The Reading Group

April 25th, 2025

Self Introductions

- Alex Wang
- Econ of IS: look at the world from (efficient) resource allocation perspective

  with
  - Behavioral Complication (biases and the boundary of rational decision making)
  - Technology Innovation (systematical/structural changes)
- The generation, diffusion, and use of information
  - Economic rationale for this process – understanding the system
  - Economic/social impact of information technology (that changes the system)

The purpose

- Group empowerment through sharing and discussion
  - Academic research/innovation is (also) a social process
  - Doing (innovative) research is lonely
  - Learning is continuous and time-consuming
  - Similar minds produce joy
- Finding a company, having fun, boosting productivity, breaking free from the mundane

The format

- Hopefully, bi-week, offline focus with online access
- (Pushed voluntary) host of each session
  - Determine the content
  - Invite co-hosts, speakers
  - The “preparation package”
  - Deliver talks, tutoring workshops, and organize discussions

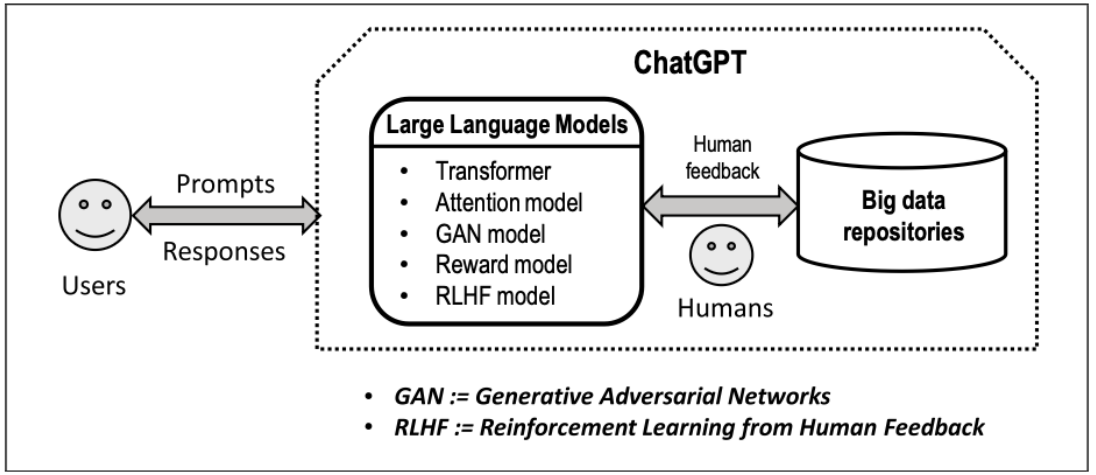
For doctoral students/faculty members

- Stay on the “important”
- Developing a systemic understanding of business research paradigms and processes on top of the learned “tricks.”
- Example:
  - The writing of an Introduction
    - Practical challenge (real and critical):
      Motivating user tipping in online PK sessions
    - The key to addressing the challenge, Y (legitimate and important):
      Enable vicarious experience can motivate engagement or Y is tipping
    - Knowledge gap – X->Y (knowledge gap and interesting):
      Does **competence balance** influence vicarious experience?
    - Practical Value: Directly changing X or facilitating X
    - Theoretical Value: Validation, Expansion, or Augmentation
  - The Role of SE, AE, and Reviewers

Agenda for Today – 1:15

- IS Research in the GenAI era [Half-baked, sorry]
  - Time to rethink about research (value chain) – A component view
  - Will there be a paradigm change?
    - Research process - AI-Human Hybrid
    - Research impact re-defined
- A recent work [Example]
  - Presented by Jingyuan Cai

What is GenAI and LLM?



- Generative Pre-trained Transformer

- LLM as aggregated unstructured data with an unstructured query language (prompt)
- Transformer and other neural networks as “models” of human information processing

- Knowledge generation

Storey, V. C., Yue, W. T., Zhao, J. L., & Lukyanenko, R. (2025). Generative Artificial Intelligence: Evolving technology, growing societal impact, and opportunities for information systems research. *Information Systems Frontiers*, 1-22.

The research topics

- Human-AI studies
  - AI versus Human
  - Reaction towards AI
- Disruption and Impact
- Human-machine Collaboration
- Dark-side of GenAI
  - Hallucination/misinformation/deception, privacy, IP rights, inequality, energy and environmental implications

Teutloff, O., Einsiedler, J., Kässi, O., Braesemann, F., Mishkin, P., & del Rio-Chanona, R. M. (2025). Winners and losers of generative AI: Early Evidence of Shifts in Freelancer Demand. *Journal of Economic Behavior & Organization*, 106845.

ABSTRACT

We examine how ChatGPT has changed the demand for freelancers in jobs where generative AI tools can act as substitutes or complements to human labor. Using BERTopic we partition job postings from a leading online freelancing platform into 116 fine-grained skill clusters and with GPT-4o we classify them as substitutable, complementary or unaffected by LLMs. Our analysis reveals that labor demand increased after the launch of ChatGPT, but only in skill clusters that were complementary to or unaffected by the AI tool. In contrast, demand for substitutable skills, such as writing and translation, decreased by 20–50% relative to the counterfactual trend, with the sharpest decline observed for short-term (1-3 week) jobs. Within complementary skill clusters, the results are mixed: demand for machine learning programming grew by 24%, and demand for AI-powered chatbot development nearly tripled, while demand for novice workers declined in general. This result suggests a shift toward more specialized expertise for freelancers rather than uniform growth across all complementary areas.

Demirci, O., Hannane, J., & Zhu, X. (2025). Who is AI replacing? The impact of generative AI on online freelancing platforms. *Management Science*.

Abstract. This paper studies the impact of generative artificial intelligence (AI) technologies on the demand for online freelancers using a large data set from a leading global freelancing platform. We identify the types of jobs that are more affected by generative AI and quantify the magnitude of the heterogeneous impact. Our findings indicate a 21% decrease in the number of job posts for automation-prone jobs related to writing and coding compared with jobs requiring manual-intensive skills within eight months after the introduction of ChatGPT. We show that the reduction in the number of job posts increases competition among freelancers, whereas the remaining automation-prone jobs are of greater complexity and offer higher pay. We also find that the introduction of image-generating AI technologies led to a 17% decrease in the number of job posts related to image creation. We use Google Trends to show that the more pronounced decline in the demand for freelancers within automation-prone jobs correlates with their higher public awareness of ChatGPT's substitutability.

History: Accepted by Duncan Simester, marketing.

Generative AI at Work

Erik Brynjolfsson, Danielle Li, Lindsey Raymond

We study the staggered introduction of a generative AI-based conversational assistant using data from 5,172 customer support agents. Access to AI assistance increases worker productivity, as measured by issues resolved per hour, by 15\% on average, with substantial heterogeneity across workers. Less experienced and lower-skilled workers improve both the speed and quality of their output while the most experienced and highest-skilled workers see small gains in speed and small declines in quality. We also find evidence that AI assistance facilitates worker learning and improves English fluency, particularly among international agents. While AI systems improve with more training data, we find that the gains from AI adoption are largest for relatively rare problems, where human agents have less baseline training and experience. Finally, we provide evidence that AI assistance improves the experience of work along two key dimensions: customers are more polite and less likely to ask to speak to a manager.

The paradigm change?

Research process – rethink

Category	Task	Usefulness
Ideation & feedback	Brainstorming	●
	Feedback	◐
	Providing counterarguments	◐
Writing	Synthesizing text	●
	Editing text	●
	Evaluating text	●
	Converting hand-written equations[24/6]	●+
	Generating titles & headlines	●
Background research	Summarization	●
	Condensing YouTube videos[24/6]	●
	Literature research	◐*
	LLM-powered search[24/6]	◐
	Formatting references	●
	Translating text	●
	Explaining concepts	◐
Coding	Writing code	●+
	Explaining code	●+
	Translating code	●
	Debugging code	●+
Data analysis	Locating data sources[24/6]	◐
	Creating figures	◐
	Extracting data from text	●
	Reformatting data	●
	Classifying and scoring text	●+
	Extracting sentiment	●+
	Simulating human subjects	◐
Math	Setting up models	◐
	Deriving equations	◐+
	Explaining models	◐
Research promotion	Social media posts	●
	Presentation slides[24/11]	●
	Blog posts[24/11]	●
	Conducting interviews[24/11]	●
	Podcasts[24/11]	●

Notes: The third column reports my subjective rating of LLM capabilities as of November 2024:

Category	Task	Usefulness
Ideation and Feedback	Brainstorming	●
	Feedback	◐
	Providing counterarguments	◐
Writing	Synthesizing text	●
	Editing text	●
	Evaluating text	●
	Generating catchy titles & headlines	●
	Generating tweets to promote a paper	●
Background Research	Summarizing Text	●
	Literature Research	○
	Formatting References	●
	Explaining Concepts	◐
Coding	Writing code	◐
	Explaining code	◐
	Translating code	●
	Debugging code	◐
Data Analysis	Creating figures	◐
	Extracting data from text	●
	Reformatting data	●
	Classifying and scoring text	◐
	Extracting sentiment	◐
	Simulating human subjects	◐
Math	Setting up models	◐
	Deriving equations	○
	Explaining models	◐

Notes: The third column reports my subjective rating of LLM capabilities as of September 2023:
○: Experimental; results are inconsistent and require significant human oversight.
◐: Useful; requires oversight but will likely save you time.
●: Highly useful; incorporating this into your workflow will save you time.

Korinek, A. (2023 – Dec 2024). Generative AI for economic research: Use cases and implications for economists. *Journal of Economic Literature*, *61*(4), 1281-1317.

We partnered with a *Fortune* 500 food company and replicated two studies the company had conducted in 2019 using an LLM (GPT-4 [OpenAI et al. 2023]). The first study was qualitative in nature and centered around business questions for the Friendsgiving celebration. The second study focused on testing a new refrigerated dog food concept. For each study we treated the original (human) studies as the "ground truth" and benchmarked the LLM-generated studies against them. This approach enabled us to objectively evaluate the quality of synthetic data and thus answer our research questions pertaining to the role LLMs could play in knowledge generation.

Arora, N., Chakraborty, I., & Nishimura, Y. (2025). AI–Human Hybrids for Marketing Research: Leveraging Large Language Models (LLMs) as Collaborators. *Journal of Marketing*, *89*(2), 43-70.

Table 2. Marketing Research and Large Language Models: Relevant Empirical Literature.

Article	Topic	Qualitative	Quantitative	Human Benchmark	Theory Testing	Incorporate Context
Brand, Israeli, and Ngwe (2023)[b]	Marketing research		✓		✓	
P. Li et al. (2024)[ab]	Perceptual maps		✓	✓	✓	
Qiu, Singh, and Srinivasan (2023)[b]	Consumer risk preference		✓	✓	✓	
Horton (2023)	Economics theory testing		✓		✓	
Argyle et al. (2023)[a]	Synthetic data for voting		✓	✓		
Aher, Arriaga, and Kalai (2023)[a]	Simulate human behavior		✓		✓	
This article	Marketing research	✓	✓	✓		✓

Some of these applications involve data generation, while others pertain to tasks that include summarization and analysis.

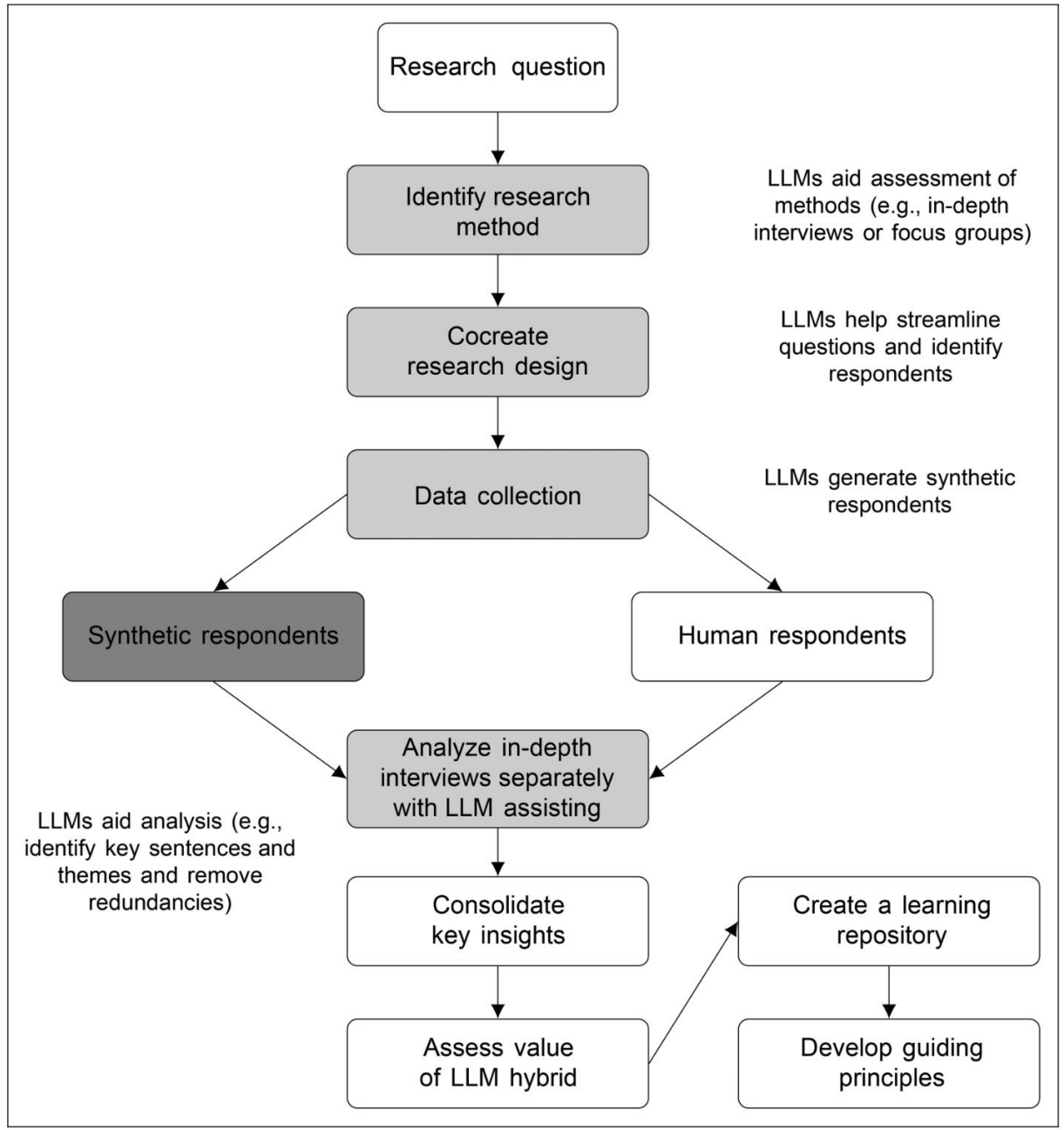


Figure 4. Incorporating a Large Language Model in Qualitative Research: A Road Map.
Notes: The white, dark gray, and light gray blocks represent human-only, LLM-only, and AI–human hybrid processes, respectively. LLMs can assist in streamlining

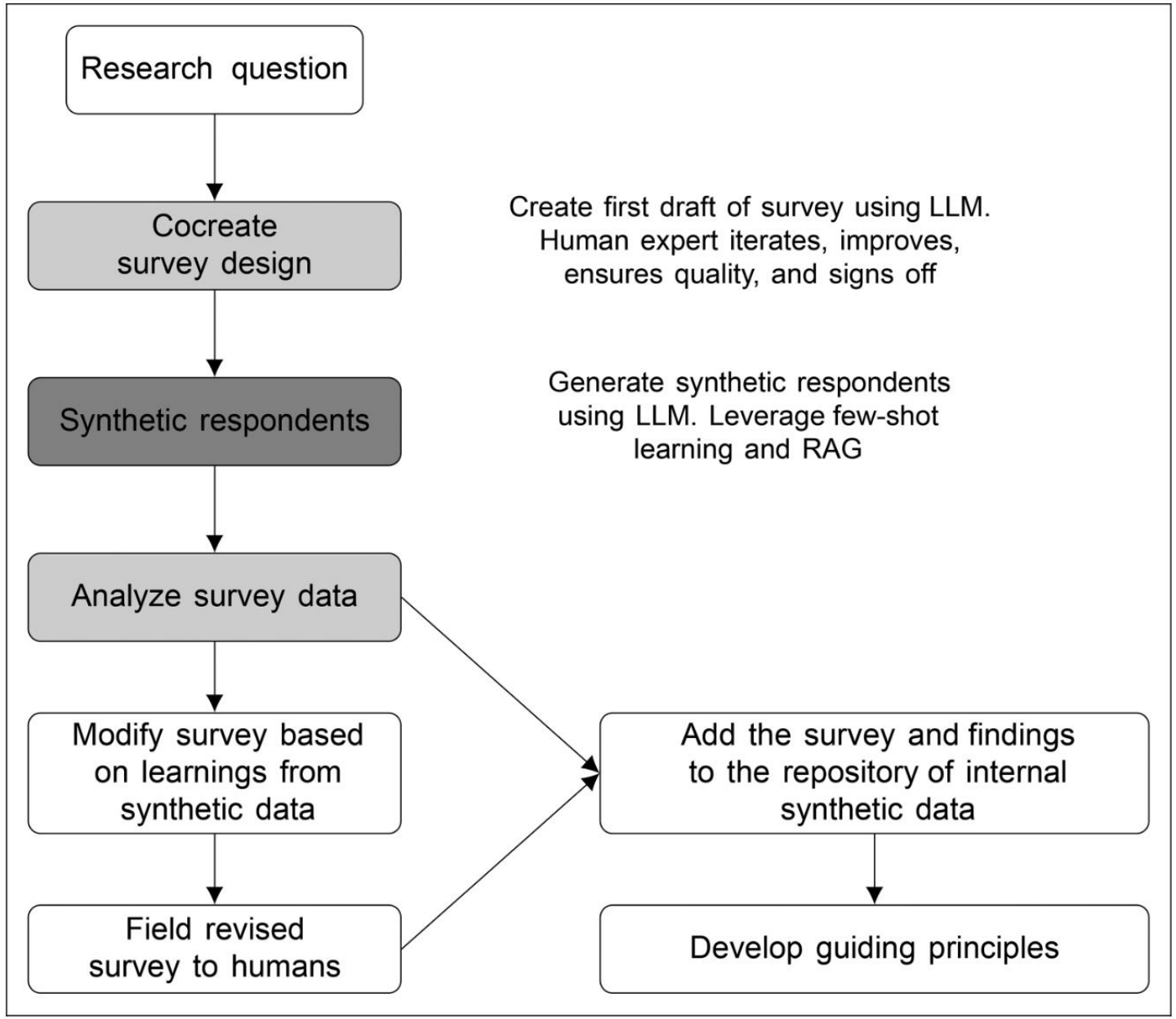


Figure 11. Incorporating a Large Language Model in Quantitative Research: A Road Map.

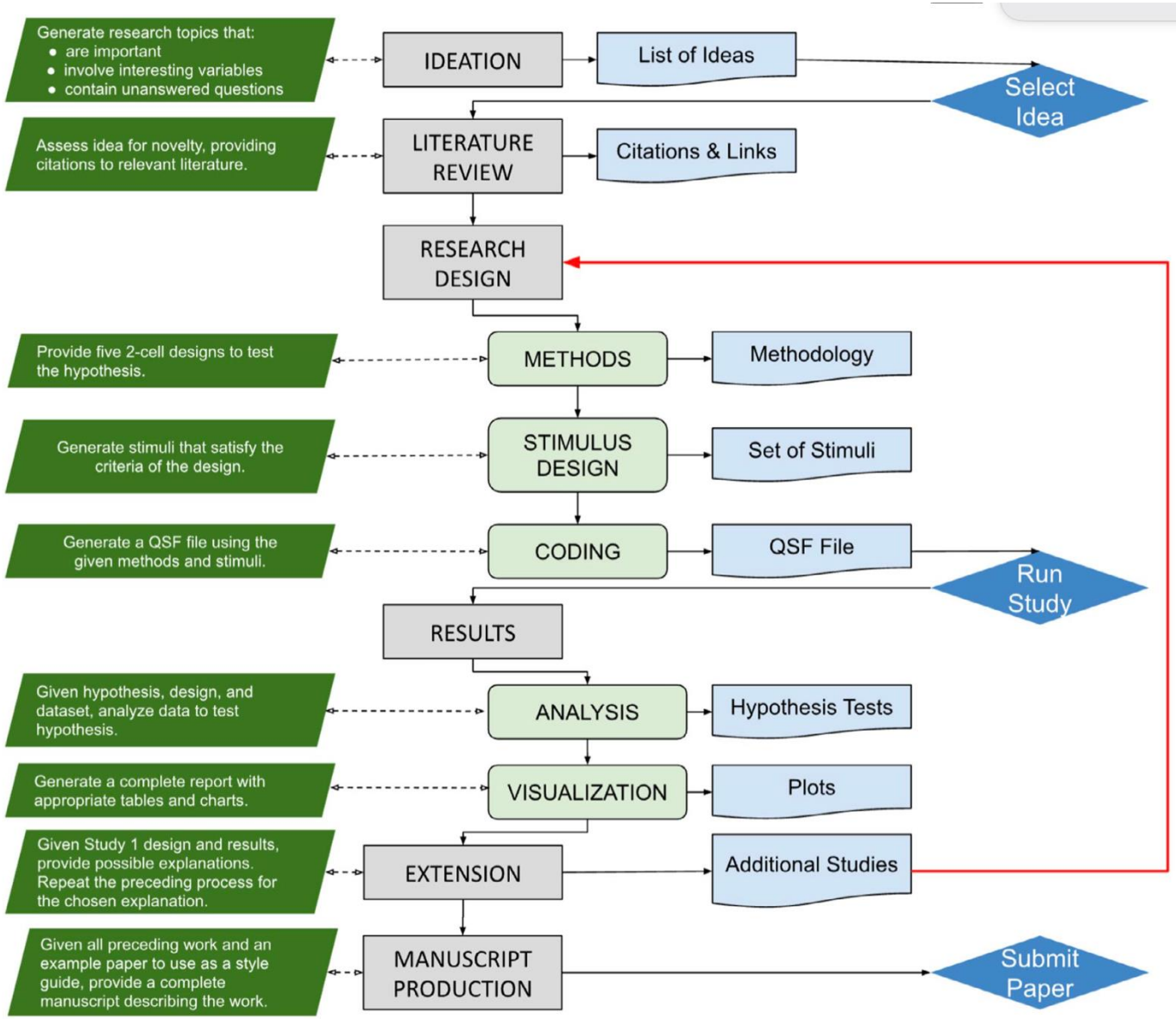


FIGURE 1 Flowchart of the AI-enabled research process.

Tomaino, G., Cooke, A. D., & Hoover, J. (2025). AI and the advent of the cyborg behavioral scientist. *Journal of Consumer Psychology*.

TABLE 1 Performance of each AI on each research stage (as of April, 2024).

Research stage	Substage	Bard/Gemini	BingChat/CoPilot	Chat GPT4
Ideation		L3	L2	L3
Literature Review		L2	L2	L2
Research Design	Methods	L3	L3	L3
	Stimulus design	L3	L2	L3
	Coding	L0	L0	L1
Results	Analysis	L0	L0	L1
	Visualization	L0	L0	L1
Extension		L1	L2	L2
Manuscript Prod.		L0	L0	L1

Note: L3, AI produced output at an acceptable level for academic research with little modification; L2, AI-produced output deemed valuable with difficulty or substantial modification; L1, AI-produced output requiring such oversight as to be without value; L0, AI unable to produce requested output.

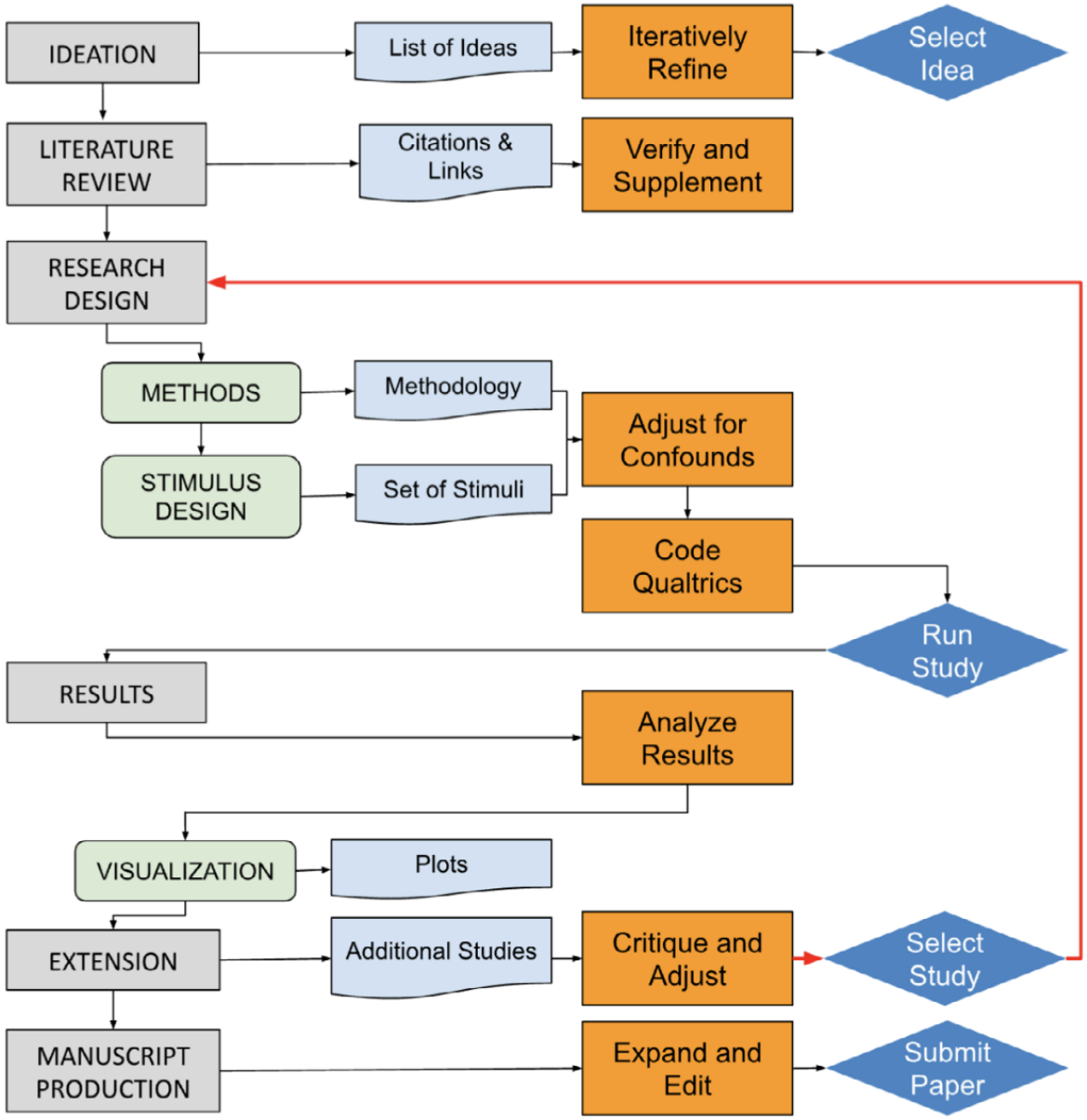


FIGURE 2 Flowchart of our recommended AI-enabled research process.

Our experience involved describing the scope of ideas in which we were interested and the criteria we used to evaluate "good" ideas, and then having the AI list research questions that it deemed worthy of investigation.

Ethical Fatigue: There will be a segment of consumers who experience "ethical fatigue" and become skeptical or indifferent to ethical branding due to overexposure to marketing messages about ethics.
This resulted in the following experimental design: all participants were asked for their perception of Nike's ethicality using a four- item scale, and then saw four statements regarding four other brands with zero, two, orfour of these statements being ethical, the rest being non-ethically-related brand positioning statements. Then all participants read the same ethical positioning statement: "Nike is committed to using sustainable materials and practices. We are also committed to promoting social re-sponsibility and empowering athletes of all levels." We then concluded by reassessing participants' perceptions of Nike's ethics using the same four- item scale.

Another limitation of the AIs at this stage was that they required the researcher to already have a fair foundation in the experimental method.

We were disappointed to find the AIs to be highly limited in their ability to analyze and report data.

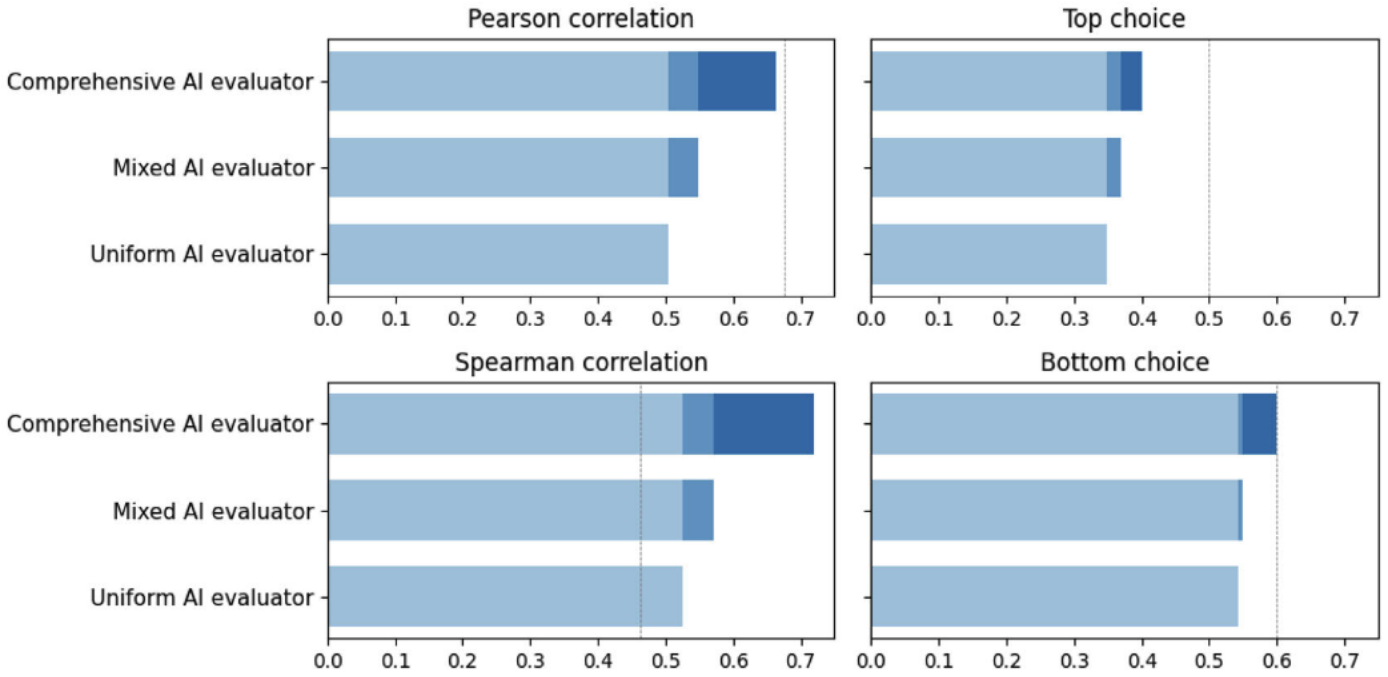
Table 2. Opportunities for gAI-Assisted Theorizing

gAI-assisted theorizing	Opportunities for use, documentation, reflection
Selection of theoretical product and focal idea	• Tool-supported idea generation and algorithmically supported identification of gaps or inconsistencies in the body of knowledge. • Will covering more research terrain lead to more variance and novelty in theories?
Settling on theory-building apparatus	• New dialogic strategies to raise novel research questions and research problems. • Human-tool dialog to develop multiple theory candidates; gAI tools to offer critiques and challenges. • Setting boundaries to establish when tools are productive and when they are not. • Will tools encourage normativity (where theorizing is reduced to following a prespecified process or a set of guidelines)?
Improve rigor and clarity	• Thought experiments with the tool. • Practices for determining what and how will be referenced in the future. It may not be possible to replicate the tools' responses reliably in prompt engineering. • Practice acknowledging the contribution of the tool. • How can we assess whether tools improve questioning, rigor, and clarity, as we have suggested in this paper?
Broader reflection	• Values that should be a condition of intended use of gAI tools, as well as values to be adhered to in use (fairness, transparency, accountability, etc.). • Best practices for gAI-assisted theory development, to be taught and trained. • Accounting for inputs when the inputs are not transparent and explainable. • New practices leading to new knowledge collectives and forms, including meta-methodological competencies, such as prompt engineering. • Do the tools enable or require a new genre of publication? • Do we need a Turing test* to identify AI-generated submissions?

Note: * "The Turing test, originally called the imitation game by Alan Turing in 1950, is a test of a machine's ability to exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human" ("Turing Test," 2023).

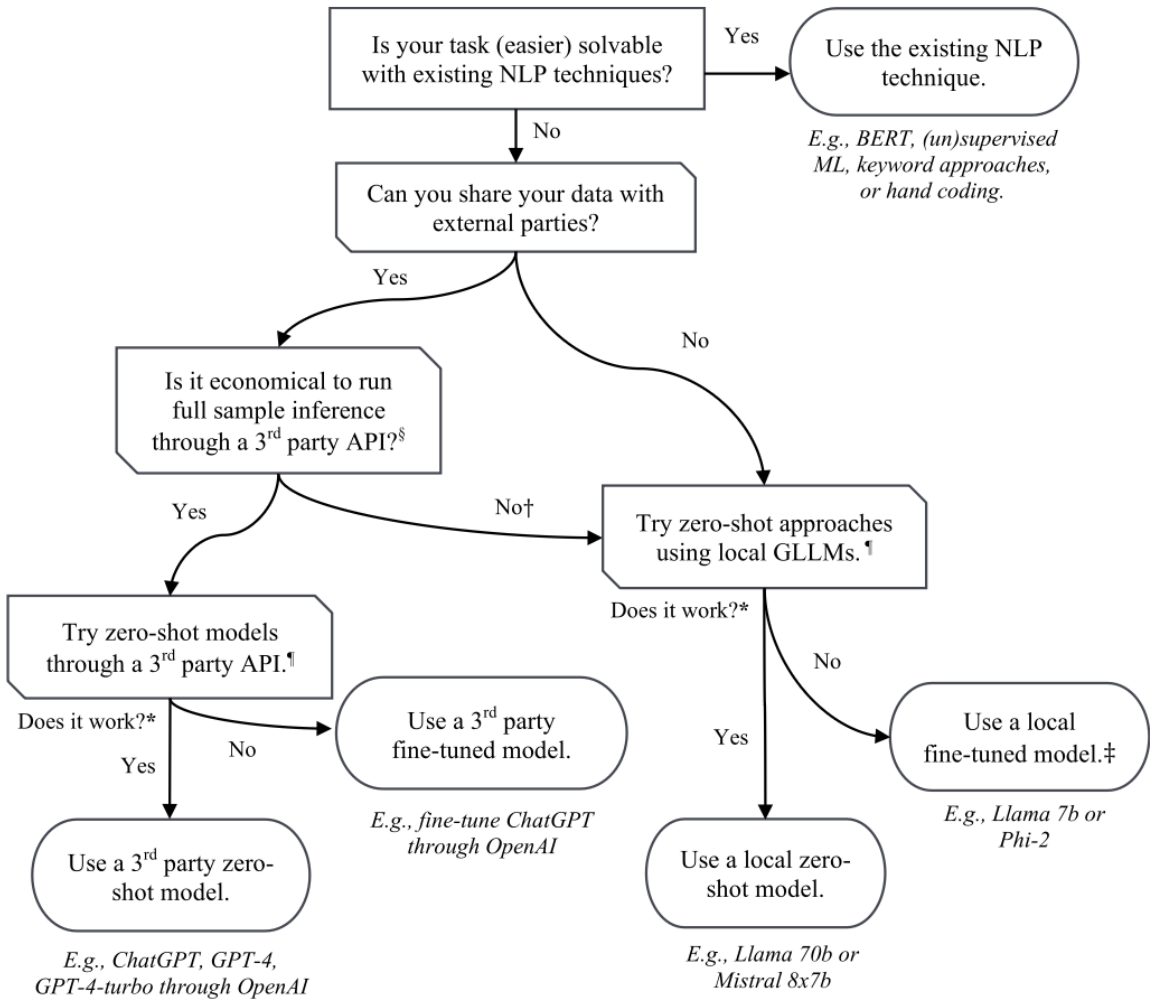
Jarvenpaa, S., & Klein, S. (2024). New Frontiers in information systems theorizing: human-gAI collaboration. *Journal of the Association for Information Systems*, *25*(1), 110-121.

Research Summary: Strategic decisions are uncertain and often irreversible. Hence, predicting the value of alternatives is important for strategic decision making. We investigate the use of generative artificial intelligence (AI) in evaluating strategic alternatives using business models generated by AI (study 1) or submitted to a competition (study 2). Each study uses a sample of 60 business models and examines agreement in business model rankings made by large language models (LLMs) and those by human experts. We consider multiple LLMs, assumed LLM roles, and prompts. We find that generative AI often produces evaluations that are inconsistent and biased. However, when aggregating evaluations, AI rankings tend to resemble those of human experts. This study highlights the value of generative AI in strategic decision making by providing predictions.



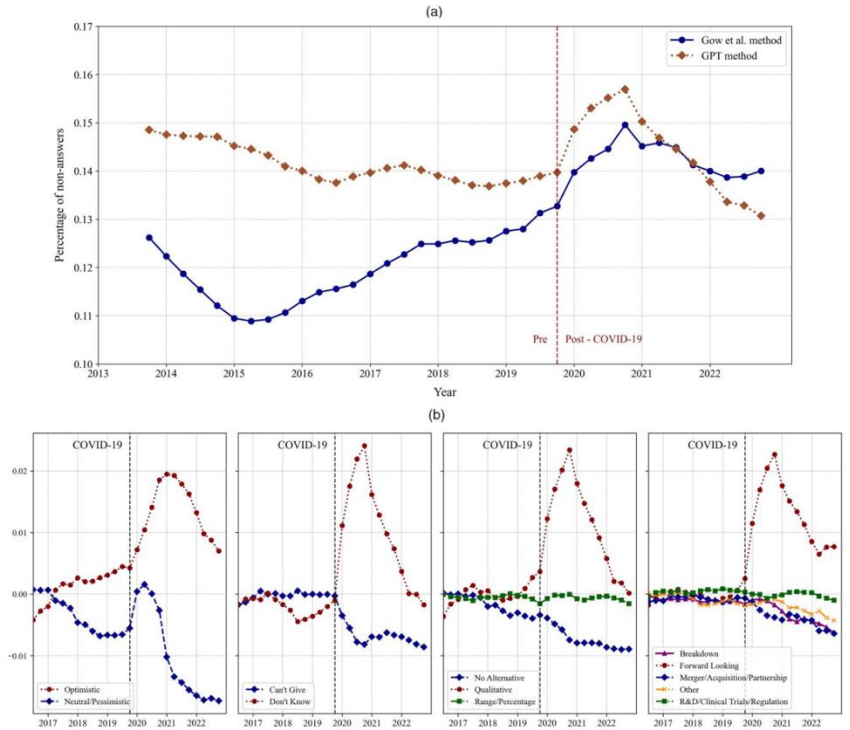
Doshi, A. R., Bell, J. J., Mirzayev, E., & Vanneste, B. S. (2025). Generative artificial intelligence and evaluating strategic decisions. *Strategic Management Journal*, *46*(3), 583-610.

Figure 1. GLLM Approach Flowchart



Gow ID, Larcker DF, Zakolyukina AA (2021) Non-answers during conference calls. J. Accounting Res. 59(4):1349–1384.

Figure 4. (Color online) Nonanswers: Time Trends and COVID-19 Impact



de Kok, T. (2025). ChatGPT for textual analysis? How to use generative LLMs in accounting research. Management Science.

Question

- The use of GAI in research is not merely a question of tool selection, but also a matter that touches on the essence of research integrity, conduct and value.
  Following our analysis and given all these characteristics of GAI, we suggest that researchers should engage in critical reflexivity and vigilance to identify, understand and robustly address the ethical issues regarding the use of GAI in their research practices involving qualitative data analysis. (ISJ 2023 editorial)
- GenAI as collaborator?
- GenAI as data generator (simulator)?
- Deep neural networks / large language models as a “paradigm core” for information systems research– understand the digitized human cognitive information system
  - Map to the breakthroughs in the structural modeling of economic interactions and consumer behavior

LLM and Digital Economics

- The cost perspective
  - Search costs
  - Replication costs
  - Transportation costs
  - Tracking costs
  - Verification costs

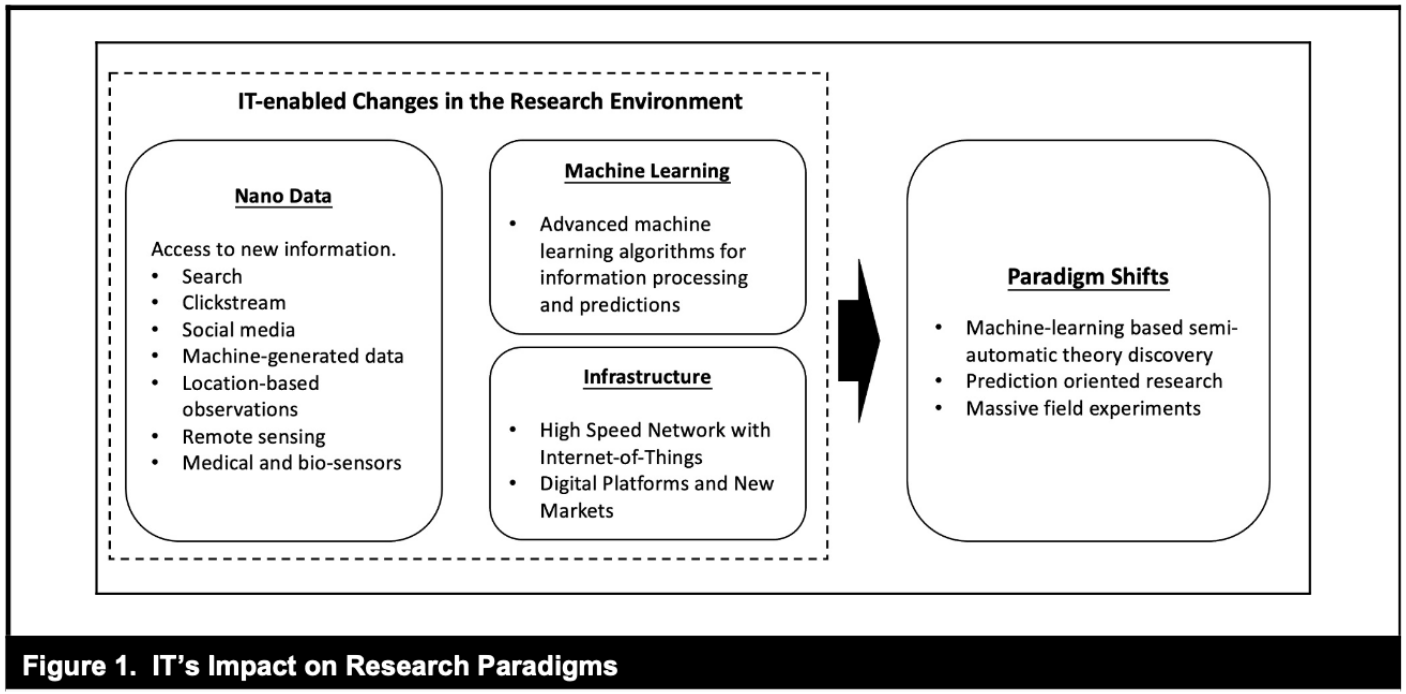


Figure 1. IT's Impact on Research Paradigms

Assignment

Will LLM have an impact comparable to the Internet, Mobile Phones, Data Analytics, or Blockchain on the social information system structure?

What are the research questions that, if answered, contribute to our understanding of the impact of GenAI?

References

- Korinek, A. (2023-2024). Generative AI for economic research: Use cases and implications for economists. Journal of Economic Literature, 61(4), 1281-1317.
- Arora, N., Chakraborty, I., & Nishimura, Y. (2025). AI–Human Hybrids for Marketing Research: Leveraging Large Language Models (LLMs) as Collaborators. Journal of Marketing, 89(2), 43-70.
- Tomaino, G., Cooke, A. D., & Hoover, J. (2025). AI and the advent of the cyborg behavioral scientist. Journal of Consumer Psychology.
- de Kok, T. (2025). ChatGPT for textual analysis? How to use generative LLMs in accounting research. Management Science.
- Rathje, S., Mirea, D. M., Sucholutsky, I., Marjieh, R., Robertson, C. E., & Van Bavel, J. J. (2024). GPT is an effective tool for multilingual psychological text analysis. Proceedings of the National Academy of Sciences, 121(34), e2308950121.
- Storey, V. C., Yue, W. T., Zhao, J. L., & Lukyanenko, R. (2025). Generative Artificial Intelligence: Evolving technology, growing societal impact, and opportunities for information systems research. Information Systems Frontiers, 1-22.

Editorials

- Jarvenpaa, S., & Klein, S. (2024). New Frontiers in information systems theorizing: human-gAI collaboration. Journal of the Association for Information Systems, 25(1), 110-121.
- Davison, R. M., Chughtai, H., Nielsen, P., Marabelli, M., Iannacci, F., van Offenbeek, M., ... & Panteli, N. (2024). The ethics of using generative AI for qualitative data analysis. Information Systems Journal, 34(5).

References – Impact of GenAI

- Teutloff, O., Einsiedler, J., Kässi, O., Braesemann, F., Mishkin, P., & del Rio-Chanona, R. M. (2025). Winners and losers of generative AI: Early Evidence of Shifts in Freelancer Demand. *Journal of Economic Behavior & Organization*, 106845.
- Demirci, O., Hannane, J., & Zhu, X. (2025). Who is AI replacing? The impact of generative AI on online freelancing platforms. *Management Science*.