conveyed in human conversations (e.g., Castelló & Lopez-Berzosa, 2023) therefore augmenting the task of qualitative researchers. Other examples include Palocsay and White (2004) investigation of the links between various dimensions of culture and perceptions of justice.

Generative AI. Thanks to recent advances in computing and algorithmic processing, AI-based systems have equaled or even surpassed human performance in complex tasks such as image classification and chess-playing multiplayer games (Huang and Rust, 2018). These systems are based on deep learning and reinforcement learning AI approaches, i.e., they can self-improve automatically by learning from various inputs (see Minbashian, Bright & Bird, 2010). They have been called generative because they can analyze text or images to generate responses and produce content (Berg et al., 2023). emulating a wide range of human cognition such as text and artwork. Deep learning implies AI can act and adapt based on what has been learned. The implication is that the deeper the learning, the more AI demonstrates its discovery and inductive capabilities (Sejnowski 2018). Thus, it is claimed that with the extension of deep and reinforcement learning to NL-AI, it is possible to construct systems with a more flexible intelligence, implying that it can learn from experience (Young, Hazarika, Poria & Cambria, 2018). The deep and reinforcement learning methods used for NL-AI have varying degrees of learning ability, adaptivity, and connectivity but is typically represented by artificial neural networks (ANN) approaches (Somers & Casal, 2009). These are advanced pattern recognition algorithms based on the concept of "neural nets"—loosely patterned on the neurons in the brain (Hoffmann, 1998). AI researchers discovered that ANN with many layers—in some cases, thousands of layers; hence the name "deep neural nets" or "deep learning"—could surpass other AI methods used for image recognition (e.g., face recognition), transcription of speech, and translation (Jordan and Mitchell 2015). In contrast to assistive AI, which relies on methods akin to rational processes such as logic and probability, generative AI uses methods that appear to think humanly or machines that act humanly (Russell & Norvig 2010).

Generative AI approaches have been used in applications such as virtual assistants or chatbots, where they can understand natural language queries and generate responses in a human-like manner. It is designed to function more flexibly than the forms of AI mentioned earlier, requiring less or even no human intervention and showing a higher degree of agency than interpretive AI. For instance, ChatGPT (and other tools are available, such as Google Bard and You Chat) is an example of generative AI with transfer learning with an ability to continually interact conversationally with a human (Chatterjee & Dethlets, 2022; Berg et al 2023). ChatGPT uses ANN and reinforcement learning to understand human language and generate responses. As a result, ChatGPT can generate natural-sounding responses to various inputs, ranging from casual conversation to more complex topics such as news and science (Berg et al, 2023).

The broad application of generative AI in various domains has paved the way for these tools, such as ChatGPT, to be leveraged in a multitude of ways. Examples of such applications include generating descriptive or creative written output (Noy and Zhang, 2023), evaluating human-generated input (Christodoulou, 2023), aiding in ideation or creative problem solving (Mollick, 2022), and assisting with programming or coding tasks (Peng, Kalliamvakou, Cihon, & Demirer, 2023). As a result of this wide range of capabilities, these tools have been rapidly adopted and utilized across multiple industries (Berg et al, 2023).

In terms of research, progress is also being made in that generative NL-AI can identify beliefs and emotions showing that there is no need for surveys instruments (for example, using chatbots to conduct interviews (Reim et al., 2022)). Where the previous forms of AI provide practical principles for understanding experience yet fail to give principles for action selection (Silver et al. 2021), generative AI can work based on non-existing parameters and, as a result, generate un-fixity in the constructs of research and offer new associations and patterns looking for divergence in the research and creating further questions and surprises. While applications of generative AI in management and organizational research are still being developed, there is increasing recognition of its value for creativity and exploring uncharted paths (Berg et al., 2023; Mollick, 2022). Furthermore, it has been argued that generative AI has the potential for phenomenon-based theorizing (Von Krogh, 2018). However, despite exhibiting seemingly intelligent behavior, generative AI applications continue to face criticism for their inability to effectively simulate intuition and emotion (Raisch & Krakowski, 2021; Kemp, 2023). A prevailing perspective suggests that this limitation stems from the fact that these machines lack conscious states, minds, or subjective awareness (Azarian, 2016).

CHALLENGES FOR AI AND QUALITATIVE RESEARCH

Undoubtedly, qualitative research is a complex endeavor beset with numerous challenges involving the human reasoning at the heart of all forms of exploration and inference. Management and organizational scholarship in qualitative research have highlighted three traditions that constitute the main goal of inference: deduction through prediction, confirmation, and refutation; induction through generalization, and abduction through explanation (Mantere & Ketokivi, 2013). While human reasoning is performed by the cognitive (human) mind, some claim that it can be "abstracted from the mind" and computed into algorithms (e.g., Thagard, 1988). Reasoning by computation here is taken in the general sense, following explicit, logically coherent set of rules (Mantere & Ketokivi, 2013). However, the limits of the computational view become especially evident as one examines theory development. Theories are partially about the people who create them; indeed, Mintzberg expresses that 'we don't discover theory; we create it' (Minzberg, 2005: 357).

Theory development, particularly in qualitative research, is also conducted by cognitively distinctive researchers (Lipton, 2004; Stanovich, 1999) who not only engage in reasoning, i.e., who do not just compute; but also cognize, that is an activity that requires integration of cognitive and emotional processing (Thagard, 2007). The latter, it is claimed, is a crucial holistic component that cannot be implemented in algorithms (Fodor, 2001). However, AI-supported research is raising intriguing questions related to reasoning, cognitive and emotional processing in research (Johnson et al., 2019). Indeed, we have summarized a gradual adoption of AI-based research tools that are already engaging scholars in a constructive debate on leveraging AI-based tools to benefit the research field (Leavitt et al., 2021). Pertinent questions are how and where we can use these tools effectively (Simon & Newell, 1958). First, an optimistic perspective further emphasizes the need to envision a fruitful collaboration between researchers and AI-based tools (Seeber et al., 2020). This is on the back of developments in NL-AI in research which comes with the claim that the approaches will produce insights superior to those of researchers by discovering the "truth" from data (Leavitt et al., 2021) and text (Puranam, Shrestha, He, & von Krogh, 2020).

However, there is a less optimistic view to AI in serving qualitative exploration. As alluded to by Lindenbaum and Ashraf (2021), most of researchers using NL-AI in qualitative research may fall into an ontological neglect, that is, understanding qualitative research from a positivist position, focusing on science’s task for prediction, neglecting social science and its quests to explain social phenomena. Indeed, scholars who adhere to positivism or empiricism may have very different perspectives to those who prefer interpretive approaches (Van Maanen Sørensen & Mitchell, 2007). That is, there is a need for more regard for understanding (specifically social phenomena), especially in inductive traditions (Lindenbaum & Ashraf , 2021).

Much of the available scholarship on AI use for research appears siloed. In one corner, the researcher, as an interpreter, finds themselves within a setting that they mainly control, often black-boxing, the AI technology. For instance, assistive AI can assist the researcher by providing computational methods (e.g., topic models) for analyzing large volumes of textual data, extracting themes and concepts from interview transcripts that can then be examined further (Tonidandel et al., 2018). In another, AI is the interpreter as it autonomously deals with vast amounts of data, black-boxing the human and organizational side (Berente et al, 2021). For instance, interpretive AI is trained on large amounts of data to be able to identify and interpret metaphorical language, emotions and other forms of indirect communication (Castelló & Lopez-Berzosa, 2023).

Leavitt et al. (2021) make the case that AI have the potential to play complementary roles in moving our field beyond siloed domains and incremental theory. However, they are criticized with the argument that this is only described within the boundary of prediction and not interpretation (Lindebaum & Ashfrat, 2022). Others, such as Mallery (et al, 1990) say we must develop a "productive logic" (drawing on Heidegger, 1976: 10) toward understanding AI and its interplay with human activity. However, it is not explained how this can be done and in what manner AI can be used at the service of interpretation.

To address the criticism of the current ontological neglect of most AI supported research, we look at hermeneutics and the importance of the researcher's choices as interpretive moves. Hermeneutical analysis involves interpreting the meaning and significance of a text within its specific historical social and cultural context (Panday, 2002). This requires a deep understanding of language and cultural norms. Indeed, contemporary hermeneutic thought has expanded the meaning of the term to include organizational practices and institutions, economic and social structures, culture and cultural artefacts, and so on (Barrett et al., 2011), following in part from Ricoeur (1971), who argued that human action in general could be considered as text. The hermeneutic circle refers to the non-linear method of analysis and allows for continual exploration into interpretation (Prasad, 2002). This suggests that the researcher must continually move back and forth between the parts of the data and the whole to fully understand the meaning of the data (see Gadamer, 1975). This means understanding the relationship between the many components of the data being interpreted, while the interaction between the researcher and the data being interpreted is equally significant (Barrett et al., 2011). This process involves interpretation and re-interpretation, where the researcher uses their own pre-understandings to make sense of the data, but also allows the data to challenge and refine their interpretations (van Maanen, 1995). However, it is important to maintain a grounded perspective since the circle may exist indefinitely, and a definitive interpretation may never be reached. Therefore, it is also crucial for the researcher to understand when to step out of the circle and commit oneself to a satisfactory interpretation (Prasad, 2002).

In much the same way, NL-AI is suggested to be closely related to hermeneutics in that it involves the interpretation of language (see Boland, 1991) for an early discussion on text-mining). The hermeneutic circle can be seen as a useful framework for understanding the process of interpreting language in a NL-AI system. This requires an understanding of the context, the relationship between words, and the nuances of meaning that are often present in natural language. Just as with hermeneutics, the interpretation of language with NL-AI involves a back-and-forth process between the parts (individual words and phrases) and the whole (the overall meaning of the text). In addition, the interaction between the interpreter (the NL-AI system), the thing being interpreted (the human language) and the mind of the researcher which takes the final decisions.

Hermeneutics can be applied to the interpretation of NL-AI outputs, emphasizing the importance of contextual factors such as the social and cultural context in which the data was generated. However, NL-AI alone is not capable of conducting hermeneutical analysis without the input and interpretation of human researchers. NL-AI is limited to the data that has been inputted and the analysis may not account for the nuances and complexities of language and culture that require human interpreting and understanding. Therefore, we suggest, following others (Garbuio, 2019), that there is a need to further our understanding of how AI can support theory building/creation adopting perspectives rooted in hermeneutics including, inductive (Leavitt et al, 2021) and abductive traditions (e.g. Timmermans, 2012; Torasso, 1995). The question is whether and how the combination of NL-AI and human researcher can ensure the most comprehensive and accurate hermeneutic analysis as possible. For this then, it is important to build on Janisik et al.'s (2009) claim that AI can improve inference quality within qualitative research by showing that it is justified to think of AI approaches as "semi-participants" in an ongoing process of interpretation rather than as a mere steppingstone on the road toward objectivity. But, conceiving NL-AI as an understanding and explanation machine to collaborate with is difficult, in that interpretation is always situated within a context. That is hermeneutics requires the ability to draw on context and generate understanding that sustains coherence with that context. What stands for interpretation for AI within a context is vital for researchers to understand. Thus, for a long time, scholars have argued for "the reformulation and refinement of ideas about both hermeneutics and AI" (Mallery et al., 1990). To answer that call, we propose a model that integrates different forms of AI, and the different modes of inductive and abductive reasoning, in the hermeneutic circle, focusing on the AI capacity of exploration.

A MODEL OF AI-DUCTIVE THEORY CREATION

Our central proposition is to define AI-ductive theory creation model in which NL-AI plays a central role. Following the hermeneutic circle of research, AI-Duction is as a non-linear, cyclical process setting a path of observation based on the understanding of what is surprising or different from expected and evaluating ideas (intuitions or hunches) (Saetre & Van de Ven, 2021). We argue that AI-ductive theory creation is not only a process of reasoning by computation (Mantere, 2013) or a flash of inspiration or just cognition (Leavit et al. 2021) but is a process of sensemaking (Weick, 1995), involving hermeneutics. The hermeneutics circle approach facilitates qualitative judgment calls, which are made in conjunction with AI approaches. We describe five steps that may recur to make sense of complex phenomena, especially in management and organizational research: 1) Setting the context and exploring ideas; 2) Promoting variation; 3) Looking for un-explored relations; 4) Finding convergence; 5) Evaluating the ideas. We argue that each of these steps are performed through judgment calls supported by traditional qualitative approaches but also by AI forms such as assistive, interpretative or generative.

These five steps and the corresponding forms of AI are useful in articulating the moves of reasoning in research and in providing a discipline for enhancing the quality and novelty of theory creation as shown in Figure 1. First, by setting the scene for exploration scholars' cognitive attention is focused on a particular community or a particular theme that is triggered by exposure to diverse experiences, familiarity with the literature or engagement with colleagues or the general phenomena. As in any exploratory research, setting the context allows the researcher to set an observational space. Interpretive AI will support this step in defining communities and configure new data samples where AI can operate as a radar of ideas that sets the scope of the phenomenon. Exploring ideas can articulate certain exploration calls, defining what is absent or what is different from expected. Interpretive AI will support the researchers to observe anomalies as well as to spot new ideas. Second, promoting variation involves unfixing the ideas but also fixing them into categories to create alternative explanations and multiple configurations. Interpretative AI will support the exploration a vast array of text or data and helping to define novel patterns. Third, looking for unexplored relations consists in looking for breakthrough ideas. Generative AI can potentiate the observation of variation and promote new unfixity that would lead to new idea generation. AI operates in this step as an amplifier, expanding the scope and reach of the research. Fourth, finding convergence is the process of connecting the ideas. Interpretative AI tools can help evaluate functioning as a convergence process. Fifth, a final step in the exploration and evaluation of ideas typically can imply the conversion of the most plausible ideas for subsequent theory construction. Assistive AI tools are utilized to test ideas, create prediction models and serve as validation tools (e.g., Kobayashi et al., 2018).

Although discussed in sequence, the five steps do not necessarily unfold in a linear progression; instead, they can occur in iterative, highly dynamic, and reflexive ways. For example, after promoting variation researchers might choose to go directly to finding convergence when a satisfactory level constructs and ideas might be generated. Also, looking for unexplored relations through generative NL-AI might lead the researcher to have to define a completely new setting and explore the new ideas generated in step 3. The creation of organization and management theories often entails a centrifugal force that propels the reasoning process towards becoming a sensemaking process. In this process, AI, in conjunction with a collective of individuals, intervenes to generate ideas, refine constructs and validating them. We now present the five steps of AI-Duction.

Insert Figure 1 about here

Step 1: Setting the context and exploring ideas

To set the context is to define the research players, the key question, and the phenomenon investigated as well as briefly presenting the underlaying conditions of research. Since research is inherently about the understanding of a community or a phenomenon, setting the context will help to define the subject of research. This phase is common to most explorative research that is open to discovery. Even early works of anthropologists such as Malinowski argued about the importance of pitching a tent in the native village (Malinowski, 1932) as a form to delineating the scope of research while being open to be surprised by the observation.

Two characteristics define setting the context step, especially in projects with big amount of data, for example online communities: Firstly, there is the need to reduce complexity in setting the scope. Here the researcher can define specific communities or narrow down the topics of conservation to be analyzed. Secondly, due to constant performativity of AI in generating new data (Levina & Arriaga 2014; Julien 2015; Ignatow & Robinson 2017; Romele & Rodighiero 2020; Harraca, Castello & Gawer, 2023) it becomes crucial for the researcher to consider how the social and technological structures supported by AI impact research practices. These structures may either reify or challenge the existing structures potentially altering and even conforming to the data being produced.

Interpretive AI tools employing probabilistic parsing models for unsupervised learning can establish coherent groups and communities sharing commonalities. This capability helps the researcher with the initial sampling exercise and can even discern a community of interest within a broader spectrum of exchanges. For example, Adams and Roscigno (2005) worked with NL-AI based on unsupervised learning in the study of the supremacist movement to get a first understanding of different communities. Castello et al (2022) utilized unsupervised AI tools to map the patterns of engagement and identify communities that confirmed the spread of disinformation regarding COVID vaccination. In all these cases, the researcher establishes the context by adopting a broad position based on profound insights coming from observation or previous literature. Also, the researcher can use advanced algorithms to reduce the dimensionality of a dataset and make it tractable for human understanding (e.g. visualizations of behavioral data).

The first step in the AI-ductive process also involves the exploration of the initial ideas. Exploring ideas involves articulating the exploration calls (Glaser & Strauss, 1967) to identify about what is absent or different from what is expected. The exploration of ideas requires of the researcher's judgement (Glaser & Strauss, 1967) typically based on information gathering activities such as direct observation, interviews enabling researchers to situate the context in which the anomaly takes place. Here the researcher pays attention to the environmental stimuli and formulating ideas that might correspond to the observation of a new phenomenon or an anomaly (Saetre & Van de Ven, 2021). Ideas grounded in new phenomenon, or the observation of anomalies can be explored by way of grounding and diagnosing the phenomenon being examined (Saetre and van de Ven 2021). Interpretative AI can also play an important role in exploring ideas and spotting anomalies. Interpretative AI techniques can be used to provide a first understandings of a phenomenon and observe some anomalies. For instance, Castello and Lopez-Berzosa (2023) used interpretative AI tools analyzing the Twitter engagements between civil society and corporations on the issue of plastic pollution over 20 years to spot the importance of emotionality on the engagements. Assistive AI techniques can also be used at this point to confirm anomalies in the data or to further define the scope of the research. For example, sentiment analysis techniques have been used to define first understanding of emotionality in political preferences in social media communities (Ceron, Curini, Lacus and Porro, 2014). Along the same lines, Jiang, Yin and Liu (2019) studied the impact of entrepreneurs' emotions on funding performance using as first step scrutiny based on sentiment analysis.

However, the process of exploring ideas and detecting anomalies is not solely determined by the strength of the signal during the initial information gathering stage. It is also dependent on the sensitivity of the observer, who possesses "a prepared mind" (Saetre & Van de Ven, 2021: 688). It is therefore the judgment calls made by the researcher that will define the validity of the ideas based on the cues provided by the different forms of AI used.

Step 2: Promoting variation

Second, the process of generating new ideas improves when scholars create variation and promote pattern recognition. This involves fixing the ideas into categories to create alternative explanations and multiple configurations. At this juncture, as advocated by Locke, Golden-Biddle and Feldman (2008), embracing the continuous experience of doubt becomes a source of generative insights. The way to make this happen is, first, to understand that the idea is recurrent, that means that it exists with some regularity. Second, it is crucial to pursue multiple explanations and explore the various configurations inherent within the idea or anomaly. This connection between the discovery process, focused on origination, and the validation process, concerned with evaluation and justification (Kordig, 1978; Siegel, 1980), facilitates a comprehensive understanding. The generation of variation and pattern recognition creates possibilities and at the same time represents bounded choices carved out of possibility. The categories or hunches generated to represent variation will be lived codes (Locke et al. 2015) repeatedly revisited as codes and left open against more observations and against the researcher's developing understanding of what is happening in his or her field sites. Typically, in this step, the patterns of social action are not perfectly bounded but they run into each other in a certain messiness of codes that are revisionary (Locke et al. 2015).

Generating high quality categories involve creative thinking that may entail an extended period of brainstorming with others. Weick (1995) maintained that a greater number of diverse conjectures is more likely to produce better theory than a process that generates a small number of homogeneous conjectures. Most creative pursuits involve individuals collaborating to solve problems they cannot solve alone (Rouse, 2020). Collective creativity occurs when concepts emerge in people's minds through interacting with others (Rouse, 2020; Verganti, 2016). Some other techniques defined in the literature to create variation and develop a list of hunches in response to the anomaly typically involve idea creativity (Amabile, 1996), variations (Perry-Smith & Mannucci, 2017; Weick, 1995), sensemaking (Drazin, Glynn, & Kazanjian, 1999; Ford, 2000), recombination (Simonton, 2003), brainstorming (Rietzchel, Nijstad & Stroebe. 2007) and guessing (Paavola, 2005).

Beyond these collaborative qualitative methods, the use of AI in this step can also be generative of variation. This step can involve certain forms of interpretive AI, that can help to explore variation in vast array of text, the outputs of which helps researchers to see novel patterns in their data. For example, some Kaplan and Vakili (2015) explore the double-edge nature of recombination in breakthrough innovation by analyzing the text of US patents with an interpretive clustering technique that was able to generate variation in the different forms of grouping the patents previously unexplored.

Also, several forms of interpretive AI have learning ability, adaptivity, and connectivity (Somers and Casal, 2009). These are advanced pattern recognition algorithms capable of self-improve automatically by learning from various inputs (see Minbashian, Bright & Bird, 2010) and therefore present variation in a new form such as the identification of multiple forms of emotions or patterns that were not previously defined. In this line, Castello and Lopez-Berzosa (2021) used interpretative AI techniques to identify different type of emotions in Twitter and to which extent these emotions were playing a role in setting the agendas in plastic pollution.

Step 3: Looking for unexplored relations

Often, in organization theory, the topic of the study seems complex and ambiguous because it has multiple dimensions, involves different disciplines and stakeholder perspectives. When the scene has been created, the initial ideas have been explored and the exercise of promoting variation has been done, AI tools can help the researchers to explore beyond what is known. The process of generating novel ideas through AI involves an exercise of unfixing, that is the deliberate act of unfettering preconceived notions, allowing for the emergence of "breakthrough ideas" (Harvey, 2014). These ideas are typically related to innovation, diversity, and provocation (Harvey, 2014). Traditionally, breakthrough ideas have been though processes of creative thinking like paradoxical framing (Hargave & Van de Ven, 2017) and multiple stakeholder engagement. Generative AI techniques can be employed to navigate and explore the landscape surrounding a defined problem space, akin to the step of exploring variation. However, researchers can push the boundaries of surprise and leverage AI to facilitate the creation of experimental work, transcending conventional cycles of hypothesis generation. This approach explicitly aims to target areas of inquiry that surpass the limitations of mere relatedness. This step aims at what Leavitt et al (2021) call exploring grand theories. The speed of application and the combinatory capacity makes AI particularly suited to study for example in understanding the influence of unexpected exogenous shocks on established wisdom as for example in the studies of employing AI to understand the aftermath of 9/11 (Bail, 2012). It has also been used in overlapping in areas of inquire, for example to reconcile definitional concerns to related constructs and identify metalevel themes drawn from multiple areas of inquiry (Leavitt, et al. 2021: 764). For example, the use of interpretive AI helped researchers to study the emotions that provoked events and the relation of these emotions to reactions to the events (Baumeister, Bratslavsky, Finkenuaer, & Vohs, 2001). In these cases, NL-AI helped to overcome not only scientific field barriers but also language barriers and thereby increase the access to multidimensional data.

Step 4: Finding convergence

In finding convergence researchers aim at reducing variation, fixing meaning to some ideas, and finding relations between these ideas. Key to finding convergence is the capacity to select the ideas and variables that conform a more comprehensive understanding of the data. Idea convergence is a convergent decision-making process though which ideas are selected and refined (Saetre & Burn, 2020). However, creating convergence also entails defining the connections amongst the ideas which has also been considered integral part of securing idea novelty and usefulness (Harvey & Kou, 2013 in Saetre and Van de Ven). At this stage, Verganti (2016) argues about the importance of taking a critical stance. A critical stance involves creating tensions, discussing differences, reshuffling things to find a new order.

The use of interpretive AI approaches has been proved especially relevant in constructing the models supporting the connection between the different concepts. Also, in detecting the decline in the predictive power of the model over time. For example, through AI models, researchers in self-esteem recognized new patterns of parenting and pedagogical practices (Baumeister et al, 2005). By finding convergence researchers evaluated which ideas and which type of influences were particularly relevant to these ideas and created relations that could help others to find meaning to these relations.

Step 5: Evaluating ideas

Evaluating ideas is the basis for further narrowing the range of plausible ideas and explanations. Idea evaluation includes idea selection judgement (Patton, 1990). This will typically happen in a process of selection and comparison of the most plausible ideas for subsequent testing. The evaluation of ideas is the ultimate form of fixity in which ideas are defined to be acceptable and generalizable. It is a process of convergence since it is the step where ideas are tested and refined (Saetre & Van de Ven, 2021). Yet, the evaluation process can also enrich idea exploration (in Step 1) by guiding and shaping creativity (Harvey & Kou, 2013) since it influences the criteria of evaluation that people attend to.

Assistive AI approaches such as prediction models can help researchers to confirm patterns and check for robustness of the data. At this point AI enables the testing of theory on novel and rich data. It can go beyond more traditional indicators and measures since it can deal with unconventional data that for example is too high-dimensional for standard estimation methods, including image and language information. Recent examples, of AI evaluating novel ideas in organization theory includes Choudhury, Wang, Carlson and Khanna (2019) use of assistive AI tools such evaluative prediction models to code video facial expression and explain CEO communication styles. Tonidandel and colleagues (2018) used qualitative survey design and compared contexts with an assistive AI model to find how different context converge or diverge (Tonidandel et al., 2018). Interpretive AI approaches are also invaluable as they enable the precise capturing of theorized relationships between complex constructs that may have otherwise remained untested due to challenges of operationalization and measurement.

CONCLUSION

The increasing utilization of AI has led to extensive speculation on theory and knowledge building in management and organizational disciplines. While some attention has been given to the epistemological implications of AI in these fields (Leavitt et al., 2021), the broader impact of these emerging technologies on theory building remains largely unexplored, despite their growing prevalence in current research practices (Lindebaum & Ashraf, 2022; Johnson et al., 2019; Seeber et al., 2020). It has been argued that AI and ML can be used to test and refine theories, expand the range of phenomena that can be explained by theory, and support local, midrange and grand theory building (Leavitt et al. 2021). However, it is important to note that this position raises concerns about reducing theory-building primarily to prediction (Lindebaum & Ashraf, 2021) and an ontological neglect (Lindebaum & Ashfrat, 2022). Our paper focuses on addressing the ontological neglect by developing a model based on a "productive logic" of the hermeneutic circle for understanding AI, particularly the latest development of NL-AI, and its interaction with human reasoning forms of research. Our paper presents the AI-Duction model for building management and organizational theory, which demonstrates the potential interplay between NL-AI at different stages of research reasoning. Our focus goes beyond the mere role of AI in theory building to emphasize the crucial collaboration between researchers and NL-AI methods in theory development, following the hermeneutical circle. Scholars can view AI-Duction as an approach that enhances their ability to draw inferences from data and reach theoretical conclusions.

We contribute to the growing number of studies exploring how AI can be used to develop and validate qualitative research in management and organizational scholarship (Kobayashi et al., 2018; Pandey & Pandey, 2019; Speer, 2020). First, instead of solely classifying AI approaches based on researcher intervention, we propose classifying them into three forms: assistive, interpretive, and generative, based on their level of intervention, role in research, and explorative quality. We provide examples that demonstrate how each form of NL-AI can assist, interpret, or generate theory building. Assistive AI tools, with higher levels of intervention, help researchers confirm patterns and strengthen their assumptions. Interpretive AI involves low levels of human intervention and is used to explore new patterns, find connections, and learn interactively from data. Generative AI aims to augment human cognition with algorithms that require no intervention from researchers and can define new research questions and explore unexplored areas. By considering the "tolerance for surprise" of different forms of NL-AI approaches (Leavitt et al., 2021) and emphasizing their potential and exploratory nature, we highlight the distinct roles that different AI approaches can play in theory building in collaboration with the human, reinforcing the significance of achieving a "theory-method fit" in qualitative research (Gehman et al., 2018).

Second, we present a process model of AI-Duction. We define AI-Duction as a theory-building process that emphasizes the role of NL-AI in exploration, particularly in qualitative methods of management and organizational research. Our model enables researchers to view qualitative research as a hermeneutic circle rather than a singular approach (Gehman et al., 2018) or a toolbox (Leavitt et al., 2021). The model consists of five steps: setting the context and exploring ideas, promoting variation, looking for unexplored relations, and finding convergence. Each step is considered in relation to the hermeneutic relation between the researchers and NL-AI. We argue that AI-Duction theory creation is not solely a process of reasoning by computation or cognition but also a process of sensemaking involving qualitative judgment calls and AI approaches working together. Thus, by integrating AI approaches into the hermeneutic circle of theory exploration, we show how AI and researchers can interact productively to generate new knowledge. Our model contributes to the understanding of qualitative research as bricolage (Pratt, Sonenshein & Feldman, 2022) and challenges the artificial separation between induction, deduction, and abduction, and demonstrates the importance of maintaining a diverse range of research approaches (Bansal et al., 2018).

Third, we also contribute to the debate on the potential danger of placing AI at the centre of theory development, which could lead to an overemphasis on prediction while marginalizing the understanding and explanation of social phenomena. By situating the AI-Duction model in the hermeneutic circle and maintaining a broader logic of research and theory generation, we aim to nuancing the criticism that AI approaches reduce science to prediction and explanation (Lindebaum & Ashfrat, 2022). We recognize that AI technologies, in their current state, cannot fully capture subtle human cues or explain the reasons behind detecting/identifying patterns. However, by describing NL-AI within the hermeneutic circle, we enable researchers to understand the potential of prediction and exploration when integrating AI into research as well as the potential for an intertwined role of NL-AI and researchers in knowledge production. We aim to include the technological progress led by NL-AI in the reflection process of developing exploratory research without undermining deductive traditions. While advocating for the importance of introducing AI in exploratory research, we acknowledge the danger of conflating logics between qualitative and quantitative research. The broad pursuit of AI possibilities may lead to a transformation of substantive rationality into formal rationality through formalization (Lindebaum & Ashaf, 2021). We propose a process that involves going in and out of human judgment, where AI cannot substitute humans but can complement them when necessary. This approach opens opportunities for dialogue between qualitative and quantitative paradigms.

Finally, we acknowledge the ethical considerations that arise with the utilization of AI in research. Questions about responsible data use, algorithmic bias, and the consequences of automated decision-making must be critically examined as AI-Duction expands the possibilities for generating insights and constructing theories. Researchers also need to adapt and develop new skills to effectively collaborate with NL-AI systems, ensuring appropriate data interpretation and maintaining a comprehensive understanding of the research process. Ongoing exploration of best practices and methodologies for conducting research in the context of AI-Duction is necessary.

In conclusion, the AI-Duction model leverages the interplay between AI and human reasoning, carrying significant implications for research. It prompts critical examination of ethical considerations and highlights the evolving role of researchers in the era of NL-AI-driven theory building. We contribute to the understanding of theory building in the context of NL-AI and emphasize the importance of maintaining diversity in research approaches. By situating the AI-Duction model within the hermeneutic circle, we overcome the potential reduction of science to prediction and explanation, while acknowledging the need to navigate the distinct logics of qualitative and quantitative research.

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TABLES AND FIGURES

TABLE 1: Forms of NL-AI for Exploration and Examples

Form of NL AI	**Purpose**	**Role in research**	**Intervention level**	**Explorative quality**	**Selected Example Studies**
Assistive	-AI is used to observe phenomena in which constructs are already known and well defined. -The purpose is to further explore the relationships and line of causation in the data.	-This form confirms patterns by leveraging repeated observations to establish relationships between categories, themes, or topics. It can also identify likely candidates for new themes. -It can explore all potential categories and help the user develop theories around unexplained phenomena, or systematically eliminate unlikely themes.	-Existing categories are used to define the parameters for analysis. -This form is typified by supervised learning methods and relies on strong human intervention. -Techniques used are probability-based topic modeling.	-Helps to define fixity by defining the analytical categories and finding convergence, identifying common themes, patterns, or agreements across different data sources.	Schmeidal, Müller & Vom Brocke, 2019 Crowston, K., Allen, E. E., & Heckman, R., 2012 Tonidandel King & Cortina, 2018 Kobayashi, Mol, Berkers, Kismihók, & Den Hartog, 2018 He, Puranam, Shrestha, & von Krogh, 2020
Interpretative	-AI is used to interpret phenomena. -The purpose is to explain or clarify concepts when researchers have a partial understanding of the phenomena.	-This form uses pattern recognition techniques to autonomously examine underlying structures in complex or multidimensional data, allowing for the identification of connections. -These techniques involve iterative learning from data, similar to how qualitative researchers search for extreme cases and work inward from the periphery to explain emerging organizational phenomena.	-Characterized as unsupervised learning. The algorithm operates independently without a specified objective or user support, allowing it to explore unlabelled data and extract hidden patterns and structures. -It primarily serves inductive purposes by uncovering previously unknown factor structures or patterns. -Techniques are called self-learning and are typically facilitated through the use of Artificial Neural Networks (ANN).	-Helps to ensure reliability through relative fixity by defining categories that are relatively stable. -It is used to explore new connections between existing questions and new categories.	Palocsay & White, 2004 Somers & Casal, 2009 Pandey & Pandey, 2019 Janasik, Honkela & Brunn, 2009 Castello & Lopez-Berzosa, 2023

Generative	-AI is used to learn from phenomena. -The purpose is to automatically generate summaries or abstracts of qualitative data, extracting key insights or themes, identifying patterns or relationships within the data.	-This form uses generative methods with goal-oriented techniques to identify and understand the underlying patterns that exist within the data. -It can identify causes and effects, exploring the relationships and potential influences between different variables or factors. Transfer learning is employed, where the final layers of training are left unspecified, allowing for the application of previously learned knowledge to new categories or contexts.	-It focuses on non-existing knowledge of parameters. It observes the environment, makes choices, and is rewarded or penalized accordingly. -The rules constructed by the algorithm to fit the data are emergent and multiplex.	-Helps to explore unfixity – or the absence of predetermined categories- by exploring the differences, discrepancies, or divergent viewpoints within the data or among researchers. -Promotes surprises and the challenge of preconceived notions. It invites researchers to reconsider their assumptions, helping them to defines the new questions.	Baumeister, Bratslavsky, Finkenauer & Vohs, 2001 Bail, 2014

FIGURE 1: Model of AI-duction