Does the use of LLM in qualitative social research contribute to understanding?

The statement that large-scale language models (LLMs) imitate but do not explain dialogues is central to this question. LLMs are capable of replicating the contingency and opacity of dialogues because they are based on the statistical analysis of vast amounts of text and calculate probabilities for the sequence of words and sentences. They can generate convincingly human-sounding dialogues and even identify patterns in qualitative data.

When qualitative social researchers outsource their work to LLMs, this can significantly increase efficiency in data processing and pattern recognition. LLMs can quickly search large volumes of transcripts, cluster themes, or suggest initial category systems.

However, this does not directly contribute to the deeper *Understand* in the sense of qualitative social research, for the following reasons:

- Imitation vs. Explanation:LLMs are essentially imitation machines. They reproduce
 existing patterns without Understanding the underlying social meanings, motivations,
 contexts, or intentional actions of the actors. The "why" or "how" of social
 phenomena, which qualitative research aims to understand, remains inaccessible to
 ITM
- Opacity of the LLM: The functioning of LLMs is itself highly opaque ("black box"). While they produce results, the path to them is not transparent or comprehensible to the researcher in terms of human interpretation.
- Lack of critical reflection: Qualitative social research requires the researcher to critically reflect on their own assumptions, the research process, and the social implications of the results. LLMs cannot provide this level of reflection.
- Contingency of LLM results: Although LLMs can mimic contingency in dialogues, their own results are contingent with respect to the training data and algorithms, which limits the generalizability and theoretical foundation of their "insights."

The use of LLM can be a**valuable tool**to prepare, structure, and support qualitative analysis by automating certain tasks and offering new perspectives on the data. However, the actual understanding remains the domain of the human researcher, who must interpret, contextualize, and theoretically classify the patterns generated by LLM. Without this human interpretation, the results of LLM remain merely a complicated form of pattern recognition.

Comparison with Algorithmic Recursive Sequence Analysis (ARS) and whether its results are more explanatory:

Algorithmic Recursive Sequence Analysis 2.0 (ARS 2.0), as described in the uploaded documents, is fundamentally different from LLM and can be considered as **rather explanatory model**be considered.

Comparison points:

• Focus on grammars: ARS 2.0 aims to provide aformal, probabilistic grammar from sequential data (e.g., sales conversations). A grammar is, by definition, an explanatory model because it defines the rules and structures that enable the generation of valid sequences. It provides an explicit model of the underlying

- communication structure. LLMs, on the other hand, do not learn explicit grammars in the classical sense, but rather statistical probabilities for token sequences.
- Transparency and traceability: The ARS 2.0 methodology is transparent and
 comprehensible. The steps of data preparation, symbol assignment, grammar
 induction, simulation, and statistical validation are explicitly defined. The induced
 grammar itself is an interpretable result that serves as a hypothesis about the
 structure of communication. In contrast, the internal workings and decision-making of
 an LLM are opaque to the user.
- Hypothesis generation and testing: ARS 2.0 works by generating hypotheses about the structure of interactions, which are then formalized using the induced grammar and statistically tested by comparison with empirical data (e.g., frequency distributions, correlation analyses). This corresponds to a scientific approach to explanation.
- Generative ability as an explanation: The ability of the induced grammar to
 generate artificial sequences that are similar to the empirical data is an indication of
 its explanatory power. If the grammar can successfully reproduce the observed
 patterns, this indicates that it has "understood" the rules of dialogue—not in the
 human sense, but as a formal model.
- Qualitative and quantitative connection: ARS 2.0 combines qualitative insights (e.g., categorization of conversational contributions) with quantitative methods (probabilistic rules, statistical tests) to create a robust and explanatory model.

Conclusion:

While LLM can impressively imitate dialogues without explaining the underlying mechanisms, Algorithmic Recursive Sequence Analysis 2.0 offers aexplicitly explanatory modelin the form of a formal grammar. This grammar reveals the rules according to which dialogues are constructed and allows hypotheses about these structures to be generated and statistically validated. In this sense, ARS 2.0 contributes directly toUnderstanding the structure and dynamics of dialogues by providing a transparent and testable explanatory model that goes beyond mere imitation.