# Technological Non-Specificity and the Toaster Test: Assessing scholarly attention to AI's Sociotechnical Properties in Information Systems Research

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## Introduction

We introduce the "toaster test" as a heuristic for assessing studies that consider the roles that digital technologies play in work. While important IS research traditions (including design science, conceptual modeling, and affordances research) have developed approaches to theorizing the technology artifact (e.g., Gregor & Hevner, 2013; Strong & Volkoff, 2010), a persistent challenge emerges when these frameworks encounter fundamentally heterogeneous technologies. As such, Orlikowski and Iacono's (2001) foundational critique of under-theorizing IS artifacts remains relevant, but the challenge today is less about whether we attend to technology and more about how we conceptualize technologies that resist unified treatment. The rapid growth in both the number and forms of digital systems that draw on one or more forms of artificial intelligence (AI) presents us with the latest technological waves to enter work. Our concern is with the insights, be they empirical, conceptual, or operational, from the many studies of AI's presence and uses.

If we can substitute "toaster" for "AI" in the empirical discussions and theoretical frameworks of works purporting to study these systems, without substantially altering core arguments, then we have failed to grapple with what makes these systems genuinely different from other technologies. This test reveals not just methodological shortcomings, but a deeper theoretical issue in how we conceptualize the relationship between technological affordances and organizational outcomes in information systems. Specifically, as artificial intelligence (AI) systems become increasingly embedded in organizational processes, information systems, and everyday practices, the need for insightful sociotechnical analysis has never been more urgent.

## The Challenges of Technological Non-Specificity

For decades, IS research has championed a sophisticated understanding of technology's role in organizational life by arguing persuasively that technological impacts are not predetermined but emerge through complex negotiations between technical capabilities and social contexts (Lamb & Kling, 2003; Star & Ruhleder, 1996). This sociotechnical perspective has been particularly successful in countering naive technological determinism while theorizing how meaning, use, and consequences of technological artifacts are actively constructed through human agency and organizational dynamics (Sawyer & Jarrahi, 2014). A key aspect of this has been attention to the IS ‘artifact’ (Lee et al., 2015).

Yet even within research traditions attentive to technological artifacts, something curious has happened when confronting AI systems. Despite rich theoretical frameworks for understanding ERP systems, social media platforms, and enterprise technologies, these same frameworks, when applied to AI, often treat fundamentally different systems (rule-based vs. machine learning, supervised vs. unsupervised, recommendation vs. autonomous decision-making) as if they were interchangeable. The sophistication lies not in whether we attend to technology, but in recognizing when technological heterogeneity within a category demands new theoretical distinctions. The same theoretical frameworks developed to understand enterprise resource planning, email adoption, or social media implementations are being applied wholesale to systems that exhibit learning, complexity, unpredictability, and emergent behaviors that their creators cannot fully predict or explain.

We refer to this stance as "technological non-specificity" – the tendency of certain theoretical frameworks in IS research to treat technologies as interchangeable variables without accounting for specific underlying technological mechanisms, constraints, and affordances that shape organizational outcomes.

We are not arguing that IS research has universally failed to engage with technological specificity. Rather, we observe that existing approaches, however successful for their original domains, face unique challenges when confronted with AI's heterogeneity and dynamism. The issue here is not the absence of artifact-centered research but rather the need for theoretical extensions that account for AI systems' distinctive characteristics.

## Why Research may Fail the Toaster Test

Understanding the reasons behind technological non-specificity in IS research and beyond requires examining several interconnected factors that shape contemporary academic practice in our field.

### *Dispensing with Technological Determinism, Again*

The reluctance to engage deeply with AI's technical characteristics often stems from decades of productive critique of technological determinism in IS research (e.g., Orlikowski & Robey, 1991). Across decades, IS scholars have rightfully been skeptical of claims that technologies directly cause organizational outcomes, particularly warranted given (often hyperbolic) claims surrounding AI in the discourses of pundits and advocates (Scott & Orlikowski, 2025). This noted, every new IS or IT appears wrapped in the rhetorical framing of direct, positive, and powerful impacts.

### *Institutionalization of Relational Theorization*

Contemporary IS research showcases remarkable success of practice-based and relational approaches to understanding IT and IS. Frameworks like sociomateriality have provided powerful lenses for understanding how technologies and organizational practices co-constitute one another in specific contexts (Orlikowski & Scott, 2008). Yet exclusive emphasis on emergence and enactment may create blind spots for capturing systems whose behaviors emerge from complex training processes shaped by both designers' decisions and organizational users in real-world applications. When everything is enacted in practice, it becomes difficult to theorize about pre-existing capacities and limitations that different AI systems bring to organizational situations (Barley, 2023).

*Long-term Orientation*

Scholarship in IS reflects a strategic balancing of analytical relevance beyond specific technological phenomena set against the specificities of any one set of digital technologies and the munificent variations of these digital technologies situated in their contexts of uses. This long-term orientation serves the critical function of developing durable theoretical insights that transcend particular technological contexts (Gregor, 2006). However, this strategic distancing can inadvertently lead to analyses too removed from material properties that define and distinguish technologies. While avoiding entanglement with rapidly evolving technical specifications serves theoretical durability, it may prevent researchers from recognizing when genuinely novel technological characteristics require theoretical innovation rather than application of existing frameworks (Eisenhardt, 1989).

*Challenges of Interdisciplinary Technical Literacy*

Many IS researchers confront technological systems that are increasingly complex and rapidly evolving. Understanding contemporary AI systems involves grappling with concepts from machine learning, image analysis, advanced data structures, distributed architectures, and other topical areas not traditionally part of IS education. This knowledge gap renders researchers likely to simplify advanced IS, arguing that the internal workings of these complex digital artifacts are irrelevant to organizational analysis. This comforting simplification leads to potentially missing aspects of how technical characteristics enable and constrain organizational interactions.

## Toward Sociotechnical Specificity in IS Research

To address technological non-specificity, we argue for research approaches that take seriously both the organizational embeddedness of AI systems and their distinctive technical characteristics. This "*sociotechnical specificity*" involves conceptualizing how different technological forms create different possibilities for organizational action while remaining attentive to how those possibilities are realized in specific organizational contexts.

Understanding AI's distinctiveness requires attending to several characteristics of these systems. First, AI systems are shaped by data dependencies and historical embedding. Unlike rule-based systems applying explicit logic, AI models learn patterns from training data reflecting social, political, and economic contexts, potentially reproducing historical organizational inequalities in opaque ways. Second, the design of many AI systems leads to where the algorithmically-driven decision-making processes aren't transparent even to organizational implementers, complicating governance and accountability (Lebovitz et al., 2022). Third, AI systems are adaptive, evolving through ongoing organizational use in ways that aren't fully predictable, requiring theoretical approaches attuned to non-deterministic behaviors (Rahwan et al., 2019). Finally, AI systems reflect designer intentionality through embedded choices about goals, architectures, and optimization metrics that influence organizational arrangements and interactions (Kellogg et al., 2020).

**Recommendations for IS Research**

Developing adequate approaches to studying AI in IS research requires both methodological innovation and practical changes in how we approach technology in organizational contexts.

*Methodological Innovation and Technical Engagement*

Researchers need to develop sufficient technological literacy to understand, question, and interpret AI system design and function in organizationally meaningful ways, but the nature of this literacy differs fundamentally from previous IS research demands. Unlike studies of previous enterprise systems we might have had a reasonable grasp of business logic and data flows, AI systems require grappling with: (1) training data provenance and bias that shapes learned patterns invisibly; (2) architectural choices (transformer models, convolutional networks, reinforcement learning) that fundamentally alter what the system can learn and how it generalizes; (3) emergent behaviors where system outputs cannot be traced to explicit rules; and (4) continuous adaptation where the artifact's capabilities change through use. This demands not just collaboration with technical experts but developing conceptual frameworks that bridge machine learning concepts with organizational theory (a good example is Strum et al (2021)). This would also lead to a more detailed discussion of the technological artifact in the papers reporting on the work: first laying out the digital arrangements and then again situating these in the findings and discussion.

As Pouloudi and Whitley (2000) suggested more than two decades ago, representing non-humans such as AI systems in social research introduces complexities not present in traditional social studies. Today, we have unique opportunities to engage with these systems directly and let them “speak” through innovative methodologies such as walkthrough analysis (Light et al., 2016) or interviewing AI (Jarrahi, 2026).

*Comparative and Longitudinal Analysis*

Comparative approaches offer strategies for clarifying what's genuinely distinctive about AI compared to previous organizational technologies. Rather than examining the take-up and uses of AI in isolation, IS researchers can develop greater insights from studies of how AI-enabled organizational change compares to past technological infrastructures, or by investigating how work processes, decision-making systems, or institutional arrangements evolve when AI-enabled systems replace or augment previous IS. Doing so will demand studies across time and taking up techniques of historical analysis.

Because AI systems learn from data and adapt through use, longitudinal designs are especially important for observing how the same AI system transforms organizational routines over time (Berends & Deken 2021), and comparative designs are crucial for contrasting different AI architectures deployed in similar settings

*Problematizing AI When One Size Does Not Fit All*

Too often, IS research treats "AI" as a single category, applying generic adoption models and overlooking how technical differences alter what organizational adoption and governance entail. Viable IS theorization needs to articulate specific system types (Jarrahi & Glaser, 2025). Rule-based, supervised, unsupervised, reinforcement-learning, and generative systems differ in how they learn, adapt, and yield organizational outcomes. Likewise, AI systems differ in their goals – e.g., those that provide recommendations viz. those that allow for human-in-the-loop decisions viz. those that may or may not provide a rationale to show their decision-making (e.g., for detection or task assignment). What should emerge is a body of findings that provides opportunities for both patterns and differences to be made visible.

*More attention to Designer Intentions and Organizational Logics*

Harkening design scholars, IS research should examine how AI systems embed design decisions reflecting technical optimization, and the competitive, ethical, and political considerations that shape organizational outcomes (e.g., Lee, et. al, 2015). This requires engaging technical work to see how AI systems align with organizational values and priorities, helping IS researchers understand intended and unintended organizational consequences. For example, we know AI systems present a distinctive challenge, which is that once designers have externalized their intentions into training processes and architectural choices, these intentions become invisible and largely unquestioned by organizational users (Dolata et al., 2022).

This combination of embedded designer intentions and lack of explainability calls for new theorization in studying designer work. In doing so, IS researchers could focus on: (1) how training data selection embeds and amplify assumptions and biases; (2) how algorithm optimization metrics encode values (accuracy vs. fairness, speed vs. explanation); (3) how architectural choices privilege certain kinds of learning while foreclosing others; (4) how these choices embedded in algorithms interact with organizational contexts; and (5) how multiple stakeholders may or may not interrogate or modify learned behaviors of the algorithms.

## Conclusion

The toaster test provides a heuristic to illuminate how research conceptualizes relationships between technological capabilities. Given the rise of AI systems in work, this seems ever more critical. Treating AI as interchangeable with other technologies risks overlooking how it’s technological arrangements are different. Meeting this challenge requires IS scholars to be attentive to both AI's technical specificity and complexity of organizational embedding.

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