Sociomateriality in the Age of Generative AI*

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Abstract

The relationship between humans and technology has shifted from automation to AI-driven augmentation or even collaboration, particularly in the field of Generative AI. This study explores the human perspective through a case study of an AI-based Natural Language Generation (NLG) tool and sheds light on how employees experience its introduction as well as how work practices, outcomes, and knowledge evolve through the lens of sociomateriality. Using a sociomaterial perspective and qualitative interviews, findings reveal that Artificial Intelligence technology does not replace employees but shifts their roles toward supervision. Knowledge further emerges as a unifying theme from a sociomaterial viewpoint. This paper explores the co-creational role that emerges as Generative AI evolves toward more proactive technology-driven interaction and investigates the consequences for the knowledge-intensive dimensions of human work.

Keywords

Sociomateriality, Generative Artificial Intelligence, Natural Language Generation

1. Introduction

The relation between human and machine has always been an interesting research field from a socio-technical perspective. But the advent of more and more powerful Artificial Intelligence technologies is shaping that relation to an extent that is unprecedented, especially in the field of knowledge work.

Whereas previous research on automated attribute-based text generation primarily focused on the technology itself, this empirical case study intends to shed light on the consequences of its introduction, focusing on how employees experience tool use, how this relates to changed work practices and practice outcomes, how these changes shape the knowledge work within the different customer organizations, and what influence context has on tool use.

Being based on the empirical case of ContiGen (a pseudonym for both a real tool used productively in a variety of companies and its vending organization, anonymized for

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confidentiality reasons), this paper reports on the findings, providing insights on the intertwining of human and machine collaboration.

The case focuses mostly on the technology of content generation using sophisticated Natural Language Generation (NLG) techniques. The common ground shared by Generative AI technologies (GenAI) is their generative nature and since this research focuses on the intensified and collaborative interaction of humans and machines on specific tasks, technical differences do not play an important role in the present study. Domain experts who do not possess technical expertise often do not distinguish between NLG and GenAI given that from the user's perspective, both types of IT systems behave similarly in their generation of content elements.

By taking on a sociomaterial perspective coupled with existing theory and current developments in the field, we aim to further elucidate the phenomenon of attribute-based text generation in e-commerce. Whereas the former draws on the entanglement between humans and technology through its relational foundations, a social-constructivist epistemology ensures to focus on the study's human-centered approach, leading to a refined model which was considered throughout the empirical research of this study and is eventually reflected in the findings.

The paper is structured as follows: Section 2 describes the conceptual foundations of this work before the case study is being introduced in section 3, followed by the specification of the research methodology in section 4. The results and findings are discussed in section 6 whereas the limitations and the summary conclude the paper in section 6 and 7, respectively.

2. Conceptual foundations

The underlying study of this article [1] is anchored in the premise that the social and the material are constitutively entangled [2] and that this entanglement unfolds through practices, enactments, and the imbrication of human and material agencies [3]. Attribute-based text generation tools, however, are not designed once and then simply used within a stable set of practices. As generative systems, they keep learning from the very employees who work with them, they participate in knowledge creation as differentiated actors rather than as a single undifferentiated tool and for some employees they may come to occupy a position considerably closer to their own cognitive apparatus than traditional non-AI-based software tools use in the domain of e-commerce. The following sections intend to extend and explain the sociomaterial framework the study is embedded in and extend it even further by weaving three additional strands into the already developed account: the temporal deepening of entanglement into co-evolution [4], its distribution across differentiated human and machine roles through the GRAI framework [5], and its potential to cross the threshold into genuine cognitive extension [6], [7], [8].

2.1. Sociomateriality as Entanglement, Practice and Imbrication of Human and Material Agency

Technology's influence on organizational life has grown steadily more pervasive, yet its influential role on everyday work practice remains underexamined [9]. Sociomateriality addresses this through a relational ontology which posits that the social and the material are

constitutively entangled rather than merely interacting. As Orlikowski [2] puts it, "there is no social that is not also material, and no material that is not also social" (p. 1437) which denies that either exists independently of the other.

This entanglement becomes tractable at the level of practice. Socio-material practices are the routines binding organization, people, and technology together [2]. Practice enactments, on the other hand, are their concrete, situated executions, always somewhat different because they are temporally emergent [11]. Practices are also performative in a stronger sense [12]: Repeated enactment does not merely yield outcomes but actively constitutes the reality it appears only to describe.

Sociomateriality further distinguishes human agency, the capacity to form and pursue goals from material agency which is the capacity of non-human entities to act apart from human intervention [3]. Both practices and technologies emerge through imbrication, the joining of an existing agency with a new one of the other kind, making stability and change two faces of the same dynamic. People experience material agency as affording or constraining their goals, prompting them to adjust practices or, where a technology feels blocking, to change the technology itself [3]. This also explains why employees sometimes resist technologies the purpose of which they privately endorse. Leonardi [13] traces this to the interplay of social and material interactions, the former of which shape interpretations of a technology's capabilities while the latter test those interpretations against its actual features.

Sociomateriality's final extension concerns knowledge, which it refuses to locate solely in the human mind. Following Carlile [14], knowledge is localized and tied to concrete problems rather than universal ones. At the same time, it is embedded in the tools and routines of daily practices and invested, a hard-won achievement people are reluctant to relinquish. These may be properties useful within a practice but a source of friction once that practice meets another.

The above-outlined concepts provided the sociomaterial groundwork for the study this article is based on [1]. The next sections seek to further extend it by embedding ideas of co-creation between humans and AI as well as of extending the human mind by AI.

2.2. Entanglement in Motion: From Imbrication to Co-Evolution

For stable technologies that rely on relational databases, for example, the entanglement of the social and the material is essentially a single occurrence: A database is imbricated with a reporting routine and the resulting practice then persists more or less unchanged. However, attribute-based text generation does not stay still long enough for imbrication to settle in this way. Where e-commerce employees continuously evaluate, correct, and re-feed such a tool with product attribute data, the material agency being imbricated with their goal of faster content production is itself changing at the same time as their own practices are [15]. Böhm and Schedlberger [4] capture this with a concept borrowed from biology: co-evolution, defined as "a reciprocal adaptation of a population that eventually leads to a dependency between each other" (p. 2). Applied to attribute-based text generation, co-evolution suggests that such a tool does not simply get used by employees. Over time, it could be shaped by them just as they are shaped by it, quantitatively through the speed of content production, and qualitatively wherever it assists with product categories or tones of voice in which the employee is less experienced [4].

Nonetheless, not every use of such a tool reaches this depth, and this is precisely where imbrication and co-evolution part ways. Böhm and Schedlberger [4] distinguish an

Application Space from a Novelty Space. Whereas in the former, a generative technology only automates tasks within an already familiar frame, in the latter, it is used to reach a tone, argument, or creative direction that neither the employee nor the tool could have produced alone. Drafting a product description from a fixed set of structured attributes would, for the most part, remain within the Application Space. Therefore, a copywriter who increasingly relies on such tools to create content would not create the same output without having moved to the Novelty Space, where reciprocal dependency and, with it, genuine co-evolution becomes possible. Whereas imbrication tells us that human and material agency have joined, co-evolution tells us how far, and in which direction, that joining is still moving.

2.3. Practice and Performativity Distributed Across Human and Machine: The GRAI Perspective

Sociomaterial practices and their enactments represent an ongoing, recursive intertwining of humans and technology in everyday activities whose outcomes are highly situational and constrained by the people and technology involved [2] (p. 1440). Furthermore, they are performative in nature, contributing to the very reality they help constitute through repetition [2], [12]. What this account leaves comparatively underspecified is which part of a given enactment is carried by the human party and which by the machine, a distinction that matters once the material side of the entanglement is not a passive tool but a system that itself socializes, externalizes, combines, and internalizes information. Böhm and Durst [5] address this directly by revising Nonaka's model of knowledge creation [16] into the GRAI (Generative Receptive Artificial Intelligence) framework, splitting each of its four phases into a human and a machine role and thereby yielding eight distinguishable interaction fields [5].

Applied to attribute-based text generation, an employee supplying product attributes and context to such a system would enact the externalization field $E_h \rightarrow E_m$, while the system's return of structured, on-brand product text would enact its counterpart, $E_m \rightarrow E_h$ [5]. Both belong to the same overarching socio-material practice, yet they need not be the same enactment, nor need they co-evolve at the same pace. The constraint on $E_h \rightarrow E_m$ is typically the effort of specifying context precisely enough, while the constraint on $E_m \rightarrow E_h$ is the employee's willingness to trust and adopt what is returned. At the same time, where colleagues once combined product information collaboratively, a generative system could come to participate in the combination field itself, drawing on patterns and associations at a scale no individual copywriter could match ($C_h \rightarrow C_m$; $C_m \rightarrow C_h$) [5]. What appears as a single enacted and performative practice would, on closer inspection, be a bundle of distinguishable human-machine fields, each of which may drift toward the Novelty Space and therefore toward co-evolution at a different rate. A workplace could consequently feel automated in how content is externalized while already co-evolving, in Böhm and Schedlberger's sense [4], in how it is combined.

2.4. Imbrication Reconsidered: From Material Agency to Cognitive Architecture

Material agency can be defined as the capacity of non-human entities to act apart from human intervention which are imbricated with human goals [3] (p. 148). Once a specific GRAI field has co-evolved far enough, this separation becomes harder to sustain, leading to presenting a

question that goes even further: Is the material agency still only entangled with the employee's practice or has it become part of the cognitive apparatus with which the employee thinks? This is where Clark and Chalmers' concept of an Extended Mind Thesis comes into play [6]. They argue that where a person is coupled to an external resource (e.g., GenAI) such that removing it would degrade their performance, that resource is not only used by cognition but becomes part of the cognitive process itself. A critical point of debate is also who initiates the cognitive process, and this is when the problem of agency becomes central. While a human actively flips through a notebook, traditional AI systems often do not decide for themselves when to retrieve external knowledge [8].

Considering the co-evolving picture developed above, this gives material agency a threshold it previously lacked. An employee who came to consult such a system's output for virtually every product description to accept it with little deliberation and who would struggle noticeably were the tool withdrawn, would meet the threshold for extension. On the other hand, a colleague who treated the same output with active skepticism, checking and frequently rewriting it, would not. Still, from the perspective of imbrication, both could be described in identical terms as sociomaterially entangled with the same tool. Still, this extension should not be claimed too readily. Smart, Clowes and Clark [8] caution that a system does not become part of someone's cognition just because information flows into it from an external source. The retrieval loop must be triggered by the agent in question and not only delivered to them by a process that acts on their behalf (p. 22). Applied to attribute-based text generation, this means that only if an employee actively calls for generating text, would there be a rise to genuine cognitive extension. The mere passive reception of whatever the system has already prepared in the background, does not suffice. Clark [17] draws the practical conclusion for precisely this situation: The skill increasingly required of employees is not resistance to such tools nor uncritical reliance on them, but "learning how to both trust and question" (p. 2) the resources they may come to think with.

2.5. Toward an Extended Framework

The authors suggest that in an age where humans and technology become increasingly connected, they are no longer to be considered mutually exclusive but rather deeply entwined. This leads to moving from the previously defined entanglement of the social and the material toward co-evolution and an extended mind where humans and technology are interdependent in the co-creation process.

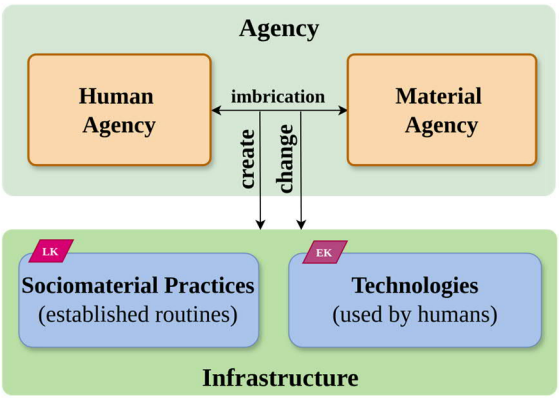


Figure 1: An Overview of the Framework of Sociomateriality, with different types of knowledge: LK – localized knowledge, EK – embedded knowledge and IK – invested knowledge (source: own creation)

Based on the previously outlined accounts of sociomateriality, figure 1 tries to illustrate this framework, highlighting the imbrication between the human and the material agent which leads to either creating or modifying the infrastructure (sociomaterial practices and technologies). Whereas theory suggests a connection between practices and localized knowledge, it also hints that knowledge is deeply embedded in technologies [14].

On the other hand, figure 2 further illustrates the impact of agency on interactions as users interpret technology relative to their goals.

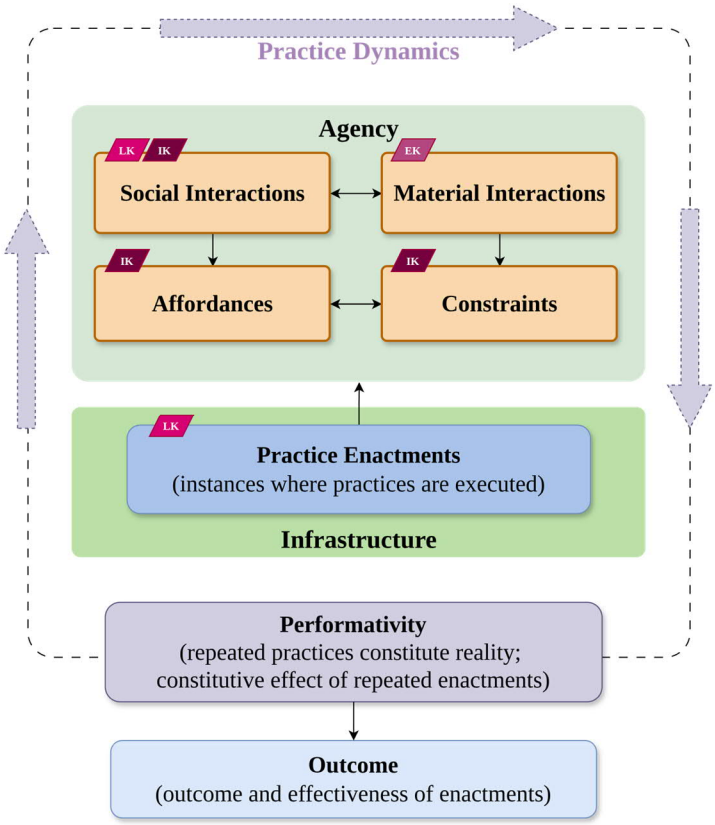


Figure 2: A more detailed perspective on the Framework of Sociomateriality, with different types of knowledge: LK – localized knowledge, EK – embedded knowledge and IK – invested knowledge (source: own creation)

Following Leonardi [3], people tend to aim for outcomes which are beneficial to them and adjust their practices accordingly. As practices are executed, users weigh in on whether technology constrains or affords them to pursue their goals. That is, affordances represent perceived possibilities for action emerging from the interaction between human and technology whereas constraints represent perceived limitations for action (also s. figure 3). This relational approach is further consistent with sociomateriality being grounded in a relational ontology [2].

This process of weighing in on affordances and constraints represents an ongoing cycle of repeated enactments which leads to constantly reconstituting reality through performativity. Performativity, hence, does not describe doing something through practice, but rather the enactment and constitution of reality through practice itself. That is, reality may change over time as enacted practices, their outcomes, and the expectations associated therewith do as well.

3. The Case of ContiGen: NLG as an example for the adoption and use of AI technologies

Natural Language Generation (NLG) refers to the automated transformation of non-linguistic, structured data into coherent natural-language text [18], [19]. While recent scholarly and public attention has centered toward GenAI and large language models, template- and rule-based NLG systems continue to underpin large parts of commercial content production, owing to a controllability and reliability that purely generative, probabilistic models have historically lacked [19], [20]. E-commerce product description generation is a paradigmatic case considering businesses must produce accurate, brand-consistent, and complete textual content across vast and continuously changing product catalogs, a requirement that favors control and reliability over open-ended creativity.

Based on its underlying case study [1], this article illustrates these dynamics through the case of ContiGen, a cloud-based Software-as-a-Service (SaaS) solution for the automated generation of e-commerce content.

ContiGen's reliability is only one of various reasons it is used in content-oriented marketing departments in its customer organizations. Based on structured input such as product attributes coming from third-party systems or Excel sheets, ContiGen transforms non-linguistic data (e.g., database fields) into coherent product descriptions using text models composed of templates, text modules, and attribute slots populated with product data. These product descriptions are then output in e-commerce web shops or catalogs. While rooted in a classical modular, template-based NLG architecture, ContiGen extends this foundation through mechanisms such as text variants, synonym management, and selective AI-assisted linguistic refinement, allowing for controlled variability beyond earlier, more rigid template systems. It is closely aligned with the paradigm of Controllable Text Generation (CTG), in which content is governed by structured attributes (content control) while style and terminology are enforced consistently (attribute control) to preserve brand voice across large catalogs [21].

Unlike purely neural, LLM-based approaches, ContiGen prioritizes determinism, consistency, and reliability over probabilistic, open-ended generation, though it can also incorporate large language models in a systematically guided manner to preserve attribute coverage and tonal alignment. ContiGen therefore represents a hybrid case within the NLG landscape, bridging traditional template-based systems and contemporary controllable generation approaches and offers a particularly instructive site for examining how employees experience, adapt to, and are shaped by AI-based text generation in data-intensive commercial environments.

4. Methodology

This study is based on a relational ontology which is consistent with sociomateriality [10]. It is further paired with a social constructivist epistemology, which allows for capturing how employees make sense of their work with the tool and highlights the relevance of interpretation and context in the construction of knowledge [22]. At the same time, it aligns closely with the distinction between social and material interactions in technology adoption [13].

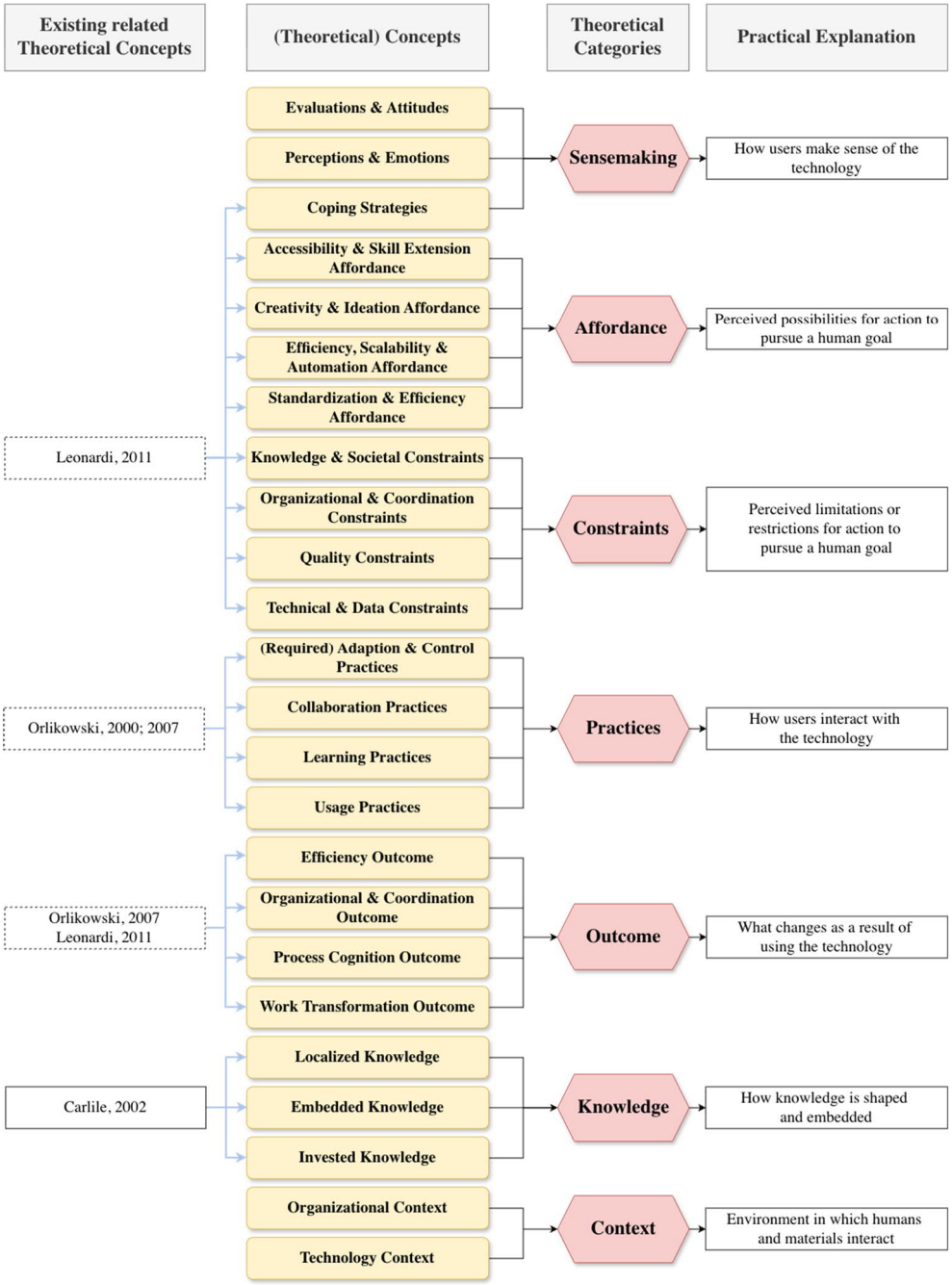


Figure 3: An overview of themes (concepts), their corresponding theoretical categories as well as their theoretical foundation (dotted/straight lines represent a partial/full theoretical match with empirically emerged concepts; source: own creation).

Due to the ontological and epistemological grounding and given that the research questions are of a *how* nature, a qualitative, exploratory, and inductive case study design was adopted [23], [24]. More specifically, the study follows a single embedded case design,

examining the case of ContiGen across five embedded units of analysis which represent the different customer organizations of the tool, or more specifically, their content-oriented marketing departments which are responsible for producing solid product descriptions both for the web and offline catalogs. This design permits an in-depth account of a single, purposefully and phenomenon-driven selected case [25] while allowing for the exploration of variation across organizational contexts rather than strict cross-case comparison [26], [27].

Data collection combined theoretical sampling [28] with semi-structured interviews structured around Critical Incident Technique (CIT) [29] and informed by Kvale's [30] seven stages of interview inquiry. Six respondents (n=6) were interviewed, one or two per customer organization, reflecting the fact that ContiGen was typically operated by only one or two employees within each organization. All respondents could therefore report from direct, first-hand experience. Interviews were conducted in German via Microsoft Teams, later translated into English with DeepL, and lasted between 22 and 64 minutes. Content-wise, interviews addressed personal and professional background, technology affinity, changes in work practices, critical incidents, and the organizational and knowledge-related implications of ContiGen's implementation.

Interview transcripts (104 pages of anonymized data) were analyzed using reflexive thematic analysis [31], [32], applying its six phases iteratively rather than linearly. Data-driven first-cycle coding was followed by second-cycle process coding, yielding 159 codes, which were then related to both empirical data and existing theoretical concepts (e.g., Carlile, 2002) following a logic of systematic combining [26]. This resulted in 24 themes organized into seven theoretical categories. These themes or their respective theoretical concepts are further illustrated in figure 3. Both coding and theming were supported by Atlas.ti. Quality was assessed against constructivist criteria of authenticity, plausibility, criticality, comprehensive data treatment, and transparency [22], [33], with generalizability deliberately excluded given the study's particularizing, single-case orientation [34]. Ethical considerations, on the other hand, included informed consent, voluntary participation, and full confidentiality and anonymity [35].

5. Findings & Discussion

This section presents the study's findings and discusses them in relation to the theoretical framework outlined earlier. Findings are organized around the study's main research question – how ContiGen users experience their work with the tool – and four related sub-questions concerning changes in work practices, their outcomes, their implications for knowledge, and the role of context. While the study surfaced a broad range of findings across these questions, three carry particular explanatory weight and form the center of this section: the centrality of knowledge as the mechanism through which AI-based text generation is interpreted, enacted, and adapted, the finding that AI adoption does not inherently produce anxiety or resistance, and a subtler, previously underexplored cognitive shift toward process thinking.

5.1. Experiencing ContiGen: Sensemaking, Affordances, and Constraints

Users' overall experience of ContiGen centered on an ongoing process of sensemaking, in which they continuously evaluated the tool's capabilities and output against alternatives such as ChatGPT. Perceived affordances included efficiency, scalability, and automation of disliked

routine tasks, standardization and consistency of language and terminology, accessibility, in that ContiGen lowered the skill threshold for producing product copy, and, more surprisingly, enhanced creativity, with some respondents describing the need to think strategically across large numbers of product variants as more creatively demanding than manual copywriting. Perceived constraints spanned limited cross-departmental knowledge exchange about AI use, organizational and coordination challenges arising from rushed implementation and unclear task division, quality concerns around the homogeneity of AI-generated text, and technical and data constraints, since output quality depended heavily on the completeness and quality of data supplied by upstream systems such as PIM or ERP platforms.

Sensemaking, in this account, is closely linked to both affordances and constraints, as users continually evaluate them through attitudes, perceptions, and emotions. This is represented through an evaluative, recursive relationship consistent with the performative character of sociomaterial practice, in which repeated enactment does not only reflect but actively helps constitute organizational reality [2]. The creativity and ideation affordance is a case in point: Rather than confirming the assumption that AI adoption diminishes the meaningfulness of work, the findings suggest that creativity and ideation can flourish once repetitive tasks are delegated to the tool, an interpretation also supported by Böhm and Durst [5]. Notably, the anxiety commonly anticipated in discussions of organizational AI adoption did not clearly materialize among ContiGen users. Where initial skepticism was present, it tended to resolve into something closer to the AI preparedness that Lee and Park [36] describe as the endpoint of a journey from AI-phobia, plausibly supported by the transparency with which ContiGen was introduced across customer organizations.

5.2. Knowledge as a Central Mechanism

Across all five customer organizations, knowledge emerged not as a peripheral theme but as the connective tissue linking practices, affordances, constraints, and outcomes. None of the knowledge-related codes belonged exclusively to a single theme but were consistently bound up with others. Furthermore, all three knowledge types could be identified across every organization studied. Following Carlile's [14] distinction, the findings identify localized, embedded, and invested knowledge as interrelated mechanisms through which employees interpret, enact, and adapt AI technologies such as ContiGen in practice.

Localized knowledge, context-specific know-how about which tool or approach works best for a given task, developed as users learned which AI tool suited which purpose, how to combine different tools for better output, and how to manage output quality through proofreading. This was also displayed relationally, through tool-related interactions with colleagues such as exchanging experiences, sharing results, and giving one another hints on which prompts were likely to produce better output. This knowledge was closely aligned with and arguably inseparable from the practices through which it was enacted.

Embedded knowledge, by contrast, was built into the technology itself. While well-structured product data in upstream systems such as PIM or ERP platforms formed the basis for consistent ContiGen output, poor data quality produced the opposite. In response, several organizations developed internal standards for data maintenance, and by implementing these standards, employees actively reshaped the knowledge embedded within the systems that fed ContiGen. This reciprocal relationship suggests that materiality, in this context, extends

beyond the AI tool itself to encompass the data infrastructures and system integrations that determine what the technology can generate and how.

Invested knowledge then reflected employees' attachment to established expertise and writing standards, most visibly in concerns over output quality and the potential loss of individuality in AI-generated text. Some respondents also reported deliberately performing certain tasks without AI assistance in order to preserve their own critical thinking. Yet such investment did not necessarily translate into hesitation about using ContiGen more broadly, suggesting that invested knowledge functioned less as a barrier to adoption than as a selective filter determining which tasks employees were willing to hand over.

Taken together, these three forms of knowledge constitute what the study identifies as the common denominator underlying AI-supported work. Affordances and constraints were found to be relational and emergent conditions under constant negotiation through evaluation and perception, giving rise to coping strategies that, in turn, produced new or changed practices. Outcomes, in this light, were not the direct result of AI adoption but rather the effects of these practice enactments. Knowledge, distributed across its localized, embedded, and invested forms, is what makes this chain of negotiation possible in the first place: The mechanism through which affordances and constraints are perceived, coping strategies are formed, and practices are ultimately changed or retained.

These forms of knowledge also correspond to differentiated fields within the GRAI framework [5]. Localized knowledge primarily enacts the externalization field (Eh→Em), through which employees specify context and intent. Embedded knowledge, on the other hand, is most closely tied to the combination fields (Ch↔Cm), through which product data is structured and recombined into output.

5.3. Changing Work Practices, Outcome, and Context

These affordances and constraints translated into four types of changing work practices, found across all customer organizations: required adaptation and control practices, such as variable proofreading regimes and deliberate choices to retain manual control over data flows rather than fully automating them, collaboration practices including the exchange of prompting strategies among colleagues and, in one case, framing AI itself as a "sparring partner", learning practices encompassing both vendor-provided onboarding and the acquisition of new, more structured and data-oriented ways of thinking, and usage practices characterized by task-specific, selective deployment of ContiGen alongside other AI tools (e.g., ChatGPT, Perplexity, DeepL) and a general flattening of ContiGen-specific usage once initial setup was complete.

These practice changes, in turn, produced four outcome types: efficiency outcomes, including markedly reduced manual effort and faster content production, organizational and coordination outcomes including more predictable resource planning and reduced dependency on internal and external resources, alongside new coordination challenges, a process cognition outcome, discussed further below, and a broader work transformation outcome which showcases a shift from copywriting toward pre- and post-editing tasks generally experienced as a change in rather than a diminishment of the meaningfulness and creativity of the work.

At the same time, both organizational context such as stakeholder involvement, managerial prioritization of AI, and available support resources and technological context, particularly

data quality and system integration, were found to condition how ContiGen was implemented, used, and experienced.

These practice changes are consistent with Leonardi's account [3] of imbrication, in which an existing human goal (faster, more consistent content production) is joined with a new material agency. The collaboration practices identified above, such as treating AI as a discursive partner, further illustrate that collaboration is no longer confined to interactions among human colleagues but increasingly draws technological systems into the same practice. This is in line with sociomateriality's core premise that the social and the material are constitutively entangled rather than separable [2]. The data-maintenance standards several organizations developed in response to embedded-knowledge constraints further indicate that aligning ContiGen with organizational data is not a one-time event, but an ongoing process of adjustment [15] and that technology and practice come to form a single, joint infrastructure rather than two separately manageable components [3].

Considering the theoretical lens developed for this study, these affordances and constraints also suggest that ContiGen's use spans both of Böhm and Schedlberger's [4] co-evolutionary spaces. Efficiency, scalability, and standardization affordances kept most organizations within the Application Space, where the tool automates already-familiar tasks. However, the enhanced-creativity affordance reported by some respondents indicates a shift toward the Novelty Space in which employee and tool jointly arrive at phrasing or ideas that neither would have produced alone [4]. The practices identified above further map onto differentiated fields of the GRAI framework [5]: the exchange of prompting strategies among colleagues concerns the externalization field (Eh→Em) through which employees specify intent and context whereas the internal data-maintenance standards several organizations developed reflect an evolving combination field (Ch↔Cm) between employees and the system's underlying data infrastructure.

5.4. AI Need Not Trigger Anxiety

Across all customer organizations, respondents described ContiGen primarily in positive or pragmatic terms. Most described it as an efficiency and productivity driver and a job facilitator that allowed them to focus on tasks other than copywriting, even while acknowledging that its output lacked the *natural flavor* of human-written content. Rather than pursuing perfectionism, several respondents explicitly reframed the tool as *cheap labor*, coming to see it as a benefit, an instrument, an extended arm, or even an idea generator. All respondents ultimately concluded that AI had become part of the job and something they would not want to do without.

Emotional responses followed a similar trajectory. Several respondents described feeling overwhelmed or skeptical at the outset and one respondent reported initial fear about the tool's consequences for their job, but these reactions were the exception rather than the rule and tended to give way to calmer, more positive perceptions as familiarity with the tool grew. As one respondent put it when describing ContiGen's inevitability: "You can't put the genie back in the bottle … that's why you have to work with it." (Respondent 4)

Only two respondents expressed concern about longer-term job redundancy. Respondent 6, for instance, situated this concern within a broader historical pattern:

"That's been the case in every phase of industrialization. People who used to do things by hand were ultimately replaced by machines … I can already see that jobs are changing drastically, and that's not just the case here, it's the same in other sectors as well."

Notably, even this respondent framed the concern as a structural, cross-industry phenomenon rather than a grievance against ContiGen specifically.

Most respondents, however, drew a sharper distinction between AI as a threat and the quality of one's own work as the real determinant of job security. As Respondent 5 argued, only those "at a very basic level of writing need to fear AI-generated content [since AI] can only cobble something together from existing material … but it can't inspire anyone", a limitation this respondent contrasted with her own, more elaborated approach to writing, and one she noted had already been apparent when earlier waves of AI first raised similar fears among colleagues.

Beyond these individual evaluations, negative emotions generally shifted toward more positive perceptions over time. Respondents reported feeling less pressured and stressed with more predictable resource and time management around deadlines which, in turn, supported efficiency and productivity gains. Where frustration persisted, it was directed not at ContiGen itself but at management, specifically at insufficient resourcing for the tool's implementation.

Taken together, these findings suggest that AI implementation does not inherently produce anxiety or resistance among employees when introduced transparently and that AI-assisted work can become more rather than less meaningful, freeing employees to shift from repetitive writing toward proofreading and other tasks that require more deliberate thought. Whether this positive reframing holds over the longer term remains an open question, however, particularly if AI-based processes come to require progressively less human supervision.

Moreover, users tended to "both trust and question" [7] (p. 2), similar to what was described by Clark [7]. Rather than adopting ContiGen's output uncritically or resisting it, most respondents accepted suggestions where confidence was high while retaining proofreading and selective task-avoidance as forms of scrutiny. This oscillation between trust and question rather than an absence of reflection may explain why AI adoption did not translate into sustained anxiety.

5.5. Process Thinking as a Cognitive Shift

Beyond changes in tasks and workload, the findings point to a subtler but consequential shift in how employees think about their work. Respondents reported approaching content, data, and internal workflows in more structured, cross-product, and system-aware terms after working with ContiGen, rather than continuing to think about individual product texts in isolation. As respondent 2 described it, working with ContiGen's data-driven logic meant that "you naturally start thinking across different products […] and want this output, and that's when we start thinking more across products and less in silos."

This cognitive shift was closely related to the organizational and coordination outcome noted above, in which resource and time management became markedly more predictable. The same respondent described how reduced dependency on other departments changed not only workflows but the way project timelines were estimated: "Using ContiGen simply gives us a little more breathing room and […] makes us less dependent on interfaces. It also allows

us to estimate the time required in a completely different way. You're not dependent on anyone else; you just do it directly in the system, get your output, and can then [...] simply forward it directly to the product manager." (Responent 2) Process thinking, in this sense, was not confined to how individual tasks were executed but extended to how entire workflows and their timelines were conceived.

This process cognition outcome suggests that the consequences of AI-based text generation extend beyond observable changes in practice or output to a reconfiguration of the cognitive frame through which employees approach their work more broadly. The study explicitly identifies this shift toward a more structured, data-oriented, and system-aware way of thinking as a phenomenon that has been largely overlooked in extant literature, and one that warrants further investigation as a distinct outcome of AI-supported work in its own right.

5.6. Toward an Extended Sociomaterial Framework

The findings discussed above can be read together as an empirical instantiation of an extended sociomaterial framework, depicted graphically in the underlying case study. At its outermost level, an organizational context frames the entire account, within which conversational dynamics unfold along two parallel channels, namely social interactions, meaning conversations with others, and material interactions, meaning direct interaction with a technology. These two channels correspond to human agency and material agency, which are joined through imbrication and it is through this joining [3] that employees create and change the technologies that make up their organization's infrastructure.

Once created or modified, these technologies are used by humans to carry out tasks. This use, in turn, gives rise to sociomaterial practices [2]. Agency, on the other hand, has a direct impact on both sensemaking and the conditions for action (affordances and constraints) as users interpret technology relative to their own goals, indicating that what a technology affords is never read off its features alone but always co-determined by what the employee is trying to achieve. Technology, in turn, sets the conditions for action which are under constant evaluation on the part of employees. This evaluation constitutes sensemaking, composed of two related but distinct layers: evaluations and attitudes, which are more durable and change gradually over time, and perceptions and emotions, which are more situational and tend to influence one-time events. Both layers feed into coping strategies, through which employees translate their ongoing evaluation of affordances and constraints into a concrete course of action.

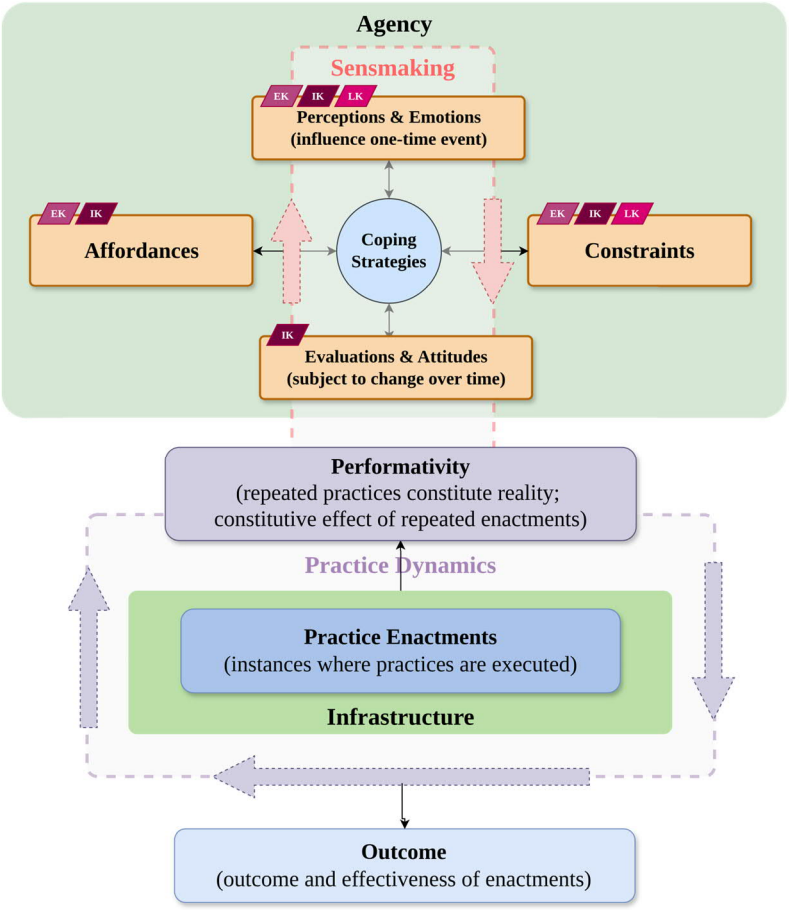


Figure 4: An Extended Framework of Sociomateriality with different types of knowledge: LK – localized knowledge, EK – embedded knowledge and IK – invested knowledge (source: own creation)

Sensemaking connects to practice execution (practice enactments and their outcomes) through performativity which represents the idea that repeated practices do not only reflect organizational reality but help constitute it, and that this constitutive effect is itself subject to change over time [2], [12]. Practice enactments, the concrete instances in which established routines are actually carried out, and the sociomaterial practices from which they draw are connected in an ongoing performative cycle, each continuously reshaping the other. Outcomes, on the other hand, capture the effectiveness of these enactments.

At the very center of this cycle is knowledge which constitutes the one factor which connects all categories. Localized and embedded knowledge are shown as continuously shaping one another, reflecting how context-specific know-how about a tool and the knowledge built into its underlying data infrastructure develop in tandem, whereas invested knowledge, employees' attachment to established expertise, sits comparatively apart from this exchange. This is consistent with the study's finding that it functions less as something woven into everyday practice than as a selective filter applied at the point of adoption.

6. Managerial Implications

The findings carry several implications of managerial relevance when it comes to implementing and overseeing AI-based tools such as ContiGen. Amongst the most fundamental ones is the consideration that the successful implementation of AI depends as much on the sociotechnical environment as on the tool itself. As ContiGen's output quality was found to depend heavily on the completeness, consistency, and correctness of data drawn from third-party systems, data governance should be treated in these source systems following standardized data-maintenance processes to avoid time-consuming corrections. Therefore, the collaboration between human and technology forms the basis for satisfying output scenarios.

Furthermore, instead of predicting that ContiGen would replace employees, findings rather indicate a shift from content creation towards pre- and post-editing tasks such as output validation, proofreading, and refinement. As a result, companies should invest in AI-related training and knowledge sharing formats to ensure their workforce is ready for the changes that come along with introducing new technology. This also includes learning to both trust and question such tools while keeping a critical mind as well as prioritizing transparent managerial communication to avoid AI-related anxiety in employees. However, instead of relying on a one-size-fits-all approach, AI implementation strategies require adjustment to an organization's specific data infrastructure, departmental division, and prior AI exposure due to the context-dependency of AI use.

7. Limitations

As a single embedded case study, this research does not aim to generalize its findings but to generate a particularized, context-sensitive understanding of attribute-based text generation in e-commerce, consistent with its social constructivist and interpretive orientation (Welch, Piekkari, Plakoyiannaki, et al., 2011). The respondent sample was correspondingly small (n = 6) with only one respondent interviewed per customer organization in four out of five cases. This reflects the fact that ContiGen was typically operated by no more than one or two employees per organization and all respondents could report from direct, first-hand experience. However, this may still constrain the range of perspectives captured within each embedded unit. Interviews were conducted in German and subsequently translated into English for analysis and reporting, introducing a further layer of interpretation between respondents' original accounts and the findings presented. The study is further limited to a single NLG-based tool and its cross-sectional design captures a single point in time rather than the longitudinal evolution of practices, knowledge, and job roles following AI implementation.

8. Summary & Outlook

This study examined how employees experience, adapt to, and are shaped by attribute-based text generation in e-commerce, using the case of ContiGen and a sociomaterial theoretical lens. Rather than treating AI adoption as a discrete technological event, the findings show AI-supported work to be an ongoing, entangled process of practice enactment, knowledge (re)formation, and contextual negotiation, in which localized, embedded, and invested

knowledge function as an interrelated mechanism through which employees interpret, adapt to, and shape AI-based tools. Contrary to research emphasizing AI-induced anxiety or resistance, most respondents experienced ContiGen as a meaningful, even creativity-enhancing shift in the nature rather than in the value of their work, provided its implementation was handled transparently and with adequate organizational support.

These findings extend the study's initial sociomaterial framework by demonstrating that materiality encompasses not only the AI tool itself but the broader data infrastructures, system integrations, and organizational arrangements within which it is embedded, and that entanglement is enacted through a continuous, graded negotiation of affordance and constraint rather than a one-off act of adoption. For practice, the findings underscore that successful AI implementation depends as much on data governance, stakeholder involvement, and cross-departmental coordination as on the underlying technology itself.

Future research could extend these findings in several directions. In the broadest sense, it remains an open question whether similar sociomaterial dynamics hold for GenAI tools operating in modalities other than text, such as image or video generation, and a longitudinal design would in any case be needed to trace how practices, required skills, job roles, and the reported shift in process cognition evolve over a longer time frame including whether AI-supported processes come to require less human supervision over time.

Another direction concerns co-evolution [4]. Because the present study could only infer rather than observe movement between the Application Space and the Novelty Space from single-interview accounts, a longitudinal design following individual employees or organizations over time would be better placed to establish whether and under what conditions a given use of attribute-based text generation actually deepens into the reciprocal dependency co-evolution describes, rather than remaining a stable, one-off imbrication.

Future research could also examine the GRAI framework in greater depth [5]. The present study could only indicate in broad terms which of its human-machine fields such as externalization or combination appeared to be at work in ContiGen's use. A design capable of tracing each field separately across a larger sample could establish whether different fields of the same overall practice indeed co-evolve at different rates, and which organizational or technical conditions accelerate or slow this drift toward the Novelty Space.

A fourth and more exploratory direction concerns the extended mind thesis [6], [7], [8]. The present, interview-based design allowed only for identifying candidates for cognitive extension based on how constantly and how uncritically employees reported relying on ContiGen's output but could not establish whether the retrieval loop was genuinely self-triggered by these employees rather than simply delivered to them. Future work could combine observational or think-aloud methods with the interview approach used here to test this criterion directly further investigate whether Clark's [7] meta-skill of learning to both trust and question such tools can be deliberately fostered through onboarding and training rather than emerging as it appeared to in this study primarily through incidental experience. Apart from that, future research may also have a look at what an extended mind could look like and whether it leads to hollow intelligence in users. Together, these three theory-driven directions would allow future research to trace not only whether AI-supported work deepens into co-evolution, differentiates across GRAI fields, or approaches genuine cognitive extension, but also how these three depths of entanglement relate to one another as they evolve over time.

9. Declaration on Generative AI

During the preparation of this work, the author(s) used Claude in order to check grammar and spelling. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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