Exploring Industry Practices and Perspectives on AI Attribution in Co-Creative Use Cases

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Abstract

The increasing adoption of generative AI in human-AI co-creative workflows has led to the development of new policies and design guidelines for disclosing the usage of AI, promoting transparency and accountability in the collaborative process. However, it remains unclear how these policies are being translated into practice in product development. Through semi-structured interviews with 12 industry practitioners, we investigated current approaches and challenges in implementing AI attribution in business products. Our results reveal high variability in AI attribution approaches across products, as they consider factors such as the type of content produced by AI, the presence of human reviewers, stakeholder needs, and regulatory requirements. We also identified technical, user, and product-level challenges of implementing AI attribution in products, including difficulty tracing and discerning the significance of AI contributions, negative impacts on user experience and sense of ownership, and a lack of precedent in product-specific contexts. Our findings offer practical design implications for effective AI attribution strategies in co-creative business use cases.

Keywords

AI Attribution, Co-Creation, Human-AI Collaboration, AI Transparency, Product Teams, Business Use Cases

1. Introduction

Rapidly advancing generative AI technology has enabled novel and increasingly complex co-creative workflows, in which users and AI collaborate iteratively to produce artifacts. These emerging workflows, in turn, necessitate novel design and algorithmic approaches for providing transparency on user and AI involvement in co-created work. A growing body of work has begun to explore how users perceive ownership over AI-generated and co-created work [1, 2, 3, 4, 5, 6, 7, 8, 9]. Simultaneously, governments and organizations are introducing policies that mandate AI disclosure in AI-assisted writing, art, and other domains [10, 11, 12]. However, it remains unclear if and how these policies are being adopted in industry products. Since regulations often do not include specific guidelines on *how* to acknowledge AI involvement, particularly in complex co-creative scenarios, the implementation of attribution is often left up to product teams.

To address this gap, we sought to understand the current state of AI attribution in the industry by investigating business use cases of human-AI co-creation. We interviewed members of product teams (i.e., developers, managers, designers, and researchers) working on business AI products with co-creative use cases to understand how they currently approach AI attribution. We found high variability in AI attribution practices, including whether AI is attributed at all, information included in AI attributions, the modality through which this information is conveyed, and who has visibility. This variability can be due to people's understanding of regulatory requirements, the types of co-created content, amount of human oversight, and stakeholder needs. Additionally, participants shared challenges at technical, user, and product levels that hinder their ability to implement attribution in their desired ways.

Based on these findings, we derive unmet needs and identify ways to improve current approaches to address these needs. Our findings reveal practical approaches, challenges, and future improvements in AI attribution that are rooted in real-world products, and we contribute to a shared understanding of

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novel forms of transparency unique to co-creation that can enhance user agency by providing control over crediting mechanisms and awareness of contribution provenance at a more granular level. We hope to spark further conversations and resources for AI attribution in practice through this work.

2. Related Work

2.1. Ownership and Credit in Co-Created Work

The complex and iterative nature of human-AI co-creative workflows pose a challenge in determining ownership and appropriate credit for co-created work. Yeh et al. [1] found mixed perceptions of ownership over co-created writing, and He et al. [2] found that participants perceived shared ownership over ideas generated with the help of an LLM. There may be a stronger sense of human ownership when users have more control and involvement in prompting, creation, and curation processes [13, 3, 4, 5, 6, 7]. Users also perceive increased ownership for themselves when they view AI as a tool rather than an agent, independent entity, or co-creative partner [8, 9, 6].

This variability in ownership perceptions raises questions of when and how AI should be visibly acknowledged for its contributions to co-created work. While ownership and crediting are closely intertwined, they are not always predictive of one another. Draxler et al. [3] found an AI ghostwriter effect in which creators of AI-generated postcards declared themselves as authors despite lacking a sense of ownership over the work. Reasons behind this effect included perceptions of AI as a tool, concerns that AI support would not be valued by the recipient, and parallels to the role of human ghostwriters [3]. Social stigma may also discourage the disclosure of AI usage. Wang and Fussell [14] posit that ESL students may face scrutiny for using AI assistance in their education, and Messer [15] found that AI usage can decrease the perceived authenticity and value of artwork and artists. In these instances, attributing AI may not be desired, even if the user views AI as an owner. In contrast, some users do find a need to disclose AI involvement for ethics, transparency, and self-protection reasons [3, 16, 17]. Adjacent research in explainability has also found that transparency measures can increase human agency by providing users with more system knowledge and control [18, 19, 20].

2.2. Transparency Regulations

Organizations have begun introducing policies governing AI disclosure. Many academic journals and publishers require the use of AI to be acknowledged, typically in a Methods or Acknowledgments section, and specify that AI does not meet the criteria to be credited as an author [10, 21, 22, 23, 24, 25]. For example, the Association for Computing Machinery (ACM)'s policy states that "the use of generative AI tools and technologies to create content is permitted but must be fully disclosed in the Work" [10]. Medium, an American online publishing platform, specifies that fully AI-generated work will not be published to its general audience, and "AI-assisted text without a disclosure at the beginning of the story (within the first two paragraphs)...will similarly be restricted to distribution on the writer's personal network" [26].

Similar requirements exist in government policies. The EU AI Act requires deployers to disclose when AI-generated text is artificially created or modified, with exceptions of human-reviewed content and systems used for law enforcement [11]. In the United States, the state of California recently signed a landmark AI Transparency Act that similarly defines requirements for disclosing the use of AI in creating content [12]. However, these requirements do not specify *how* to disclose AI involvement, particularly in complex, iterative co-creation workflows that are becoming more commonplace. As these requirements and regulations become more widespread, AI product teams must grapple with ways to ensure that content generated with their products satisfy regulations while considering users' ownership and disclosure needs.

2.3. Methods for AI Attribution

To address emerging transparency needs and policies, researchers and practitioners have started developing technological and design approaches to identify and disclose AI involvement. One common technological approach is watermarking. For example, Meta's Stable Signature creates a watermark for AI-generated images by fine-tuning the model with a custom watermark [27]. When applied to AI-generated images, these images will carry a unique watermark that includes source information such as model version, company, and user. Google's SynthID similarly watermarks AI-generated images, audio, and text [28]. However, recent work suggests that watermarks remain limited in effectiveness as they can be removed, stolen, or copied [29]. Furthermore, watermarking may not capture the full complexity of co-creative workflows — for example, Stable Signature's watermark remains the same regardless of subsequent modifications made to generated images [27]. SynthID is slightly more robust, providing a watermark that persists after content undergoes mild paraphrasing but becomes less detectable when it is significantly rewritten or translated [28].

Design approaches offer ways to visually differentiate AI-generated contributions within artifacts that contain both human and AI content. IBM's Carbon for AI framework provides reusable style elements, including an AI label and explainability panel, to lend a unique visual identity to AI-generated content [30]. iA Writer enables authors to denote the source of text within collaboratively written works and stylizes AI text in a distinct grey color [31]. Some applications also include capabilities to disclose AI involvement within their platforms, such as Draft One, an AI-assisted tool for creating police reports that asks users to check a box indicating their use of AI [32]. Research in HCI has recommended various approaches and types of information to include in an AI disclosure based on users' transparency needs. For example, Persson and Zhang [17] proposed a "decision package" that includes the model name, input parameters, prompt, and data sources. El Ali et al. [16] developed a set of questions to consider when implementing transparency measures to comply with the EU AI Act, including the types of information that should be disclosed, who the information matters to, and considerations for enhancing user agency through transparency.

Prior work has provided useful insights into people's perceptions of ownership over co-created work and existing algorithms, guidelines, and applications for AI attribution. However, little is known about if and how AI usage is disclosed in practice, particularly in business use cases. Our work seeks to address this gap by understanding AI attribution practices and the extent to which product teams consider ownership perceptions, regulatory requirements, and different crediting techniques.

3. Method

We conducted semi-structured interviews to assess AI attribution practices and perceptions of people who develop or manage generative AI products for co-creation use cases. Our study investigated the following research questions:

- **RQ1**. What are the current approaches to AI attribution in enterprise co-creative use cases?
- **RQ2**. What factors impact the use and design of AI attribution in generative AI products?
- **RQ3**. What are the current challenges in attributing AI, and how might we address them?

3.1. Participants

We interviewed 12 participants who are responsible for various aspects of the product development process including product managers, designers, and developers of a large, multinational company, working on generative AI products for co-creative use cases. Their roles, products, and co-creative use cases are described in Table 1. Participants were located in a range of geographies: four were based in Europe, one was based in Asia, and seven were based in the Americas. We recruited participants by advertising our study on internal Slack channels, and in some cases, the participants recommended additional people who might be eligible. All participants signed an informed consent form.

Table 1
Participant information including roles and the products and co-creative use cases that they work on. Note that some participants worked on the same product.

ID	Job Title	Product Type	Example Co-Creative Use Case
P1	Design Lead	Insurance data assistant	Collaboratively correct data
P2	Project Manager	Course creation tool	Co-create an online course content
P3	Product Manager	Course creation tool	Co-create an online course content
P4	Asset Development Leader	Course creation tool	Co-create an online course content
P5	Product Manager	Code assistant	Assist code generation
P6	Product Manager	Multi-purpose chatbot	Collaboratively write a document
P7	Product Manager	Code assistant	Assist code generation
P8	UX Research Lead	Data management tool	Collaboratively enter metadata
P9	Senior Technical Staff Member	Visualization	Collaboratively create data charts
P10	Design Lead	Data management tool	Collaboratively enter metadata
P11	UX Design Lead	Data management tool	Collaboratively enter metadata
P12	Generative AI Enablement	Productivity assistant	Co-create product management artifacts

3.2. Procedure and Interview Protocol

Interviews were conducted via a video conferencing platform and lasted about 30 minutes. They typically consisted of one participant and two or three researchers; some interviews included more than one participant when they were from the same team. We began by asking questions about the product's co-creative use cases, including the user flow and the AI and users' roles and contributions. Next, we asked questions related to AI attribution, such as whether and how AI is currently acknowledged to stakeholders, how they anticipate AI attribution will evolve in their product, and whether their opinions on AI attribution change depending on factors such as the type of contribution made by the AI, the amount of contribution to the final content, and proactive or reactive engagement of AI. The interview protocol we followed can be found in Appendix A.

3.3. Analysis

We conducted a thematic analysis [33] using interview transcripts and detailed notes taken during the interviews. Two researchers independently coded the interviews and identified potential themes. The researchers then discussed the themes until they reached a consensus and created a final set of themes.

4. Results

4.1. Current Approaches to AI Attribution

In studying RQ1, we learned that participants use a variety of designs and methods to attribute AI in artifacts co-created in their products, revealing a lack of consistency across current approaches.

Of those we studied, two products include a general acknowledgment of AI involvement in artifact creation, such as a tag that states, "assisted by [AI tool name]" (P5, P7) or "powered by [model name]" (P2-4). Two products include more transparency, providing information specific to the co-creative process, such as the source of granular contributions and whether AI contributions were human-reviewed. P11, the design lead for a data management tool, created a framework in which AI contributions are tagged with different colored dots to denote the following states: (1) above a confidence threshold and automatically incorporated, (2) below a confidence threshold and needs human review, (3) reviewed and approved by a user. Some products also provide technology-specific information, such as the model used and confidence scores. Participants described a variety of design modalities used to convey attribution information, including text statements, icons, and color-coding.

Three participants said their tools do not currently provide any form of AI attribution in co-created content. Instead, some of them provide a notice to content creators that AI is used to power the product. For example, P6's multi-purpose chatbot provides a *"generative AI notice"*, developed with legal teams and AI experts, which informs users on how they can use the application and *"to use caution on how they use the responses."* However, this notice differs from attribution, as it applies to the tool rather than the artifact produced by the tool. When asked why they do not attribute AI in generated artifacts, participants cited lack of awareness of transparency requirements, along with time and resource constraints to implement AI attribution. In response to whether they were aware of AI transparency requirements for their product, P9 responded, *"I am also not sure. If there was, then we would be required to do something along those lines."* P12 said that although AI attribution was not a priority at the moment, they *"are working on some ways of addressing that...[by] providing guidelines."* They envisioned a three-tiered framework for tagging content based on the contribution type and level of human involvement: "AI-assisted" to denote intermediate tasks invisible in the final product (e.g., summarization and grammar checks), "AI-UX team" to denote cases in which users and AI both contributed meaningfully (e.g., reasoning tasks), and "AI-generated" to denote content with minimal human involvement.

4.2. Factors that Impact AI Attribution

To understand the reasons behind the variability in attribution practices, we analyzed participants' responses for factors that impact their current approach (RQ2). We identified four factors: awareness and interpretation of regulatory requirements, type of content, human oversight, and stakeholder needs. These factors also explain why products do include AI attribution, in contrast to those that do not.

Differing **awareness and interpretation of regulatory requirements** play a key role in determining both the presence of AI attribution and information included within it. When asked why AI needs to be acknowledged in their use case, P3 said, *"it's a legal requirement"* for them, and P6 said they worked with their company's AI governing body to develop the AI notice shown in their product. Others were not aware of legal requirements that applied to their products, as discussed in Section 4.1. P7 further speculated on the importance of granular attribution in legal accountability: *"how I would imagine this type of information to be used would be in a court of law...you would want to see how something was produced...we want to be able to ultimately point the finger at who was responsible and clear yourself of wrongdoing - that could be a person, or it could be an organization."* Hence, participants' understanding of regulatory requirements could impact the presence and granularity of attribution information.

The **type of content** produced by AI, and more specifically, the extent to which it can be mistaken as human-created, also affects the need for attribution. For example, P12 said, *"I think [attribution is] important first for ethical reasons...because AI can mimic reasoning...It's important to make sure that the...person that is consuming your information knows...that this is coming from a model."* Hence, when working with types of content that emulate human creation or thinking, there is a stronger need to disclose AI involvement to avoid deceiving consumers.

Participants also discussed the need to differentiate between content that is entirely AI-generated vs. co-created. P1 and P11, the designers of data-filling assistants, use color-coding to flag parts of a table that were automatically populated by AI – this coloring disappears following user review or revision. Hence, **human oversight** in the co-creation process is another consideration for product decisions on AI disclosure. In cases with less human oversight, additional transparency into the AI's reasoning may be needed. P11 said, *"we received feedback in the past that customers would appreciate if we can give as much insight into why an AI is...coming up with that content"*. Similarly, when asked whether attribution approaches should differ for proactive AI agents, P9 personally wanted to know *"what was the system thinking when it generated that visualization"*.

Lastly, differences in **stakeholder needs** is an important consideration for product teams in determining their attribution approach. Variability in stakeholder needs resulted in differences in the visibility of attribution information, either across products or within the same product. Across products, needs of the same stakeholder type can vary. In a user study that they conducted, P8 identified end user needs for granular attribution information in their data management tool: *"users wanted to see the last human reviewers' name...so having some sort of source lineage...if there's maybe some sort of information* *that you want to follow up or that you did not understand, maybe you can just go that person and ask for context.”* In contrast, developers of a course creation tool believed their end users have no need for such transparency: *“I don’t think the student is necessarily going to care...It doesn’t matter whether it’s human-generated or AI...They’re not looking for an intellectual challenge”* (P3). Similar differences can occur in stakeholders of the same product. In P11’s data management tool, color-coded dots that indicate AI generation are visible only to data authors in the draft state. They explained, *“the idea was that once you publish that to production, you don’t need all of these indicators...we didn’t want to overload that table with all the information of where things were coming from.”*

4.3. Challenges

Across products teams, regardless of attribution practices, participants described challenges (RQ3) that hindered or complicated AI attribution for co-created work at a technical, user, and product level.

Traceability poses a technical challenge: participants noted that it is difficult to track and differentiate between human and AI contributions, especially when multiple users and AI are involved in complex and iterative workflows, and when AI contributions are imported from or exported to third-party platforms. For example, P4 said, *“since you can edit literally anything, there’d be no good way to track...because you can add, remove, delete, change bold.”* P11 similarly noted that they were working towards a feature that allows users to revert to a previous AI suggestion after editing, but currently do not have a means to track the history of changes. **Discerning the significance of a contribution**, and in turn, whether it warrants attribution, also poses a challenge. P12 discussed this difficulty in the context of quantifying contributions made by a productivity assistant: *“It’s hard because sometimes, it’s not quantity, it’s quality...For instance, imagine that I did all the connection between the dots and I used AI to help me articulate the text. So as you can see, 100% of the text is AI, but the thoughts are mine...It’s hard to give that a number.”* P9 spoke of a similar challenge in a data visualization assistant: *“so I asked for a chart, and then I asked it to add tool tips, and then I asked it to zoom in...Is that 100% AI-generated? Or was all that guidance I just provided meaningful?”*

At a user level, participants noted that their users may develop a **sense of ownership** after reviewing or revising AI-generated content, and hence felt that it would not be suitable to credit AI for the contribution. For example, P1 commented that it is unclear what should happen to color coding denoting AI suggestions following user revisions, and whether changes should be recorded in a version history. Incorporating attribution information into a user interface can also **compromise user experience**. P5 speculated that due to the static nature of the text tags used in their product to acknowledge AI usage, users may become desensitized and ignore them over time. Three participants raised concerns of the friction introduced by existing attribution methods. In P7’s code assistant, every piece of AI-generated code is tagged with an AI acknowledgment, including single lines of code, and they noted that *“people were really irritated by the amount of space that it took up”*. P6, who works on a multi-purpose chatbot in which users can generate and copy out AI-generated content, said, *“introducing a watermark would add one step of removing that watermark when they’re using [the content] somewhere else, which is why we just introduced a copy with no watermark functionality.”*

Finally, on a product level, it can be difficult to delineate user and AI credit due to a **lack of precedent** in defining ownership in product-specific contexts. P7 explained, *“that transition from produced by generative AI into...human-owned - I think it’s something that we grapple with our legal team frequently, and they were difficult philosophical discussions...and they were never conclusive. There is no precedent for this.”* This challenge, compounded with the lack of specificity in transparency regulations, can make it difficult to understand how AI disclosure should appear in complex co-creative scenarios.

Participants have addressed some of these challenges in certain instances. For example, in the data management tool described by P8, P10, and P11, color-coded tags denoting AI generation disappear after a user has edited the data, acknowledging that content becomes human-owned after review. However, this approach is limited in that any change made by the user, even as minor as a punctuation correction, would result in the removal of AI acknowledgment. The majority of these challenges remain open questions, and we propose possible approaches to address them in Section 5.1.

5. Discussion and Future Work

Our work investigated practices and perceptions of AI attribution from the view of product teams, revealing considerations and challenges rooted in real world, business use cases of co-creation. We build on prior literature in human-AI ownership by contributing a set of considerations that impact approaches to attribution in industry, including legal requirements, content type, human oversight, and stakeholder needs. Additionally, prior work has revealed social factors that discourage disclosure of AI involvement [3, 15, 14]. Our study identified additional, practical challenges of AI attribution, including limitations in tracing and identifying meaningful contributions, introducing unwanted friction in a user experience, and a lack of precedent to follow.

Overall, we observed variability in attribution practices despite all participants working in the same company with a unified AI governing body, possibly due to a lack of specific guidelines on how to implement transparency regulations in different domains. There was some alignment between industry practices and HCI research on ownership and disclosure methods. For example, some participants' products remove AI attribution following user intervention, in alignment with research that has found increased user ownership with higher involvement in content creation and curation [3, 5, 7]. Participants' attribution considerations also aligned with aspects of El Ali et al. [16]'s framework, such as when users need AI disclosure, what should be disclosed, and where to label content. We did not observe any product teams using watermarking techniques; instead, they opted for design interventions that made attribution visible to end users. In the following sections, we discuss recommendations for improving these design interventions and opportunities for future work.

5.1. Design Recommendations for AI Attribution

Based on the approaches, challenges, and factors that we identified, we propose design recommendations and future approaches to improve AI attribution.

In some instances, **traceability** of AI contributions was important, particularly for purposes of troubleshooting and identifying responsible parties. Traceability can be achieved through a human-driven approach, in which users denote the source of contributions. Some existing tools support this approach – for example, iA Writer allows users to mark pasted text as AI-generated and subsequently greys out that text. A blog post describing this feature states, *"the only person that can safely discern human from artificial text is the person writing...It's up to you to decide how honest you want to be with yourself"* [31]. This human-driven approach poses a trade-off – while it gives users the control to determine the significance of contributions and claim ownership where desired, it also creates significant overhead and manual effort. Automated approaches may help. Drawing on research advancements in watermarking and identifying AI-generated text post-hoc [28, 27, 34], it may be possible to suggest an appropriate attribution statement based on the AI contribution detected. Additionally, using LLM-as-a-judge may be a viable way to determine the significance and quality of AI contributions [35]. However, given the limitations of these techniques [29, 36, 37], a hybrid human-AI approach is likely needed.

While source lineage information may address user needs for traceability, highly granular and detailed attribution information can interfere with the user experience of a product. To make AI attribution **unobtrusive**, designers can consider following a progressive disclosure approach, in which transparency is provided only when requested by a user [38]. Another user experience need is **streamlined cross-platform collaboration**. Given that many generative AI workflows consist of moving and curating AI-generated content between platforms, attribution methods should provide copy-and-paste workflows with simple ways to include or exclude attribution tags at the user's discretion.

As participants explained, the level of transparency and exact information needed varies by stakeholder. In addition to determining appropriate attribution approaches for different stakeholders, attribution techniques must also adhere to legal and institutional requirements. Hence, AI attribution approaches will need to **balance multiple stakeholder needs**, including those of governing entities. In some product teams, we observed that an understanding of stakeholders' attribution needs was speculative. User research and methods such as value-sensitive design [39] can help practitioners ground their understanding in real user needs. Additionally, the lack of awareness of transparency regulations implies a need for greater dissemination and support for implementation within organizations.

Finally, given that AI attribution in co-creation is a new and constantly evolving issue, product teams could benefit from **open-sourcing attribution methods** to begin setting domain-specific precedents. In our interviews, participants expressed interest in learning about other teams' approaches, indicating a need for shared understanding and resources as they tackle this issue.

5.2. Future Work

In this study, we have focused on the perspectives of product managers, developers, and designers. While these participants provided valuable insights into their current practices and challenges in managing and developing generative AI products, their perspectives on end user needs are limited as they can only provide an indirect view of based on feedback and data. Additionally, they might focus on achieving business goals, technical feasibility, or product release timelines, and AI attribution might be given lower priority. To gain a more comprehensive understanding of user experiences and needs for AI attribution, we plan to conduct further research to investigate other stakeholders such as end-users and regulators, and compare the findings.

6. Conclusion

In this work, we have shared current AI attribution practices in business co-creation products within our organization, comprised of diverse perspectives and design approaches. Based on the needs and challenges faced by product teams, we proposed a set of design recommendations to support comprehensive, effective attribution, including methods for traceability, ways to make attribution unobtrusive and streamlined for cross-platform collaboration, addressing the need to balance multiple stakeholder requirements, and an invitation to open-source resources for attribution. As generative AI technology and use evolves over time, we anticipate that attribution policies and practices will evolve as well. We invite other researchers and practitioners to investigate these evolving practices in a variety of domains and organizations to contribute to a shared understanding of how we might design and develop effective, human-centered AI attribution approaches.

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A. Semi-Structured Interview Protocol

Use Case:

1. Can you describe the user flow for this use case?
   - What role does the user/AI play?
   - What types of contributions does the AI make?
2. How much of the final content is AI-generated in most cases?
3. Does the AI suggest content proactively or does it only provide content when asked?

AI Attribution:

1. In this use case, is the use of AI acknowledged to any of the stakeholders?
   - *If yes:*
     - Who sees the acknowledgment?
     - Why does AI need to be acknowledged in this use case?
     - How does the acknowledgment appear?
     - What information is included in the acknowledgment?
   - *If no:*
     - Why not?
     - Do you think the use of AI should be acknowledged? Why or why not?
2. Would your views on acknowledgment change if the AI…
   - made a different type of contribution?
   - produced <more/less> of the final content?
   - contributed <proactively/only when asked>?
3. Would your views on acknowledgment change if the content was entirely created by AI vs. if a person and an AI worked together to create it?
   - *If yes:*
     - How should the acknowledgment appear differently?