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AI in the Research Process

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Abstract

Artificial intelligence (AI) is increasingly being integrated into knowledge-intensive activities that have traditionally been the domain of human researchers. While prior studies have examined the impact of AI on education, organizational decision-making, and knowledge work, limited research has systematically investigated how AI affects the research process itself. This paper addresses this gap by developing a theory-building framework that examines the extent to which AI can augment, automate, or replace activities across the research lifecycle. Building on the research process articulated by Sarker et al. (2013), the study decomposes the research process into eighteen discrete steps. Each step is evaluated across four dimensions: activities that remain inherently human, activities AI can perform today, activities AI is likely to perform within one to three years, and activities that may become feasible beyond three years. Using an exploratory, inductive theory-building approach that emphasizes pattern recognition, we produce a heat map that visualizes the evolving division of labor between human researchers and AI systems. The findings suggest that AI already demonstrates substantial capability in information processing, synthesis, coding, and writing support, while activities requiring contextual understanding, trust building, reflexivity, and theory development remain predominantly human-centered. The resulting heat map functions as a theory-building artifact that explains current patterns of AI adoption in research and provides directional predictions regarding the future evolution of scholarly research.

Keywords: Artificial Intelligence, Research Process, Generative AI in Research

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1. INTRODUCTION

For Information Systems (IS) educators, the current AI revolution is not merely an external disruption but a core disciplinary challenge. For the first time, the technologies we study are beginning to encroach on the very activities that define us as researchers from formulating questions, to analyzing data, and constructing theory. This is not simply a matter of new tools improving efficiency. It represents a potential reconfiguration of the intellectual division of labor between humans and machines. If AI systems can increasingly perform tasks once considered central to scholarly expertise, then the nature of research itself, and therefore the role of the researcher, must be reconsidered. Yet, despite widespread discussion of AI's capabilities, there has been little systematic effort to examine how these capabilities map onto the research process as a whole. Which elements of research are being automated, which remain resistant, and where are the boundaries shifting? This paper addresses these questions by decomposing the research process into discrete steps and evaluating the extent to which each can be performed by AI across multiple time horizons. In doing so, it advances a theory-building perspective on the transformation of research in the age of AI, challenging long-held assumptions about what it means to generate knowledge.

This study adopts an exploratory, inductive research design (Eisenhardt, 1989; Thomas, 2006) to examine how advances in artificial intelligence are reshaping the research process. Rather than focusing on the application of AI within a single stage of inquiry, this study takes a process-oriented perspective by systematically mapping AI capabilities onto established stages of the research process as articulated in prior IS research (e.g., Sarker et al., 2013). The objective is not to test predefined hypotheses, but to develop a structured understanding of where and how AI currently augments, partially substitutes, or is unlikely to replace human research activities. This approach is consistent with traditions of nascent theory development (Weick, 1995) and inductive inquiry in interpretive information systems research (Klein & Myers, 1999; Walsham, 1995), where the goal is to generate conceptual insights grounded in emerging phenomena. In this case, the phenomenon of interest is the evolving division of labor between human researchers and AI systems across the research lifecycle.

Prior research (e.g., Felten, et al., 2021 and 2023) suggests that university faculty are among the professional groups most exposed to disruption from artificial intelligence (AI). We argue that AI constitutes a disruptive general-purpose technology with the potential to significantly reshape the roles and responsibilities of business school faculty, as well as the dynamics of academic journals. This paper examines both the current and anticipated effects of AI on faculty research and considers broader implications for knowledge creation, the market for business scholarship, and the academic labor market.

2. LITERATURE REVIEW

The rapid emergence of artificial intelligence has generated significant interest within the Information Systems (IS) education community, particularly regarding its implications for teaching, learning, and curriculum design. Journals such as the *Journal of Information Systems Education (JISE)* and *Information Systems Education Journal (ISEDJ)* have increasingly documented how AI tools are being incorporated into classroom settings, reshaping pedagogical practices and student expectations (e.g. Kakhki, et al., 2024; Gimpel, et al., 2025; Zhong & Kim 2024; Firth, et al., 2024). Prior work has examined the use of AI for coding assistance, writing support, and problem-solving, highlighting both opportunities for enhanced learning and concerns regarding academic integrity and skill erosion. Collectively, this stream of research positions AI as a transformative educational technology, but largely treats it as a tool to support learning outcomes rather than as a force that fundamentally alters the nature of scholarly work itself.

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Parallel to these developments, the broader IS research literature has explored AI as a general-purpose technology with far-reaching organizational and cognitive implications. Foundational work has emphasized the ways in which AI reshapes decision-making, knowledge work, and the distribution of expertise (Burton-Jones, et al., 2020; Faraj, et al., 2018). These studies highlight an emerging "augmentation–automation" dynamic (Raisch & Krakowski, 2021), in which AI systems increasingly perform tasks previously reserved for human experts while simultaneously enabling new forms of collaboration between humans and intelligent systems. However, while this literature provides important insights into the changing nature of work, it has not explicitly examined how these dynamics translate to the research process itself.

Within the IS methodology literature, prior work has articulated the research process as a structured yet iterative set of activities involving problem formulation, data generation, analysis, and theorizing (e.g., Sarker et al., 2013; Klein & Myers, 1999; Walsham, 1995). These frameworks emphasize that research is not merely a sequence of technical steps, but a socially and cognitively embedded process requiring judgment, reflexivity, and contextual understanding. More recent discussions in outlets such as *Communications of the Association for Information Systems (CAIS)* have begun to reflect on the implications of digital tools and automation for research practices **(**Recker, 2026)**,** yet these discussions remain largely conceptual and do not provide a systematic breakdown of how emerging AI capabilities intersect with specific stages of the research lifecycle.

Taken together, these streams of literature reveal a critical gap. While IS education research (e.g., JISE, ISEDJ) has focused on how AI affects student learning, and top-tier IS journals have examined how AI transforms organizational work, there has been limited effort to integrate these perspectives into a coherent understanding of how AI impacts the research process itself. In particular, there is a lack of fine-grained, process-level analysis that maps AI capabilities onto the discrete activities that constitute scholarly inquiry. Addressing this gap, the present study develops a structured, step-level framework of the research process and evaluates the extent to which each step can be performed by AI across different time horizons. In doing so, it contributes to both IS education and IS research by reframing AI not only as a pedagogical tool or organizational technology, but as a force that is actively reshaping the production of knowledge.

3. METHOD

Methodologically, the analysis involves constructing a comparative framework that categorizes research activities according to the extent to which they can be performed by AI at present and over anticipated future time horizons. These categorizations are informed by an integration of prior literature on research methods and contemporary research on AI capabilities and limitations. Consistent with an inductive and interpretive approach, the analysis emphasizes pattern identification, conceptual differentiation, and thematic synthesis rather than statistical inference.

We present a heat map, which provides a visual tool that identifies patterns and trends in data. Specifically, we use a heat map for patterns to emerge in the distribution of AI capabilities across the research process and to make visible the shifting boundaries between human and machine contributions. The aim is not to establish causal relationships, but to provide a theoretically informed framework that can guide future empirical investigation and theory development regarding AI's role in scholarly research.

This paper adopts an exploratory, inductive research design (Eisenhardt, 1989; Thomas, 2006) to examine how advances in artificial intelligence are reshaping the research process. As a foundation, we draw on the process model articulated by Sarker et al. (2013), which provides a widely recognized synthesis of the activities involved in conducting rigorous research in information systems. While Sarker et al. (2013) present these activities at a relatively aggregated level, the present study extends this framework by decomposing the research process into a more granular set of eighteen (18) distinct steps. This elaboration is necessary to enable a more precise mapping of AI capabilities onto specific research activities. For each stage, we assess AI's present capabilities, forecast its likely progress in a one to three-year time horizon, and anticipate developments over a four-year horizon and beyond.

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The expansion from Sarker et al.'s (2013) seven activities to eighteen distinct steps was conducted through an interpretive decomposition of the stages outlined by Sarker et al. (2013), supplemented by established methodological literature (e.g., Klein & Myers, 1999; Walsham, 1995; Gioia et al., 2013). In particular, broader phases such as data collection, analysis, and theorizing were decomposed into their fundamental activities, including problem identification, literature immersion, research design, data generation, coding, interpretation, construct development, and theoretical articulation. This resulted in the following 18-step representation of the research process: (1) identifying the research problem or motivation, (2) understanding the theoretical background and immersing in the literature, (3) framing research questions, (4) selecting the research approach and methodology, (5) gaining access to the research site, (6) building trust and rapport with participants, (7) designing data collection instruments, (8) conducting interviews or observations, (9) recording and transcribing data, (10) initial coding, (11) pattern identification and relationship analysis, (12) iterative data analysis and interpretation, (13) developing constructs or concepts, (14) building theoretical relationships, (15) ensuring rigor (e.g., validity, reliability, triangulation), (16) reflexivity (researcher positionality and bias awareness), (17) writing the narrative and articulating the theoretical contribution, and (18) positioning the contribution within the existing literature.

This more granular representation serves as the analytical backbone for the study. Each step is treated as a unit of analysis and evaluated in terms of the extent to which it can be performed by AI systems across different temporal horizons (current capabilities, near-term development, and longer-term potential). The classification of AI capability at each step is informed by an integration of prior research on AI and automation (e.g., Brynjolfsson & McAfee, 2017; Agrawal et al., 2018; Raisch & Krakowski, 2021) and methodological scholarship on the research process. Consistent with an inductive, theory-building approach (Gregor, 2006; Weick, 1995), the goal is not to produce definitive predictions, but to develop a structured conceptualization of the evolving division of labor between human researchers and AI systems.

Specifically, the decomposition is as follows (all headings below are adopted from Sarker et al., 2013).

Problem Formulation and Research Motivation is represented by:

1. Identifying the research problem or motivation
2. Understanding the theoretical background and literature immersion
3. Framing research questions

These steps collectively capture the early-stage activities through which a research domain is identified, situated within prior work, and translated into specific researchable questions.

Research Design and Planning represented by:

4. Selecting the research approach and methodology
5. Designing data collection instruments

These activities correspond to the structuring of the inquiry, including methodological choices and the development of instruments to guide data generation.

Gaining Access and Engaging the Research Context is represented by:

6. Gaining access to the research site or context
7. Building trust and rapport with participants

While often embedded within data collection discussions, Sarker et al. (2013) emphasize the importance of engagement with the research setting. These activities are explicitly separated to reflect their distinct social and relational nature.

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Data Collection is represented by:

8. Conducting interviews or observations
9. Recording and transcribing data

These steps capture the generation and preparation of research material for subsequent analysis.

Data Analysis is represented by:

10. Initial coding
11. Pattern identification and relationship analysis
12. Iterative data analysis and interpretation

This decomposition reflects the multi-stage and iterative nature of analysis, moving from initial categorization to more abstract pattern recognition and interpretation.

Theorizing and Concept Development is represented by:

13. Developing constructs or concepts
14. Building theoretical relationships

These steps align with the movement from empirical patterns to more abstract conceptual and relational formulations.

Ensuring Rigor and Reflexivity is represented by:

15. Ensuring rigor (e.g., validity, reliability, triangulation)
16. Reflexivity (researcher positionality and bias awareness)

Although treated as cross-cutting concerns in Sarker et al. (2013), these are modeled here as distinct analytical steps to reflect their central role in shaping research quality and interpretation.

Writing and Positioning Contributions is represented by:

17. Writing the narrative and articulating the theoretical contribution
18. Positioning the contribution within the existing literature

These final steps capture the articulation, communication, and scholarly positioning of the research contribution.

This explicit mapping ensures that the 18-step framework remains grounded in established methodological literature while providing the granularity necessary for the present study's analysis. By decomposing Sarker et al.'s (2013) higher-level categories into discrete, observable activities, the framework enables a more precise and systematic evaluation of how AI capabilities intersect with different components of the research process.

Following the development of the 18-step representation of the research process, the next stage of the analysis involved translating this process model into an evaluative framework capturing the role of AI across each step. This was accomplished through a structured, theory-informed assessment procedure. The resulting framework, operationalized through a heat map representation, functions as a theory-building artifact that makes visible patterns in how AI capabilities intersect with different stages of the research process.

Each step was evaluated across four dimensions reflecting the evolving capabilities of AI:

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1. Activities that are inherently human-only
2. Activities that AI can perform at present
3. Activities that AI is likely to perform within 1–3 years
4. Activities that AI may perform beyond a 3-year horizon

These dimensions reflect a temporal and capability-based view of automation and augmentation, consistent with prior work on AI and task substitution (Agrawal et al., 2018; Brynjolfsson & McAfee, 2017; Raisch & Krakowski, 2021).

For each step–dimension pair, a categorical assessment was assigned using a three-level coding scheme:

- **Green (🟢)**: Strong support in the literature that the AI capability exists (or clearly does not exist, in the case of human-only activities)
- **Yellow (🟡)**: Partial, emerging, or contested capability; AI can assist but not fully perform the activity
- **Red (🔴)**: No credible evidence that AI can perform the activity

The assignment of these values was informed by a structured review of two bodies of literature: 1) research methodology literature (e.g., Klein & Myers, 1999; Walsham, 1995; Gioia et al., 2013), used to characterize the epistemic, social, and interpretive requirements of each research step. 2) AI and automation literature (e.g., Dwivedi et al., 2023; van Dis et al., 2023; Floridi, & Chiriatti, 2020; Miller, 2019, Jarrahi, 2018), used to assess the current and anticipated capabilities of AI systems. For example, steps involving mechanical or text-processing tasks (e.g., transcription, initial coding) were coded as green, 🟢, under current AI capabilities based on strong empirical evidence of successful automation. In contrast, steps requiring social interaction, contextual judgment, or reflexivity (e.g., rapport building, problem framing) were coded as red, 🔴, or yellow, 🟡, due to well-documented limitations of AI in these domains. Appendix A gives more detailed citations to support this process.

The construction of the heat map followed an iterative, interpretive process:

1. Step characterization: Each of the 18 steps was first defined in terms of its underlying cognitive, social, and analytical requirements
2. Capability matching: AI capabilities were then matched to these requirements using evidence from the literature
3. Initial coding: A provisional color assignment was made for each cell
4. Cross-step comparison: Assignments were reviewed across all steps to ensure internal consistency
5. Refinement: Ambiguous cases were re-evaluated and assigned yellow, 🟡, where evidence was mixed or evolving

This process aligns with inductive theory-building approaches that emphasize pattern recognition and conceptual consistency rather than statistical reliability (Eisenhardt, 1989; Weick, 1995).

Characterizing each step into the underlying cognitive, social, and analytical requirements is shown in Table 1. This is a critical step, as it forms the basis to be able to do AI capability matching, which is shown later in the heatmap (see Table 2).

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Step	Underlying Cognitive Requirements	Social Requirements	Analytical Requirements
1. Identifying research problem / motivation	Recognizing important phenomena and gaps	Engagement with stakeholders and scholarly communities	Evaluating relevance and feasibility
2. Understanding theoretical background / literature immersion	Synthesizing and critiquing prior knowledge	Interpreting disciplinary conversations	Identifying patterns and conceptual relationships
3. Framing research questions	Translating broad ideas into focused questions	Refinement through collaboration and feedback	Assessing coherence and the level that the problem can be investigated
4. Selecting research approach / methodology	Abstract conceptual reasoning	Positioning within scholarly debates	Mapping constructs and relationships
5. Gaining access to field / site	Evaluating methodological fit	Negotiating institutional and collaborator expectations	Assessing rigor and methodological tradeoffs
6. Building trust / rapport with participants	Judging relevant cases and participants	Building access and trust with participants	Evaluating diversity and saturation
7. Designing data collection instruments (interview guides, protocols)	Understanding ethical principles and risks	Interacting with review boards and participants	Assessing risk-benefit tradeoffs
8. Conducting interviews / observations	Translating objectives into practical questions	Designing for rapport and communication sensitivity	Aligning instruments with constructs
9. Recording and transcribing data	Reflecting on procedural effectiveness	Gathering participant and peer feedback	Evaluating preliminary data quality
10. Initial coding (open coding)	Active listening and adaptive interpretation	Building trust and rapport	Monitoring data richness and saturation
11. Pattern identification and relationship analysis	Ensuring accuracy and contextual integrity	Protecting confidentiality	Structuring data for analysis
12. Iterative data analysis & interpretation	Interpreting and categorizing meaning	Collaborating on coding consistency	Systematic classification and abstraction
13. Developing constructs / concepts	Synthesizing broader patterns	Collaborative interpretation and peer debriefing	Clustering categories into themes
14. Building theoretical relationships	Connecting findings to theory and context	Reflexive dialogue with collaborators	Evaluating explanations and implications
15. Ensuring rigor (validity, reliability, triangulation)	Critically assessing credibility	Conducting member checks and peer review	Comparing evidence and triangulating findings
16. Reflexivity (researcher positionality, bias awareness)	Translating insights into coherent narratives	Responding to audience and coauthor expectations	Structuring arguments and evidence
17. Writing the narrative / theorizing contribution	Adapting findings for diverse audiences	Engaging academic and practitioner communities	Highlighting key contributions and implications

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18. Positioning contribution to literature	Reflecting on strengths and limitations	Learning through scholarly dialogue	Identifying future research directions

Table 1: Characterizing each step into the underlying cognitive, social, and analytical requirements

4. RESULTS

The resulting heat map is not intended as a measurement instrument but as a conceptual artifact that makes visible patterns in the distribution of AI capabilities across the research process. In line with Gregor (2006), it functions as a theory-building device that explains how different types of research activities vary in their susceptibility to AI augmentation. It also predicts directionally where AI capabilities are likely to expand. Finally, the heat map structures future inquiry by identifying boundary conditions between human and machine contributions. By systematically linking the 18-step process model to AI capability assessments, the heat map provides a coherent analytical bridge between established research methodology and emerging technological change.

Research Step	Human-only	AI can do now	AI in 1–3 yrs	AI after 3 yrs
	Present		Future	
1. Identifying research problem / motivation	🟢	🔴	🟡	🟡
2. Understanding theoretical background / literature immersion	🔴	🟢	🟢	🟢
3. Framing research questions	🟢	🟡	🟡	🟡
4. Selecting research approach / methodology	🟡	🟡	🟢	🟢
5. Gaining access to research site	🟢	🔴	🟡	🟡
6. Building trust / rapport with participants	🟢	🔴	🔴	🟡
7. Designing data collection instruments (interview guides, protocols)	🔴	🟢	🟢	🟢
8. Conducting interviews / observations	🟢	🔴	🟡	🟢
9. Recording and transcribing data	🔴	🟢	🟢	🟢
10. Initial coding (open coding)	🔴	🟢	🟢	🟢
11. Pattern identification and relationship analysis	🟡	🟡	🟢	🟢
12. Iterative data analysis & interpretation	🟡	🟡	🟡	🟢
13. Developing constructs / concepts	🟡	🟡	🟡	🟢
14. Building theoretical relationships	🟡	🟡	🟡	🟢
15. Ensuring rigor (validity, reliability, triangulation)	🟡	🟡	🟡	🟢
16. Reflexivity (researcher positionality, bias awareness)	🟢	🔴	🟡	🟡
17. Writing the narrative / theorizing contribution	🟡	🟡	🟢	🟢
18. Positioning contribution to literature	🟡	🟡	🟢	🟢

Where: 🟢 = clearly true, 🟡 = arguably true, 🔴 = not true

Table 2: Heat Map of AI impact across the 18 steps of the research process

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5. DISCUSSION

AI is already strong in literature processing, transcription and coding, and writing assistance. The rapid automation of mechanical and semi-cognitive tasks suggests a near-future shift where AI becomes the first-pass analyst. But AI is weak in problem origination, field access, and trust-building. Thus, there are bottlenecks in the shift from humans to AI. Frey & Osborne (2013:26) divide these bottlenecks into the following three categories: 1) perception and manipulation tasks which require the ability to handle irregular objects or navigate cluttered spaces with skill, 2) creative intelligence tasks which require the ability to produce clever and novel ideas in response to a given issue or scenario, as well as the ability to creatively problem-solve, 3) social intelligence tasks which require the ability to be aware of your own feelings and the feelings of others, as well as the ability to negotiate or persuade in a convincing manner and provide care.

For the research process, creative and social intelligence tasks are obviously the most relevant. This implies an interpretivist tradition of the information systems artifact, in this case, AI. Technology implementations and use are not purely technical phenomena. The same system can produce very different outcomes depending on organizational culture, power relations, user perceptions, and social practices. AI augments pattern detection, but is not yet capable of making meaning out of a particular situation that is influenced by power and politics.

As might be expected, social intelligence tasks are the areas of the research process most resistant to AI. Developing a sampling strategy requires cognitive judgment regarding which participants, cases, or contexts are most likely to provide meaningful insight. Researchers must reason about representativeness, theoretical saturation, and relevance to the research question. Social requirements are substantial because access often depends on trust-building, negotiation, and relationship management with gatekeepers or participants. Analytically, sampling involves evaluating inclusion criteria, diversity of perspectives, and the adequacy of cases for generating credible interpretations.

Socially, writing is shaped by audience expectations, disciplinary conventions, reviewer feedback, and coauthor collaboration. Analytically, the process involves selecting evidence, structuring arguments, integrating quotations or field notes, and presenting interpretations persuasively. At present, these are distinctly human attributes, but it is possible to imagine that in the 3+ year horizon, these might become something that AI can handle as well as a human.

The heat map suggests that very limited parts of the entire research process will remain human-only. This starts with identifying the research problem and providing a motivation for the study, along with framing the research questions. Whether a piece of research can make a contribution, be useful and interesting, requires high levels of social intelligence. Gaining access to the research site and building trust with the research participants is the next human-only part of the process. Again, this requires high levels of social intelligence. However, if the research does not require such human interaction to acquire the data, for instance, with stock prices, or sales data for a company, then this is moot. Finally, researcher reflexivity and bias are purely human characteristics, though this does seem like it is, and will be, an issue for AI as well. Reflexivity refers to the researcher's ongoing examination of how their own background, experiences, assumptions, values, and relationships may influence the research process and findings. Bias awareness involves recognizing that researchers inevitably bring assumptions and expectations into a study. This is certainly also applicable to AI, as there are well-known and documented issues with AI bias from training.

6. CONCLUSION

As humans get squeezed out of the research process, it begs the question as to what becomes of academics and academic institutions that focus on research. How should the reward and incentive, and indeed tenure, process change when much of the research is being conducted by AI? And what becomes of the research journals? How do the top-tier journals survive when AI can produce research at scale, quickly, and accurately? We do not have answers to these questions here, but this paper suggests that these are going to be very important questions to have answers to, and that the time for this is coming very quickly.

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7. AI USE DISCLOSURE

Consistent with the theme of this paper on AI use in the research process, the follow is our *AI Use Disclosure* for this paper: It is important that any output that has been assisted by artificial intelligence (AI) and presented for publication be done so ethically and responsibly. This paper has been written with the assistance of a University-provided subscription to the Chatgpt 5.2 model generative AI platform from OpenAI, configured as a RAG by our university's Career and Learning Center. We understand that generative AI can be used as a crutch to replace human effort, or instead as an assistant to do much of the repetitive and easily-duplicated work. We have only used generative AI as a tool to perform simple tasks that we could do ourselves, but the generative AI can do more efficiently. We asked the questions (prompts), had the generative AI do the work, and personally checked the output. Checking the output is the critical component of the responsible use of generative AI. Most important when AI has been used is that you can trust the final output that you are being given, in this case, the paper here. When we personally checked the output from generative AI, you can be assured that we are bringing in the decades of experience in working with, and researching on, information systems. It is these decades of experience, and our application of it to the generative AI output, that allows you to trust what is being said by us in this paper.

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APPENDIX A:

Citations supporting the determination of 🟢, 🟡, and 🔴 in the heat map

1. **Human-only (🟢 in column 1)** applies to (#1) problem motivation, (#3) framing research questions (#5) gaining research site access, (#6) building trust and rapport, (#8) conducting interviews, (#16) reflexivity.

These are human-only at present, because meaning is socially constructed, research depends on situated human interpretation, dealing with humans on complex matters requires a human, and reflexivity is inherently human and experiential.

Research supporting these conclusions includes Walsham, G. (1995) "*Interpretive case studies in IS research*"; Klein & Myers (1999) "*A set of principles for conducting and evaluating interpretive field studies*"; Orlikowski & Baroudi (1991), "*Studying information technology in organizations*"; and Myers & Newman (2007) "*The qualitative interview in IS research: Examining the craft*

2. **AI can clearly do this now (🟢 in column 2)** applies to (#2) literature review support, (#7) designing data collection instruments, (#9) recording and transcribing data, and (#10) initial coding.

That AI can clearly do this now is supported in the literature by Guetterman, et al., (2018) "*Augmenting qualitative text analysis with natural language processing*"; van Dis, et al. (2023) "*ChatGPT: five priorities for research*; Dwivedi, et al. (2023) "*So what if ChatGPT wrote it?*"; Liao, et al. (2020) "*Questioning the AI: informing design practices for explainable AI*"

3. **Arguably true / partially achievable by AI (🟡 in Column 2)** applies to (#3) framing the research questions, (#4) selecting the research approach and methodology, (#8) conducting interviews and making observations, (#11) pattern identification and relationship analysis, (#12) interpreting data, (#13) developing concepts and constructs, (#14) building theoretical relationships, (#15) ensuring rigor, (#17) writing the narrative and theorizing contribution, and (#18) position the contribution in the literature.

When it comes to AI as augmentation, and not replacement, key citations in the literature supporting the heat map selection of "Arguably true / partially achievable by AI" include Jarrahi, (2018) "Artificial intelligence and the future of work: human-AI symbiosis"; Raisch & Krakowski (2021) "*Artificial intelligence and management: the automation–augmentation paradox*".

When it comes to the limits of AI in interpretation, supporting literature includes Floridi & Chiriatti, 2020 "GPT-3: Its nature, scope, limits, and consequences. Minds and Machines"; Miller, 2019, "Explanation in artificial intelligence: Insights from the social sciences"; Suchman (2007) "Human–machine reconfigurations: Plans and situated actions"

When it comes to AI in theorizing, the following are supporting citations, Floridi & Chiriatti, 2020 "GPT-3: Its nature, scope, limits, and consequences. Minds and Machines"; Miller (2019) "*Explanation in artificial intelligence: Insights from the social sciences*"

4. **Not currently true that AI can do this (🔴 in Column 2)** applies to (#1) Identifying the research problem, (#5) gaining access to the research field or site, (#6) building trust and rapport with participants, (#8) conducting genuine interviews, and (#16) reflexivity

When it comes to autonomous fieldwork, AI has a lack of social presence and trust. This is supported in the literature by Gefen et al. (2003) "*Trust and TAM in online shopping: An integrated model*"; and Glikson & Woolley (2020) "*Human trust in artificial intelligence: Review of empirical research*".

When it comes to conducting interviews, AI has issues with embodiment and situated action. This is supported in the literature by Suchman (2007) "Human–machine reconfigurations: Plans and situated actions", and Jarrahi (2018) "Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making".

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As it relates to reflexivity, AI has limitations in understanding context. This is supported by Floridi & Chiriatti (2020) "*GPT-3: Its nature, scope, limits, and consequences*", and Bender, et al. (2021) "*On the dangers of stochastic parrots: Can language models be too big*?"

5. **For Column 3 (AI can do in 1-3 years) and Column 4 (AI will be able to do after 3 years),** we have taken the approach that 🔴 will become 🟡, and 🟡 will become 🟢, except where the activity is human-only. This follows the notion that there will be an expansion of AI into higher-order cognition, but a continued human dependence in social and ethical domains. The research supporting this includes Brynjolfsson & McAfee (2017) "Machine, platform, crowd: Harnessing our digital future"; Agrawal et al. (2018) "*Prediction Machines*"; Faraj, et al. (2018) "Working and organizing in the age of the learning algorithm", and Kaplan & Haenlein (2019). "Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence".

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