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MSc Human-Computer Interaction

Master's Thesis

Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production

Distributed and Interactive Systems

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Abstract

This thesis explores how to disclose human-AI collaboration in news production through visual representations. As generative AI becomes more integrated into journalism, it is important to maintain trust and transparency, which are core values for news organizations. This requires transparency about both human and AI contributions. However, existing AI disclosure visualizations often fail to capture the nuanced collaboration between humans and AI, reducing complex editorial processes to overly simplistic labels. Through co-design sessions with designers (n=10), new disclosure visualizations were created to close this research gap, focusing on visualizing different ratios of human-AI collaboration. Based on prior works on visualization principles within HCI and Information Visualization, we narrowed down our set of 69 design ideas to four diverse designs that represented human-AI collaboration, and were feasible to test within the practical constraints of a controlled user study. The four designs that were turned into prototypes were a menu-based chatbot, a human-AI role-based timeline, a task-based timeline, and a standard text disclosure. These prototypes were evaluated in a lab-based user study (n=32) using behavioral measurements (incl. eye tracking) and user feedback. The study examined how visualization type and human-AI collaboration dynamics influenced perceived clarity, perceived information, perceptions of AI and journalist contributions, and visual attention patterns when engaging with news articles and disclosure visualizations. Each visualization was effective in communicating the human-AI collaboration. Specifically, while the chatbot disclosure was more suitable for providing in-depth information, the task-based and role-based timelines were better suited for providing an overview of human-AI collaboration in journalism. These findings show that the choice of representation depends on the article topic, information needs, and reader engagement. Integrating these visualizations in the journalism workflow can potentially help normalize AI use in journalism, and strengthen transparency practices by disclosing human-AI collaboration visually.

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Contents

1. Introduction

Artificial intelligence (AI) technologies such as large language models (LLMs) are increasingly being used in news media production. Generative AI (GenAI), in particular, is used for a variety of tasks in the newsroom [1]. GenAI is a category of AI systems that can produce high-quality outputs in various formats, including images, text, code, and music, based on user inputs [2]. The GenAI models can process extensive datasets and learn statistical patterns, utilized to generate multimodal artefacts based on the natural-language inputs (i.e. prompts) [3]. Examples of popular GenAI tools are ChatGPT[1] for written results, DALL-E 3[2] and Midjourney[3] for text-to-image generation, and Adobe Firefly[4] which is used for both text-to-image generation and editing specific elements in an image. These tools are used in various ways, often in collaborative workflows where GenAI assists journalists rather than replacing them entirely. Journalists use GenAI for tasks such as news generation, validation, distribution, and moderation [4]. Research shows that the task primarily executed with these tools is content production, particularly when it comes to text-based outputs [5]. This is also in line with the public's perception of the usage in journalism. Fletcher and Nielsen [6] focused on the concept of 'using AI with some human oversight,' as that was already common practice in the newsroom. Their research reveals that tasks such as text editing, translation, and data analysis are where people most expect human-AI collaboration.

As GenAI is increasingly used in journalism and its use becomes more widely known, ethical concerns are growing, particularly regarding the need for transparency in the usage of GenAI in news production. These concerns focus primarily on trust and misinformation [7] [8], while privacy and accountability are also important factors in the discussion [9]. Ensuring that readers are informed about the extent of GenAI's contribution in news creation is important to maintain trust in journalism.

The EU AI Act aims to address the risks of AI usage through Article 50: trans-

[1]ChatGPT: https://chatgpt.com
[2]DALL-E 3: https://openai.com/index/dall-e-3
[3]Midjourney: https://www.midjourney.com
[4]Adobe Firefly: https://www.adobe.com/nl/products/firefly

parency obligations [10]. The European Parliament published the final revision of the EU AI Act, the result of a very long process, on the 12th of July 2024 in the Official Journal of the European Union, which has been in force since the 1st of August 2024. Article 50 of the EU AI Act states that deployers of AI systems must disclose when content is artificially generated, especially when informing the public on matters of public interest. Piasecki et al. [11] argue that while the EU AI Act introduces transparency measures for AI-generated journalism through Article 50, its current provisions may be too limited to satisfy user's expectations due to unclear disclosure requirements. Additionally, as noted by El Ali et al. [12], the vague description in Article 50 such as "authentic" and "context of use" leaves room for interpretation, creating challenges in implementation. Moreover, noting that transparency measures must be meaningful in a way that users understand the role of AI while avoiding losing trust or confusing the user.

While the EU AI Act addresses transparency obligations for content generated with AI, its execution ultimately relies on journalists actively including disclosure practices into their workflow. Prior research suggests that LLM users might engage in passive non-disclosure or active concealment of the usage of AI [13]. Yet, in journalism, where trust and accountability are crucial, this study assumes that journalists are inclined to use disclosure representations. To facilitate this, disclosure representation must be designed in a way that can be easily integrated into the news media workflow and provides meaningful information to readers.

Therefore, disclosure mechanisms, such as watermarking or labels, are necessary but must be user-centric to be effective. This is also supported in the work by Fletcher et al. [6], in which the majority of respondents expressed a desire for disclosure or labeling when news is produced primarily by GenAI with some human oversight. Disclosure labels appear to be a solution to address this need for transparency, with research exploring various strategies for labeling in journalism and social media. Different types of disclosures have been researched, ranging from certification labels [14], to more detailed AI Usage Cards [15], or showing more details progressively [16]. All of these have different effects on improving transparency and trust, yet much currently remains unexplored.

Despite the growing number of research on transparency in AI-generated journalism, a gap remains in effectively representing the extent of AI and human collaboration in news content production. Human-AI collaboration refers to a dynamic and adaptive partnership in which humans and GenAI systems work together towards a shared goal. Both entities give input and ensure mutual learning, trust and ethical transparency [17][18][19]. Although representations such as certification labels, AI Usage Cards, and progressive disclosure improve transparency, they do not address the nuanced need for visual or contextual representations of human-AI collaboration ratios in news production. These ratios or proportions represent how much of the content was created by humans versus GenAI. It is important to writers to keep their identity and sense of authorship, which can be altered when using GenAI [20]. The effect of GenAI on their writing and on the collaboration ratio also differs depending on the writing stage, and the type of task executed by the GenAI system. The lack of focus on content creation ratios limits readers' ability to critically assess the use and implications of the increasing presence of GenAI systems in journalistic workflows. Bridging this gap is essential to developing transparency strategies that not only disclose GenAI involvement but also provide meaningful insights into the interplay between GenAI and human creativity, enabling more informed and empowered audiences.

To address this research gap, this thesis used a two-part research design: co-design sessions with designers to generate disclosure design ideas for human-AI collaboration, followed by a lab-based user study to evaluate their effectiveness. 69 designs were generated in the co-design sessions, indicating a wide variety of ways to communicate human-AI collaboration. From these, four diverse designs were selected for prototyping using predefined criteria from Human Computer Interaction and Information Visualization principles. The results showed that all four designs were effective in communicating human-AI collaboration, with the two timeline visualizations providing clear overviews, and the chatbot supporting more in-depth information exploration.

Accordingly, this thesis focuses on answering these two research questions:
RQ1: *How can we visually represent the ratios of human-AI collaboration output in news production?*
RQ2: *Which disclosure visualizations are most effective in communicating human-AI collaboration in news media?*

1.1 Project Approach

This study consists of two main parts: design, and evaluation. The design phase focuses on developing AI disclosure prototypes for news media. This is done through co-design sessions with designers, followed by a design selection and prototype development. The evaluation phase consists of a lab-based user test in which the developed prototypes are assessed on their effectiveness in expressing human-AI collaboration to news readers, generating qualitative and quantitative results. The study pipeline is illustrated in Figure 1.1. The Ethics and Privacy Quick Scan of the Utrecht University Research Institute of Information and Computing Sciences was conducted (see Appendix F). It classified this research as low risk, without requiring a fuller ethics review or privacy assessment.

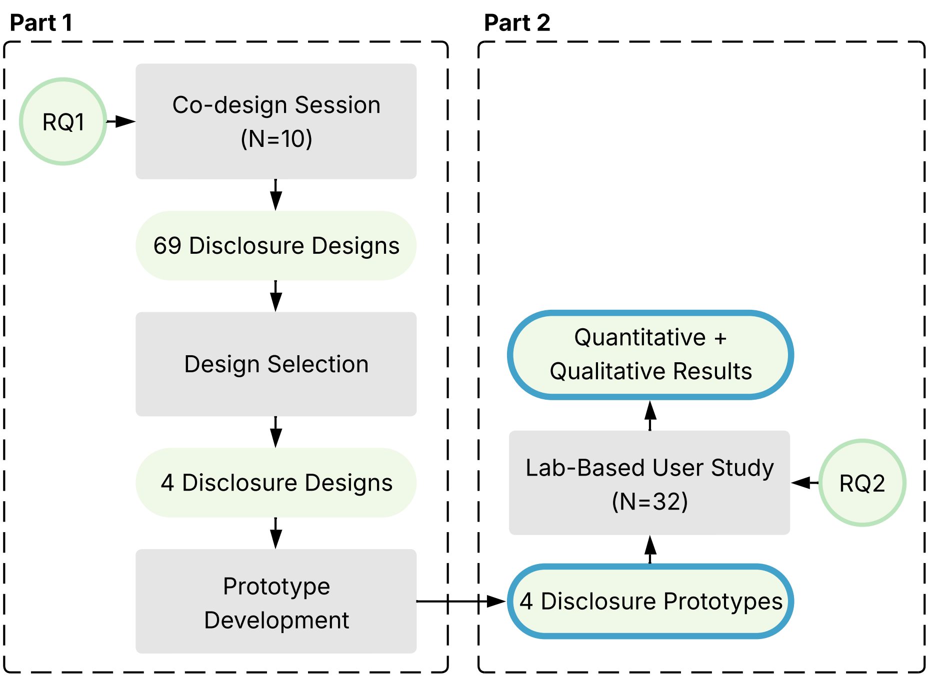


Figure 1.1: The two part study approach with contributions outlined in (bold) blue.

2. Literature Review

2.1 Human-AI Collaboration in News Production

There are multiple stages in the news production workflow in which human-AI collaboration can occur. The task executed by GenAI depends on where in the pipeline GenAI is used, from story ideation to publishing. This also has an effect on collaboration ratio, for example, the amount of GenAI contribution is different when GenAI does a fact check, in contrast to writing the entire draft. There are five stages in news production: story ideation, research & information gathering, content creation, editing & reviewing, and publishing [21][22]. In the story ideation phase, GenAI can help with idea generation, and content recommendation [23]. GenAI can assist in research and information gathering by gathering information, processing data, analyzing data, and fact checking [22][23]. During content creation, GenAI is often used to write drafts, generate summaries and headlines, translate text, and produce images or audio from text [22][23]. In the editing and reviewing phase, GenAI can correct styles so that it matches the news organization style, and verify the content [22][23]. Finally, at the publishing stage, GenAI systems can personalize feeds and customizing content to improve audience engagement [22]. Figure 2.1 illustrates this workflow, and the potential contributions of GenAI at each stage. This pipeline shows that the ratio of human-AI collaboration is not uniform across all stages, as more or less human oversight is needed per task, and the amount of contribution by GenAI in the final output also differs.

Human-AI interaction is a dynamic relationship between humans and AI systems. It is important to understand this relationship, especially since the ratio between AI and human contribution can differ. Concepts such as AI assistance, AI automation, AI augmentation, human-AI synergy, human-AI co-creation, human-AI cooperation, and human-AI collaboration each describe different levels of involvement, interaction, and contribution toward the created output.

AI assistance refers to AI systems that provide support to users, stressing human control and responsibility for the outcome [24]. Additionally, AI automation, accord-

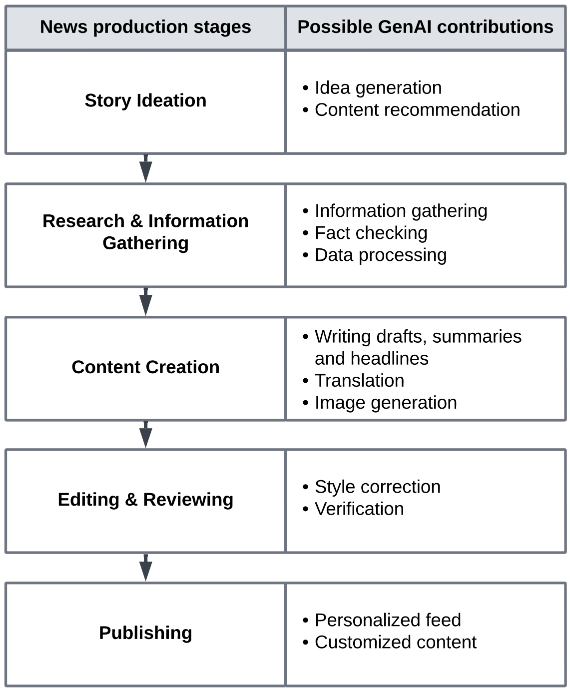


Figure 2.1: News production workflow

ing to Thäsler-Kordonouri [25], can play an autonomous role at various levels in the creation of news. These AI systems integrate journalism and data analysis, ranging in sophistication to generate data-driven news stories. However, journalists remain involved to ensure editorial standards, ensuring a partnership between AI systems and humans [25].

When it comes to the concepts of human-AI synergy and AI augmentation within human-AI interaction, it is approached by looking at performance, as Vaccaro et al. [26] did. They describe human-AI synergy as a system that outperforms both AI alone and human alone, which is the case for creation tasks with GenAI. Human-AI augmentation is described as the system that only outperforms a human alone [26].

There is also the concept of human-AI cooperation, here the AI can be viewed as more than a tool for assistance [27]. The AI is an independent entity that understands human preferences to accomplish the shared goal together with humans [27][28]. Human-AI co-creation is another concept in which humans and AIs interact. It refers to a dynamic partnership in which humans and machines leverage their strengths to achieve a shared goal. This partnership is characterized by iterative feedback, mutual learning, and constant integration of insights [29].

All these concepts are a more narrow view of the human-AI interaction, either containing a hierarchy between machine and human, or a one-directional relationship. In contrast, the term human-AI collaboration combines these perspectives into an overarching concept that captures the dynamic and adaptive nature of interactions between humans and AI systems, where both give input to contribute to an output.

According to Saha et al. [17] human-AI collaboration is a symbiotic relationship where humans contribute creativity, intuition, emotional intelligence, and contextual knowledge, while AI offers computational power, data-driven insights, pattern recognition, and efficiency. Together, they work to complete a common goal. Additionally, there is a mutual benefit for humans and AI systems when both contribute to a shared result, as they learn and adapt together [18]. Fragiadakis et al. [18] proposed a framework in which human-AI collaboration has four elements: tasks, goals, interaction, and task allocation. Human-AI collaboration systems can deal with various tasks, which impacts the type of collaboration needed between humans and AI. The drive of these systems is a shared goal, either individual objectives improving AI efficiency or human knowledge, or collective objectives which combines the two. Communication and feedback mechanisms enhance the quality of interaction, ensuring mutual understanding [30], while task allocation shifts in real-time to utilize the strengths of both contributors. Holter & El-Assady's [19] framework is in line with this, but only mentioning three dimensions: agency, interaction, and adaptation, which boils down to the same definitions. Again, stressing the need for a flexible, balanced, and adaptive partnership in human-AI systems. This strengthens trust, efficiency, and innovation [17]. Formosa et al. [31] discuss the human-AI collaboration in journalism, aligning with previous research in which both humans and AI systems contribute to generate an output, focusing on creative and textual content. Emphasizing continuity and responsibility, meaning, to what extent AI-generated content is used in the final output, and how contributions from both humans and AI are credited, respectively. Therefore, the concept of human-AI collaboration also contains trust-building and ethical considerations. These are critical for enhancing trust, ensuring transparency, maintaining ethical standards [32], and address authorship questions. Particularly as more AI involvement reduces the perception of humans as sole authors, increasing the need for transparency and disclosure [31].

To further clarify the concepts of human-AI interaction, a taxonomy has been developed (see Table 2.1). The taxonomy organizes the concepts based on their interaction types and the nature of their output relationships.

Concept	Interaction Type	Output Relationship	Literature
AI Assistance	One-directional	AI supports human actions	[24]
AI Automation	One-directional	AI replaces human tasks	[25]
AI Augmentation	One-directional	AI enhances human performance	[26]
Human-AI Synergy	Bidirectional	Superior performance together	[26]
Human-AI Cooperation	Bidirectional	AI operates as an independent entity working towards a shared goal	[27][28]
Human-AI Co-Creation	Bidirectional	Iterative, mutual learning, towards shared goal	[29]
Human-AI Collaboration	Bidirectional	Iterative, mutual learning, towards shared goal, including communication, trust and ethical considerations	[17][18][19] [30][31][32]

Table 2.1: Taxonomy of human-AI interactions

Human-AI collaboration is not a static relationship, but a ratio or spectrum of changing interactions. It integrates aspects of the related concepts, while taking the dynamic, ethical and adaptive partnership between humans and AI systems into account. For this research, human-AI collaboration is defined as a dynamic and adaptive partnership in which humans and AI systems contribute their unique strengths toward achieving shared goals. This collaboration is characterized by iterative feedback, mutual learning, and trust, including transparency and ethical considerations. This definition is the most fitting to describe the multifaceted relationship, especially considering the interplay of human and AI contributions in the news production process.

2.2 Existing AI Disclosure Representations

AI disclosure can be represented in many different ways. Annotations or metadata could be used, for example bylines in journalism is metadata used to attribute authorship to an author, but could also be assigned to GenAI systems [33]. Labeling is often used to reduce the risks of GenAI, it covers the content with visible warnings to alert users [34], such as watermarks [35], filter tags, or platform warnings [33]. Labeling can also reduce misinformation belief, and increase trust in the newsroom process [36][37]. According to Wittenberg et al. [34] it is important to establish the goal of the label, either process-based or impact-based. This current research will build on this framework by focusing on process-based representations, which aims to communicate the technical process by which the content was created or edited, taking into account the human-AI collaboration ratio. Impact-based labeling goals will not be included to keep a neutral stance towards the consequences of GenAI usage in news media. Zier & Diakopoulos [36] state that showing human involvement in combination with GenAI's contribution could be a good way to adhere to transparency goals, and demystify any assumptions about GenAI. It can make readers understand how the tools work, so they do not think GenAI wrote the entire piece, keeping the accountability and ownership with the journalist. Research by Altay & Gilardi [38] showed a decrease in belief and willingness to share headlines labeled "AI-generated", due to the unrealistic expectation that these headlines are only written by AI without human involvement. They emphasized that labels need more transparency on what they really mean, to avoid negative effects. This aligns with Burrus et al. [37], they emphasize that any labeling solution should thoughtfully address how, when, and where GenAI was used in the creation process. These disclosure mechanisms are necessary, but must be user-centric to be effective. This is also supported in the work by Fletcher et al. [6], in which the majority of the respondents expressed a desire for disclosure or labeling when news is produced primarily by AI with some human oversight. Piasecki et al. [11] also stated that news readers want to know whether AI was involved, regardless of its impact on public opinion or perceptions of its accuracy, and trustworthiness. Even though Article 50 of the EU AI Act [10] mentions exemption of disclosure that has had human review, readers still want to be informed about the origin of the content [11]. Therefore, disclosure labels appear to be a solution to address this need for transparency, with existing labels used in social media, and research exploring various strategies for labeling in journalism.

In social media, AI disclosures range from simple labels to more detailed frameworks. For example, platforms such as TikTok and Meta have introduced specific AI disclosure labels, visual examples can be found in Appendix A. Meta's approach involves adding "AI Info" labels to video, audio and images, on which users can click for more information (see Figure A.1a) [39]. TikTok includes labels such as "creator labeled as AI-generated" and "AI-generated" (see Figure A.1c) [40]. Both TikTok and LinkedIn use Content Credentials by Coalition for Content Provenance and Authenticity to detect AI by using metadata of the content (see Figure A.1b) [41]. YouTube chose for a broader label such as "Altered or synthetic content" (see Figure A.1d) [42]. These representations showcase different options to disclose AI involvement in content creation.

Prior work on AI disclosure representations have had various approaches, focusing on design, context, and impact on user understanding, trust, and engagement. Epstein et al. [43] pointed out that the language used in labels greatly influences public perception. Labels like "AI generated", "Generated with an AI tool", and "AI Manipulated" are the terms that participants most consistently associated with content that was constructed using AI, regardless of being misleading. Research by Sivakumaran [44] investigated consumer preferences for labeling practices that provide clear and accessible information, finding a preference for pictograms and explicit details about AI usage. Sivakumaran also designed possible AI labels in various involvements of AI in the creation process (see Appendix A, Figure A.2a). Other work was done using different phrases for labels, such as "[*Warning Signal in Yellow*] Content Generated by AI" [45], "Written by artificial intelligence" (translated from Dutch "Geschreven door kunstmatige intelligentie) (see Figure A.2b) [11], and stimuli with "AI-Generated", and "Altered" as labels (see Figure A.2c) [46]. Moreover, Wahle et al. [15] proposed "AI Usage Cards" (see Figure A.2d), an elaborate representation of the used AI tools in scientific research, which could also work as a standardized reporting on GenAI involvement in content creation. Scharowski et al. [14] further demonstrate that certification labels (see Figure A.2e) for trustworthy AI significantly improve user trust in both low- and high-stakes contexts. Additionally, Springer & Whittaker [16] demonstrate another type of disclosure, progressive disclosure. This can help user comprehension and trust by revealing basic AI involvement upfront, and leaving more detailed explanations upon user request. This approach minimizes risks of overwhelming users with too much information while ensuring trust by allowing those with greater interest or expertise to dive deeper. The progressive disclosure approach could be suited for illustrating human-AI collaboration in journalism. It ensures that casual readers, who might only be concerned with whether GenAI was involved, are informed quickly, while giving the possibility to delve into specifics, such as the type of GenAI system used or the extent of human oversight. Burrus et al. [37] also stressed that the cognitive load of the user should also be taken into account. Users want information on which elements GenAI created and which were done by the humans, but too much technical details will be overwhelming. Therefore, an effective label should enable viewers to recognize the human-AI collaboration at first glance.

2.3 Information Visualization

Information visualization is the interactive, computer-generated graphical representation of data and is traditionally seen as a set of methods that help humans understand and analyze large, complex datasets [47] [48]. This includes the design, development and application of these representations. Transforming complex information to intuitive, accurate, and meaningful representations, with the goal to give users insights [47]. Moere & Purchase [48] claim that the element of design is an inevitable process to create new representational methods. With design, there needs to be a balance between utility, soundness, and attractiveness, this implies that the design needs to be functional, reliable, and appealing. While also taking into account human constraints, like visual perceptual and cognitive limitations that may hinder understanding the represented information [48].

The main challenge in disclosing human-AI collaboration is how to effectively represent these ratios. The visual representation of proportions is one of the most common data visualization tasks encountered in media [49]. There are various visualization techniques that can be used to depict these ratios. The most used representations are pie charts, donut charts, stacked bar charts, tree maps, waffle charts, and numerical and textual representations (see Table 2.2).

A pie chart shows the proportions by dividing a circle into multiple slices, whereas a donut chart has the shape of a ring instead of a circle [50]. This visualization is often criticized because humans are not good at judging areas, in comparison to lengths [51]. However, there are subjective preferences to pie charts, which explains why they are so widely used [49]. These two charts, together with the stacked bar chart, are most common visualization techniques in media [49]. The stacked bar chart represents proportions by dividing the bar into segments. Furthermore, a tree map can also organize the data more hierarchically, by adding multiple levels. In which a tree is visualized as squares, and the different nodes can be seen as smaller squares. If there is only one level, a tree map is similar to a pie chart, just square shaped [50]. The waffle chart is a grid in which each small square represents a percentage of the data [50]. Cui et al. [52] investigated how proportions are visualized in info-graphics, where visual and textual features are often combined. They also stated that it is often illustrated in forms like '#%', '# in #', '# / #' or 'half of ...'.

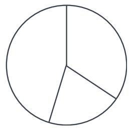
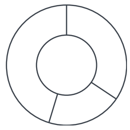
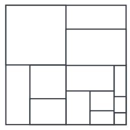
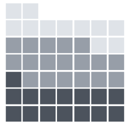
Visualization Type	Description	Example
Pie Chart	Divides a circle into proportional slices.	
Donut Chart	Similar to a pie chart, but with a central hole.	
Stacked Bar Chart	Uses segments within a bar to represent proportions.	
Tree Map	Represents hierarchical data using nested rectangles.	
Waffle Chart	Uses a grid of squares to show proportions.	
Numerical/Textual	Directly states proportions (e.g., "75% AI, 25% Human").	

Table 2.2: Overview of common proportion visualizations

These visualization techniques are a starting point for creating human-AI collaboration ratio disclosures. However, they are static and simple, without embellishments. It is often mentioned that embellishments can distract, but contradictory research also shows that embellishments do not interfere with the perception of the information represented and could even help with long-term memorization [52]. Therefore, design and animation techniques can help with attracting attention, and raising awareness of the AI disclosures.

Including design techniques in information visualization offers opportunities for enhancing AI disclosures representation of the dynamic human-AI collaboration relationship. Therefore, it is important to consider design principles from human-computer interaction (HCI) and information visualization when designing and evaluating these representations. However, not all usability heuristics and interaction principles are equally relevant to this research. Nielsen's [53] usability heuristics are prominently used in interaction design. There will be a focus on three of these heuristics: *aesthetic and minimalist design*, *recognition rather than recall*, and *match between system and the real world*. These align with the aim to create a representation for human-AI collaboration ratios. Other principles can be tied to these heuristics, so the overarching terms used for the principles are simplicity, cognitive load management, and a user-centered approach. These principles will ensure that users can accurately interpret AI involvement, avoid misperception, and interact with information at different levels of detail. Other heuristics from Nielsen's framework, such as *user control and freedom*, *visibility of system status*, *consistency and standards*, *error prevention, flexibility* and *efficiency of use*, *help and documentation*, or *help users to recognize, diagnose, and recover from errors*, are important when creating interactive systems, but less relevant for AI disclosure visualizations. This is due to the focus on information visualization rather than facilitating complex user interactions. AI disclosure representations are informative items rather than tools for direct user manipulation, in contrast to interactive systems where users take actions that could result in errors. Likewise, additional *help and documentation* would contradict the goal of creating self-explanatory and understandable visualizations.

Creating AI disclosure representations that are clear and free from unnecessary information is crucial for usability, Nielsen [53] also states this in his aesthetic and minimalist design heuristic. This is in line with one of the basic design principles for interaction described by Rees et al. [54], simplicity. An important element in achieving simplicity is clarity [55], as misleading or ambiguous representations can misrepresent the role AI played in the creation process. Altay and Gilardi [38] showed that when there is no clear distinction between human and AI contributions, users may overestimate or underestimate AI's role. Ensuring clarity means that the human-AI collaboration ratio is immediately understandable, without the need to make sense of complex graphics or detailed descriptions. Therefore, it is important to keep the interaction mechanism simple, as they otherwise might not be easily adopted by users [56].

Managing cognitive load in the disclosure representation is essential, as understanding human-AI collaboration can be complex. Nielsen's [53] heuristic on recognition rather than recall states that the user should not rely on memory, but should be able to immediately understand the information. If a visualization shows too much information at once, users may feel overwhelmed and ignore it. On the other hand, if too little information is provided, the visualization can cause misperception of AI's role. A good solution to minimize cognitive load is the aforementioned progressive disclosure, giving users the option to see more details. This also aligns with the information visualization principle on user interaction of Engelbrecht et al. [57], the detail-on-demand interaction, only showing details when requested by the user, which also helps with limited display size.

To ensure that the representations are meaningful and accessible, they must adhere to Nielsen's [53] heuristic of a match between system and the real world. Therefore, the designs needs to use language and symbols that are familiar to the user, avoiding technical jargon, and focusing on the user's perspective. Using familiar information visualization techniques as shown in Table 2.2 could enhance understanding of the human-AI collaboration ratio. Hurter et al. [56] supports this principle by arguing that interactive visualizations should not only be functional, but also intuitive and engaging. Additionally, representations such as bylines or watermarks are formats that users are already used to in media, which are representations that are kept close to the real world, and keeping the focus centered around the user.

An overview of the principles that will be used to design the AI disclosure representations in this research can be found in Table 2.3. This selection of heuristics aligns with the specific goal of creating AI disclosure visualizations for human-AI collaboration ratios in journalism. By explicitly defining these principles, it is ensured that the AI disclosure representations will be evaluated on clarity and user friendliness while taking cognitive load into account.

Principle	**Description**	**Related Heuristic**
Simplicity	The design should be clear, free from unnecessary elements, and immediately understandable.	Aesthetic and Minimalist Design [53]
Cognitive Load Management	Users should be able to grasp the AI-human ratio without needing to remember prior information or interpret complex details.	Recognition Rather than Recall [53]
User-Centered Approach	The visualization should align with user expectations and avoid unnecessary technical complexity.	Match Between System and the Real World [53]

Table 2.3: Principles for AI disclosure visualizations

3. Design

The aim of the first part of the study is to create AI disclosure prototypes to use in news media. A co-design methodology was used to generate various disclosure design concepts during collaborative sessions with designers. This was followed by an evaluation based on predefined criteria from the literature, to acquire a selection to be turned into functional prototypes. These prototypes were evaluated in a lab-based user test, which is described in the next chapter.

3.1 Co-Design Session

This method fits the objective of this study because co-design leverages the collective creativity of designers to design together [58]. It is an effective approach to combine ideas and knowledge, making it possible for participants with different experiences to come up with a solution together [59]. This method is especially useful in designing AI disclosure visualizations as participants will have varying levels of familiarity with AI, and different expectations of how to effectively disclose such collaboration ratios.

The goal was to explore various ways to visually communicate the human-AI collaboration ratio in news media. The sessions facilitated idea generation for different levels of AI involvement in the journalistic workflow. Designs were created for both static and interactive representations, where static means showing all the information at once, and interactive designs show information progressively after user interaction [16]. Although dynamic representations, such as animations, are also a possibility to show GenAI involvement, they could require too much cognitive attention in a news environment. Therefore, the focus was on static and interactive designs for human-AI collaborations, to prioritize clarity and simplicity.

3.1.1 Participants

Co-design sessions were conducted with UX/UI designers, HCI experts, and design students (N=10) to develop user-centered and effective AI disclosure representations. The ten participants were divided across three separate co-design sessions, each participant took part in only one session. It was deliberately chosen to involve only design-focused participants rather than journalists, as the goal was to generate design concepts that can effectively communicate the human-AI collaboration dynamics in journalism. The focus would have shifted towards workflow integration if journalists had been involved, rather than focusing on communicating usability and clarity from a design perspective. However, journalistic feasibility was taken into account in the subsequent design selection phase (see Section 3.2).

Participants were recruited through multiple platforms and snowball sampling. Each participant received a €20 gift card after completing the co-design session. The participants that joined the online session were required to have access to a drawing tablet. There were varying experiences with design, AI (self-reported), and news reading frequency (see Table 3.1).

No.	Current Job	Design Experience	AI Experience	News Consumption Frequency
1	UX Design Research Assistant	2 years (industry)	Intermediate	Daily
2	UX Design Researcher	10 years (academia + industry)	Beginner / Intermediate	Monthly
3	PhD Candidate HCI	NA	Advanced	Daily
4	PhD Candidate Interaction Design	Recently (academia)	Intermediate	Multiple times a week
5	Design Researcher	2 years (academia) + 4 years (industry)	Intermediate	Multiple times a day
6	Design MSc Student	6 years (academia)	Intermediate	Multiple times a day
7	Design MSc Student	2 years (academia) + 7 years (industry)	Intermediate	Daily
8	Design MSc Student	6 years (academia)	Intermediate	Twice a week
9	Design MSc Student	5 years (academia) + 1 year (industry)	Beginner	Weekly
10	Design MSc Student	6 years (academia)	Intermediate	Daily

Table 3.1: Participant information of co-design sessions

3.1.2 Procedure

The co-design sessions were divided into two parts: a sensitizing booklet filled out beforehand (∼20 min), and the main co-design session (∼90 min). Figure 3.1 illustrates the study procedure.

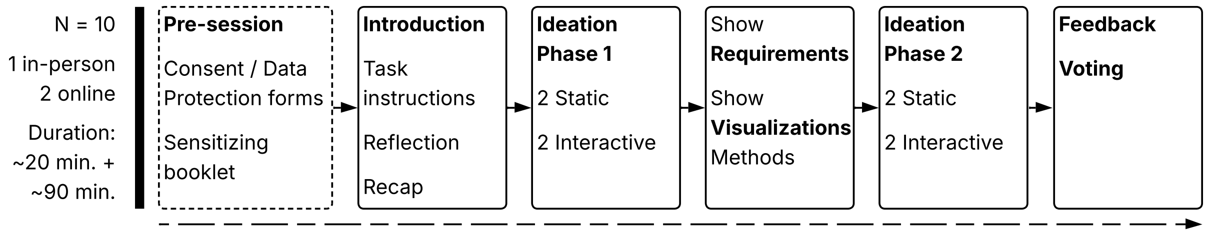


Figure 3.1: Co-design session procedure

Sensitizing Booklet

Sensitizing booklets were sent to the participants prior to the co-design session. This booklet was an important preparation step, as it helped participants reflect on GenAI usage in news media, introduced them to the concept, and gained confidence to contribute their experience, even if they were not yet familiar [60].

It took approximately 20 minutes to complete the booklet, which had to be submitted before the session together with the signed consent form (see Appendix B.1). The sensitizing booklets were filled out in Miro[1] (Figure 3.2). The data gathered from the sensitizing booklets were transcribed in Excel for analysis, and were used during the co-design session.

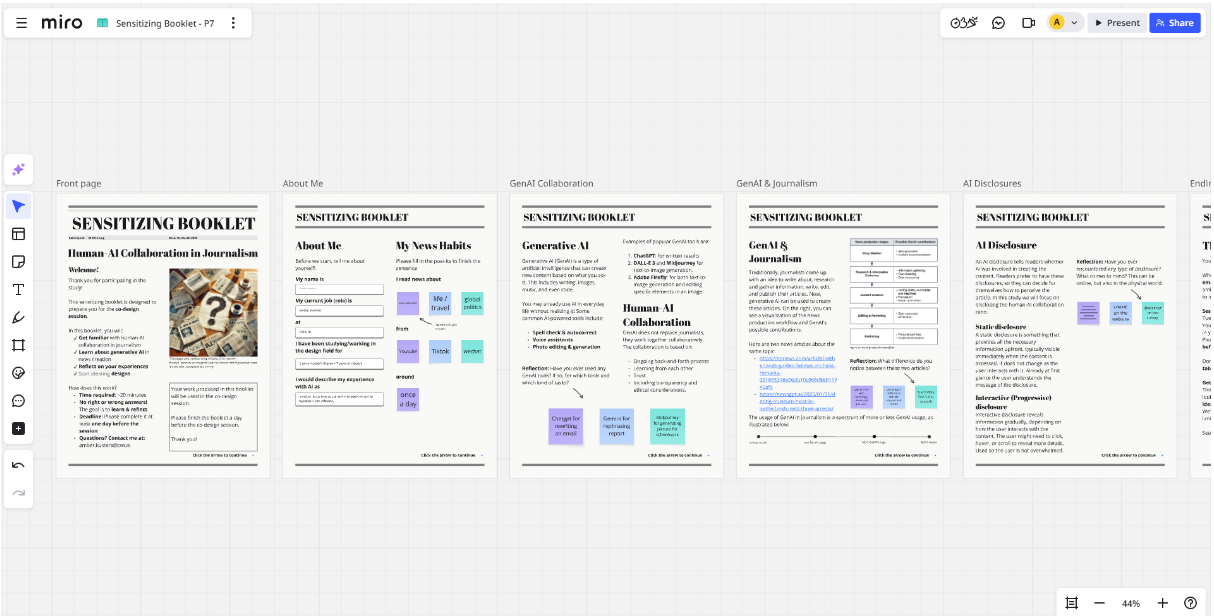


Figure 3.2: Completed sensitizing booklet of participant 7

[1] Miro board of sensitizing booklet: `https://miro.com/app/board/uXjVLhVnry8=/?share_link_id=270962526928`

The booklet started with an introduction page that explained the purpose of the booklet and how it worked (a detailed page view can be found in Appendix B.1). This was followed by questions about the participant regarding their experience with design, self-reported AI experience, and about their news reading habits. The following pages provided information about important concepts that needed to be understood for this study. First, GenAI was defined and common use cases were given to illustrate GenAI usage. Second, the definition of human-AI collaboration was provided. Third, the usage of GenAI in journalism was explained by showing GenAI contributions in the journalism workflow, and presenting two articles written about the same topic with and without AI. Finally, AI disclosures were explained, focusing on static and interactive (progressive) disclosures. Reflection questions accompanied every information section, to stimulate the participants to think about the content, and to make sure they were prepared for the co-design session. In addition, encouraging them to start thinking of designs, as there was limited ideation time during the session.

Figure 3.3: In-person co-design session setup

Main Co-Design Session

Two co-design sessions were conducted online via Zoom and a shared Miro board for collaboration, and one session was conducted in person (Figure 3.3) at Centrum Wiskunde & Informatica, using papers, pencils, markers, etc. to design. This was done to accommodate designers that did not have access to a drawing tablet. Additionally, creating a space where slightly more interaction and collaboration was possible, compared to an online session. The designers in the online sessions were asked to set up their drawing tablet beforehand. They had already built familiarity with Miro when they completed the sensitizing booklet. The duration of the session was approximately 90 minutes.

During the sessions, designers were divided into teams of two designers, combining more experienced designers with designers who had relatively less experience. In the online sessions, the teams were put in separate breakout rooms, while the designers in the in-person session stayed in the same room but were asked to focus on collaboration with their teammate. This was done to stimulate more interaction between participants, so they could equally contribute to the session in their team.

The co-design session consisted of five parts: introduction, ideation phase 1, showing requirements and data visualization techniques, ideation phase 2, and evaluation. An overview and flow of the Miro board[2] used during the co-design is shown in Figure 3.4. A more detailed view of each page of the Miro board can be found in Appendix B.2.

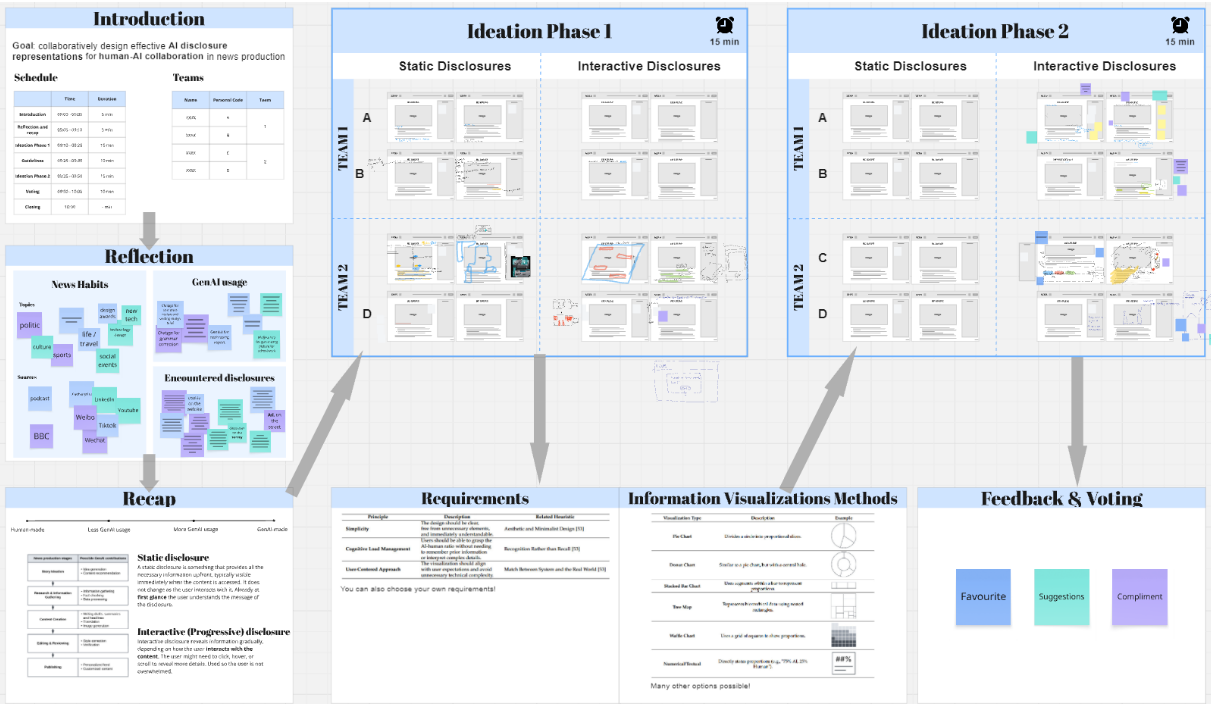


Figure 3.4: Miro Board used during the co-design sessions

The session started with an introduction in which the goal and timeline of the study were explained, everyone introduced themselves, and the teams were shown. This was followed by a short reflection on the sensitizing booklets. The news habits, AI usage,

[2]Miro board of co-design session: `https://miro.com/app/board/uXjVILuPkmM=/?share_link_id=330092544705`

and knowledge on existing disclosures were anonymously shared. This was done to show the different perspectives of the group on these topics, which could have been taken into account during brainstorming. A recap of the information in the sensitizing booklet was also discussed, focusing on human-AI collaboration, the news production workflow, static and progressive disclosure. Participants also had the opportunity to ask questions before continuing.

This was followed by the first round of ideation, in which the designers worked in teams of two to co-create the disclosure visualization designs. They designed both static and interactive representations for news articles with two different dynamics of human-AI collaboration. In one scenario, the journalist selected the topic, conducted research, and let ChatGPT-4o write the first draft, after which minor revisions were done by the journalist. In the other scenario, ChatGPT-4o generated ideas requested by the journalist, who then chose a topic, conducted research, and wrote the first draft. Then, AI tools were used to for a spell and grammar check, and to generate an image, after which the journalist again did minor revisions.

On the ideation board, each participant had one row in which they could create their designs, and two rows were grouped per team. In each row there were two static and two interactive disclosure templates. Both had the same two scenario's of human-AI collaboration ratio's as described above. The layout of the template was a wireframe of an online news website (Figure 3.5). It had a standard layout of a headline and image. The text that described the scenario was where the article would be, and the box on the right side normally containing advertisements, was turned into a comment section (see Appendix B.3 for all scenario wireframes). The participants were free to work on any of the disclosure as long as they created at least one design for each of them. The wireframes were printed on paper for the in-person sessions, during which the Miro board was used as a slideshow.

After this round, there was a short feedback round in which everyone shared some of their designs, to encourage interaction between the teams. Then, requirements and information visualization methods were discussed to inspire the designers, while also emphasizing that they can come up with their own ideas and requirements, so as not to limit their creativity.

The second round of ideation started, using the same scenarios, allowing the designers to revisit their ideas or come up with new ones. During this session they used

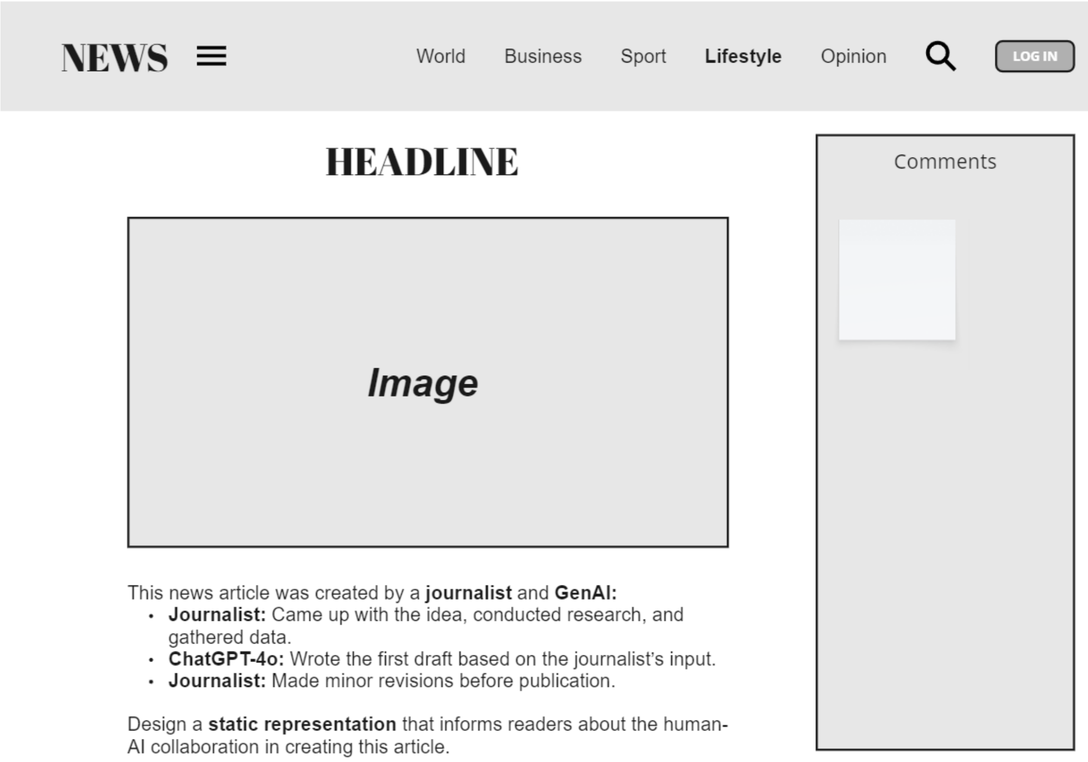


Figure 3.5: Example scenario for co-design session

the inspiration they got from the other team and from the requirements and visualization methods to come up with more designs.

Again there was a short feedback round in which each team shortly presented and explain their designs. At the end, there was an opportunity to give feedback and vote on their favorite designs.

3.1.3 Results

The design ideas from the in-person sessions were scanned to create digital copies, and saved together with the concepts from the online sessions. A wireframe often contained multiple ideas. Therefore, to analyze these designs, all ideas were turned into a description and put in an Excel sheet together with labels for disclosure type (static or interactive), category (see Table 3.2), and placement (headline, image, body, bottom). Duplicate ideas were combined as one idea.

The category labels were developed with inductive thematic coding [61]. All design ideas were iteratively reviewed, coded, and grouped into categories that were found

Disclosure Type	Category	Count
Static	Labels / Icons / Stamps	9
	Textual	12
	Elaborate	8
Interactive	Sliders / Adjustable	5
	Click / Toggle	14
	Hover / Reveal	9
	Pop-up	5
	Scroll / Floating	4
	Chat	3

Table 3.2: Number of design ideas in each category per disclosure type

by looking for patterns and similarities. This resulted in a total of 69 different design ideas, of which 29 were static designs, and 40 were interactive designs. The static designs were categorized into three types.

- *Labels / Icons / Stamps*: small indicators of AI contributions.
- *Textual*: textual description of the AI contribution.
- *Elaborate*: more intricate designs, for example, a bar of icons of AI and humans, or a gauge meter from human to AI.

Interactive designs were grouped in six categories:

- *Sliders / Adjustable*: interactive visualizations that allow users to slide and adjust different levels of human-AI contribution.
- *Click / Toggle*: users can click and toggle elements to show more or less information.
- *Hover / Reveal*: additional information is revealed when hovering over an element.
- *Pop-up*: overlays on the page and the user needs to click it to close.
- *Scroll / Floating*: elements that float or update as the user scrolls.
- *Chat*: chatbot-style interfaces, offering interactive explanations.

Table 3.2 gives an overview of the number of design ideas per category. Furthermore, the placement of the visualizations varied a lot with 19 visualizations placed around the headline, 24 around the image, 21 around the article body, and 5 bottom at the bottom. A full overview of the results can be found in Appendix C. Figure 3.6 shows four examples of the output of the co-design sessions, the color in the top two varies slightly due to the digitization process.

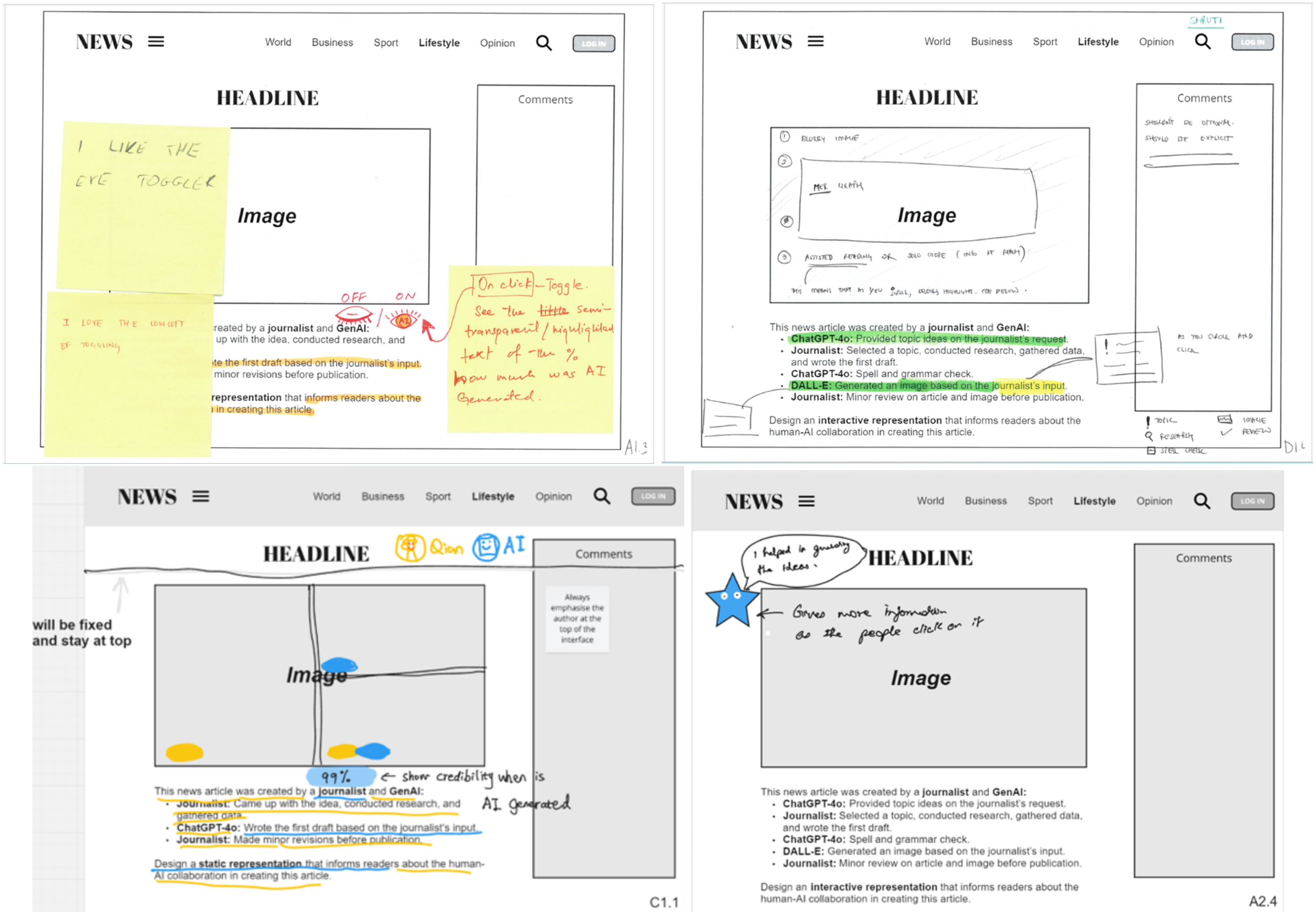


Figure 3.6: Four examples of the results of the co-design sessions

3.2 Design Selection

The 69 design ideas that were created during the co-design sessions were reviewed to select a small diverse set of ideas that could be used in the controlled user study. The aim was to include different designs that represented human-AI collaboration, ensuring that each selected design communicated the roles of the journalist and AI. The set was purposefully limited to four prototypes to balance the need for diverse designs with the practical constraints of a lab-based user study, including experiment duration, multiple measurements, and participant attention.

The selection process was based on various criteria (Table 3.4), derived from HCI and Information Visualization principles (Section 2.3) and practical requirements of the study context. This selection process was conducted collaboratively by the researcher and academic supervisor to ensure the criteria were consistently applied.

Criterion	Description
Human–AI collaboration	Must represents both human and AI contributions, not only AI usage.
Feasibility (technical)	Can be implemented as a working prototype for the study.
Feasibility (journalistic)	Realistic to integrate into journalistic workflow.
Simplicity	Clear [62], free from unnecessary elements, and immediately understandable [53].
Cognitive load management	Users should be able to grasp the AI-human ratio without needing to remember prior information or interpret complex details [53].
User-centered approach	The visualization should align with user expectations and avoid unnecessary technical complexity [53].
Low interaction count	Minimizes number of required interactions, which aligns with simplicity and reduces cognitive load.

Table 3.4: Criteria used for evaluation and selection of design ideas for prototyping.

Firstly, it was assessed whether the designs showed human-AI collaboration, as a few designs only focused on showing AI usage, which was not in line with the research focus. Secondly, the designs should not only be feasible to turn into a prototype, but also feasible for a journalist to use. This means that the format should be straightforward for journalist to provide the necessary input, without having to make precise measures (e.g. percentages of AI input). Rather, the design should reflect their collaborative workflow in which they can use the stages and qualitative descriptions to inform the reader. Thirdly, the designs were evaluated with the design principles explained in Section 2.3, summarized in Table 2.3. These principles were simplicity in which clarity is an important factor for good information visualization design [62], cognitive load management, as minimizing cognitive load ensures a design that is easy to grasp for the reader. and a user-centered approach. Additionally, the number of interactions were considered, as a lower number of interactions is in line with the simplicity design principle, and minimizes cognitive load.

In addition to these criteria, diversity across modality and interactivity was ensured. The designs were labeled on modality, as it became apparent from the results that designs were either visual-centered or textual-centered. Based on this filtering, four designs were selected for prototype development: two static design ideas (one textual and one visual), and two interactive design ideas (one textual and one visual). Table 3.5 shows the design concepts that were turned into prototypes for the user study.

Interactivity	Modality	Visualization Type	Description
Static	Textual	Textual Disclosure (TD)	Textual GenAI model description and its contribution, resembling the simplistic AI disclosure labels currently in use by some organizations
Static	Visual	Role-based Timeline (RT)	Icons of person and robot to show division of work
Interactive	Textual	Chatbot (C)	Menu-based chatbot with predefined questions and answers by ChatGPT-4o model
Interactive	Visual	Task-based Timeline (TT)	Icons showing different steps in the workflow, hover to show the contribution of journalist and GenAI

Table 3.5: Selected design ideas

3.3 Prototype Development

The four selected design ideas were turned into fully functional prototypes for the user study. These final prototypes (Figure 3.8) were created using JavaScript, JSON, and CSS, as they would be embedded in a React-based web application. All visualizations are similar in size for consistency and easy comparison.

The **Textual Disclosure (TD)** describes the used AI model, its contributions, and the journalist's contributions. The **Role-based Timeline (RT)** visualization shows a linear progression of the roles between the journalist and AI, including icons as visual elements with a textual explanation underneath. The AI is displayed as a robot, this was also often done by the designers in the design sessions. The **Chatbot (C)** disclosure is menu-based with predefined questions about the AI model, and human and AI contributions. The **Task-based Timeline (TT)** shows the five stages of news article creation, visualized with icons, and a sparkle symbol that indicates human-AI collaboration. When users hover over the icons, additional information about the contributions is revealed. Each visualization went through multiple design iterations.

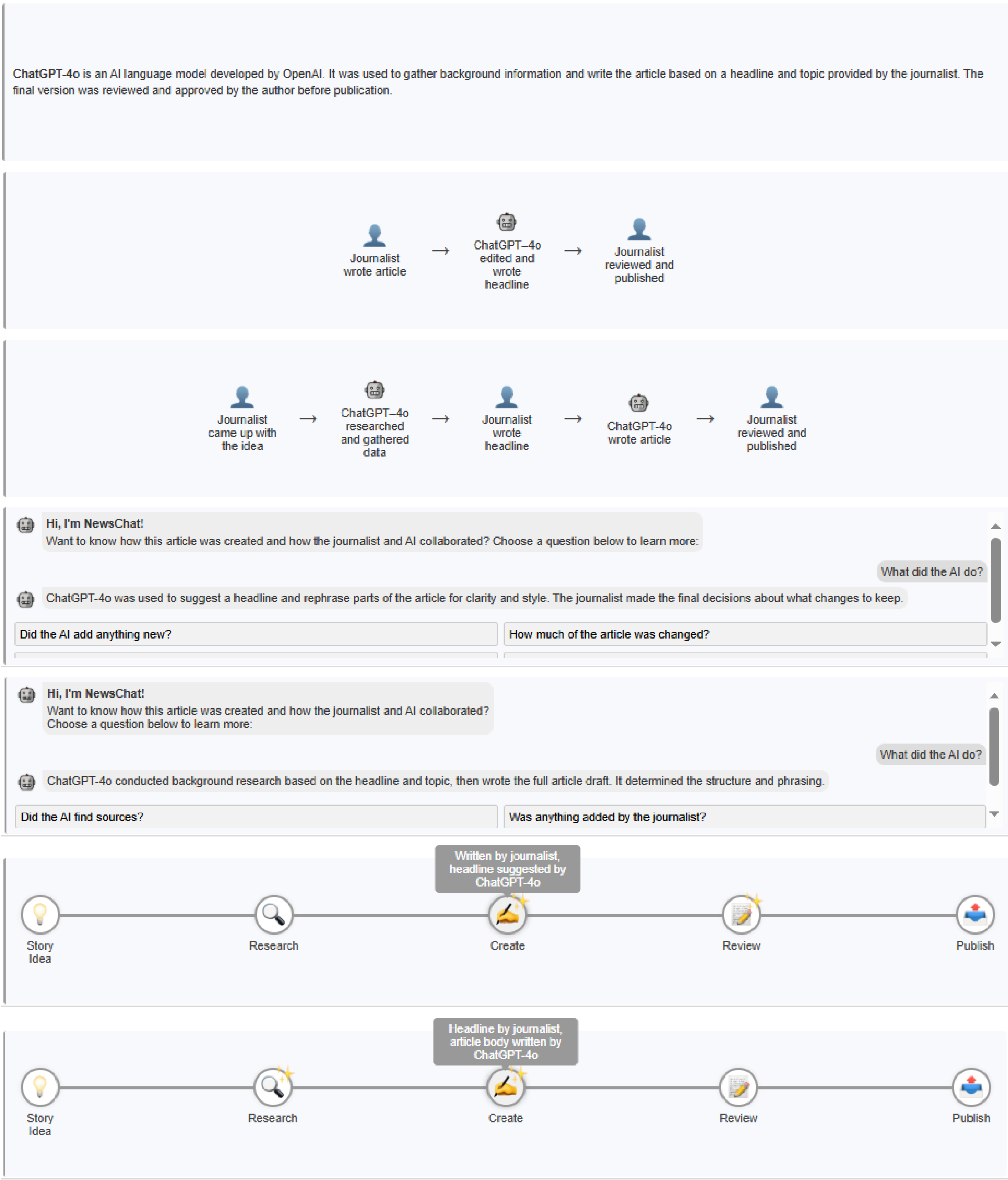


Figure 3.8: Final prototypes of human–AI collaboration disclosure visualizations. From top to bottom: (1 & 2) Textual Disclosure, (3 & 4) Role-based Timeline, (5 & 6) Chatbot interface, and (7 & 8) Task-based Timeline. The first version of each displaying more human, and the second more AI contribution.

4. Evaluation

4.1 User Study

The aim of the user study was to investigate how users perceive, interpret, and interact with the different disclosure visualizations of human-AI collaboration in online news articles. A mixed methods study was conducted, combining quantitative data from eye tracking, and questionnaires, with qualitative data from semi-structured interviews.

The study follows a 4 (visualization types) x 2 (human-AI collaboration ratio: more human vs. more AI) within-subject study design. Each participant completed 16 trials (2 articles x 2 versions x 4 visualizations), and the visualization order was counter-balanced using a 4x4 Latin square to minimize order effects. All sessions were conducted between May 22 and June 6, 2025 at Centrum Wiskunde & Informatica (CWI) in Amsterdam. The sessions took approximately one hour, and no tasks prior to the experiment were asked of the participants.

4.1.1 Participants

Participants were recruited through multiple platforms and snowball sampling. The only requirement was that they did not have significant visual impairments, as this could affect the accuracy of the eye tracker. Each participant received a €10 gift card right after the experiment.

32 participants[1] (19 female, 12 male, 1 non-binary) were recruited through multiple platforms and snowball sampling. The age distribution included four participants aged 18–24, nineteen aged 25–34, three aged 35–44, none aged 45–54, and six aged 55 or older. The educational backgrounds were diverse, with 5 participants having completed high school, 7 holding a bachelor's degree, 14 a master's degree, and 6 a doctorate. In terms of frequency of news consumption, 14 participants reported reading news daily, 13 multiple times a day, 3 a few times per week, and 2 rarely. The most common

[1] For effect size f=.25 under α=.05 and power (1-β)=.95, with 16 repeated measurements within factors, one would need a minimum of 15 participants.

news sources were news websites (n=14) and social media (n=12), followed by television (n=3), other sources (n=2), and newspapers (n=1). Regarding prior experience with AI in the news, 21 participants were unsure, 10 indicated having experienced it, and 1 reported no experience. Participants' self-reported ChatGPT experience on a 1–7 scale (7 = very experienced) averaged 4.22 (SD = 1.96). Finally, AI literacy, measured using the 0-10 MAILS scale [63], showed a mean of 5.69 (SD = 1.58), with values ranging from 2.8 to 9.4.

4.1.2 Setup

The participants were seated at a desk with a monitor to which the Tobii Pro Fusion screen-based eye tracker[2] was attached (Figure 4.1). The monitor and eye tracker were connected to a laptop running Tobii Pro Lab[3], to collect and later analyze the eye tracking data. A custom built and locally hosted React web application was developed for use during the experiment. The web application was used to present the stimuli and collect the questionnaire responses. The monitor height was adjusted to make sure that the eye tracker was properly calibrated. At the start of the experiment the researcher was next to the participant, but during the trials the researcher was at the other side of the room to reduce distractions.

Figure 4.1: User study setup

[2]https://www.tobii.com/products/eye-trackers/screen-based/tobii-pro-fusion
[3]https://www.tobii.com/products/software/behavior-research-software/tobii-pro-lab

4.1.3 Stimuli

Each stimulus consisted of one news article and one disclosure visualization. Two real low-stake news articles were selected from the MiRAGeNews dataset [64], which contains both real and AI-generated news articles. Low-stake topics were chosen to minimize bias in disclosure effectiveness due to the subject of the article. Each article was transformed into two versions that vary in human-AI collaboration ratio in the writing process:

- **More human**: The original article was used as input for ChatGPT-4o to generate a headline and change the style. This prompt mimicked the Gilardi et al. [65] prompt style: "*Here is a newspaper article: [article text]. As an AP journalist, write a headline for this article and do small adjustments to the text to keep it in AP style.*" This generated an article that was almost entirely written by the journalist, but still collaborating with GenAI.
- **More AI**: Only the article headline was provided to ChatGPT-4o, using an adapted prompt from Gilardi et al. [65]: "*As an AP journalist, you must write a 400-word article on this topic: [article headline].*" This generated an article that was almost entirely written by GenAI.

The versions of the articles used in the user study can be found in Appendix D.1. Each version was paired with the four disclosure visualization prototypes (Figure 3.8 in Section 3.3): Textual Disclosure (TD), Role-based Timeline (RT), Chatbot (C), Task-Based Timeline (TT). All visualizations were displayed at the bottom of the article to control for placement effects, and to ensure a fixed area of interest for eye tracking analysis. The four visualizations and four article versions were shown in counterbalanced order using a Latin square. During the trials, the screen was split: the left side displayed a realistic news website interface with the stimulus (article and visualization), while the right side was filled with questionnaire questions (Figure 4.2).

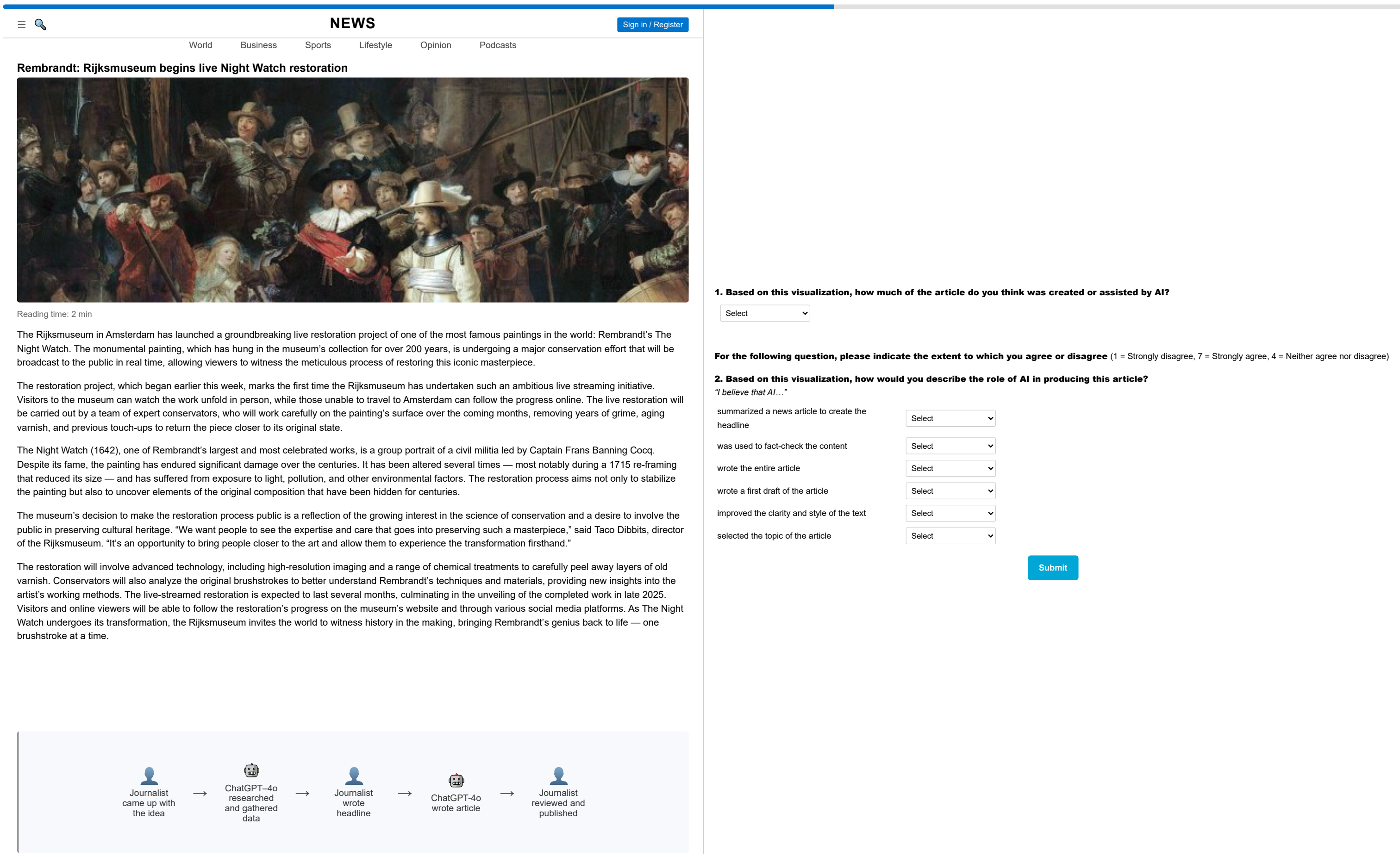


Figure 4.2: Example trial setup with the stimulus (left), and the questionnaire (right).

4.1.4 Procedure

The user study consisted of three parts, the introduction, the disclosure evaluation task, followed by a semi-structured interview. Figure 4.3 gives an overview of the user study design.

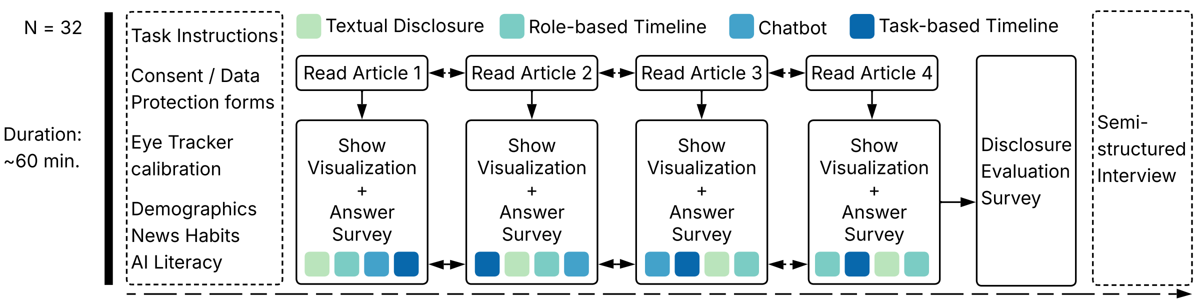


Figure 4.3: User study procedure

Introduction and pre-task questionnaire

Participants were informed about the study goal and procedure, they did not get any explanation on what the visualizations would look like to make the encounter as organic as possible. Then, they signed the consent form and answered questions about their vision (Appendix D.2). This was followed by the eye tracker calibration, and a pre-task questionnaire about demographics, news consumption and experience with AI (Appendix D.3). The demographic questions were about age, gender and education level, this was followed by news consumption questions on frequency, news sources and familiarity with AI-generated news articles. There were two questions on AI experience. The first focused on experience with ChatGPT from Formosa et al. [31]. The second was a shortened and adapted version of the MAILS scale by Carolus et al. [63], which is an AI literacy questionnaire. The adapted version, focused on AI understanding, detection, ethical awareness, and persuasion literacy.

Disclosure evaluation

Participants did 16 trials (2 articles × 2 versions × 4 visualizations). In each trial the stimuli and questionnaire were shown in a specific order:

1. The news article without disclosure
2. One disclosure visualization underneath the news article
3. The questionnaire on the right side screen

Participants continued to each step by pressing a button on the right side of the web page. This sequential order was chosen to enable the creation of Areas of Interest (AOIs) for the eye tracking analysis. AOIs are pre-defined regions of the stimulus that are designated to capture and analyze gaze data in a comparable way [66]. First the participants read the article without a visualization. Then the visualization appeared, so eye tracking data connected to the visualization was collected. After interacting with the visualization they filled out the questionnaire. The split screen gave participants the opportunity to look at the visualizations while answering the questions. Then the next visualization appeared, until all four were shown for this article. After that, the next article appeared, and the same steps were executed.

Participants completed two questions per trial on human-AI collaboration (Appendix D.4). The first question was based on IBM's AI Attribution Toolkit [67] which creates structured attribution statements based on the co-creation with AI. This question focused on the proportion of work created or modified by AI, ranging from entirely AI to entirely human created, and also including an even blend of human and AI contributions. The second question drew on prior work by Altay et al. [38], looking at the perceived role of AI on specific tasks in the article creation. These two questions were chosen to understand the overall perceptions of human-AI collaboration, and the perception of AI involvement in specific tasks, creating insights into how readers interpret human-AI contribution dynamics based on the disclosure visualizations.

After the sixteen trials, the participants were asked to answer two more questions (Appendix D.5) per visualization type (Figure 4.4). These questions asked them to evaluate the disclosure visualizations on clarity and value, and the type of information the participants gained from them. The first question, adapted from Wittenberg et al. [46], assessed the visualizations on qualities such as being clear, helpful, and easy to understand. The second question focused on the information that was conveyed by the visualizations, either on information depth, or human-AI collaboration. These two questions were chosen to understand how well participants interpret the visualizations, and what kind of contribution related information they took away from them.

Semi-structured interview

After completing the questionnaire, participants took part in a short semi-structured interview (Appendix D.6) which was audio-recorded. The aim was to get a better understanding of their preferences, and feelings towards the disclosures. There were also questions regarding the design elements, for example, interactivity and role vs. task based elements. Participants also reflected on how these disclosure visualizations might affect their reading behavior in a real world setting, and looking at a different context (low vs. high stakes). At the end of the interview, there was room for suggesting alternative design ideas, and open feedback. This qualitative part provided deeper and nuanced insights into how participants perceived and evaluated the disclosures, complementing the quantitative data.

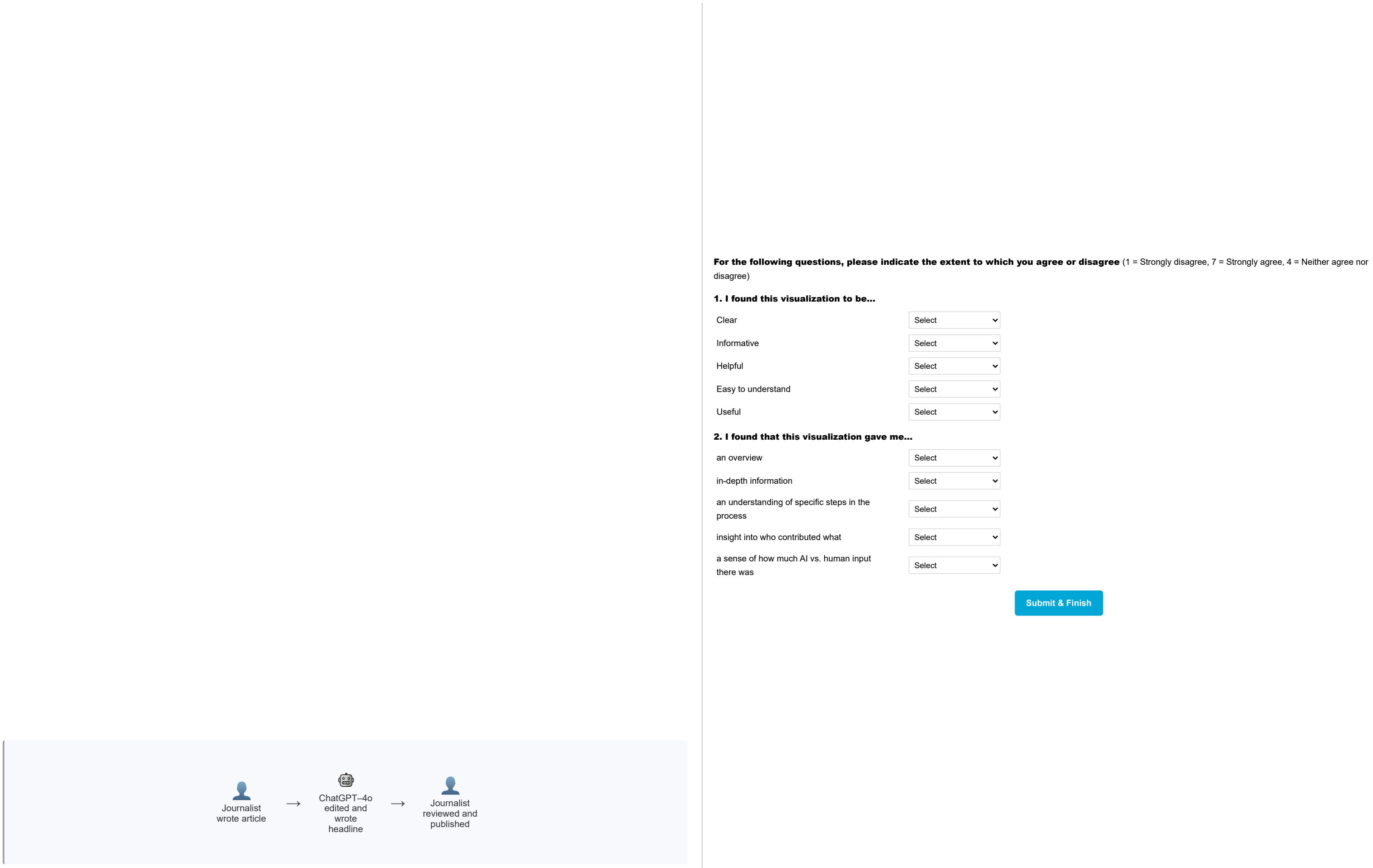


Figure 4.4: Example of disclosure evaluation after the 16 trials

4.2 Results

4.2.1 Quantitative Questionnaire Results

This section reports the questionnaire-based measures collected during each trial, including engagement time, perceived human–AI collaboration, and perceived AI roles in specific tasks. This is followed by an analysis of the disclosure evaluation questionnaire showing the perception of the visualizations.

Data processing

Responses to the questionnaire items were recorded on 7-point Likert scales. For multi-item questions, internal consistency was evaluated with Cronbach's α [68] to see how closely related the items were.

Normality was assessed with the Shapiro–Wilk test for each variable. All variables significantly deviated from normality ($p < .05$), so the Aligned Rank Transform (ART) method [69] was used for ANOVA analyses.

Effect sizes are reported as partial η^2 for main effect tests and Cohen's d for pairwise contrasts (small≤0.2, medium 0.2< d <0.8, large≥0.8) [70]. Multiple tests were conducted for different features. To control for potential inflation of Type I Error, False Discovery Rate (FDR) correction [71] was applied to adjust the p-value across features, and for post hoc comparisons. Due to the exploratory nature of this study, FDR was chosen instead of more conservative Bonferroni or Tukey adjustments.

Mean time spent per trial

First, the time participants spent during each trial was examined (i.e. from the moment each visualization is displayed until the survey is submitted for that visualization), as an indicator of potential disengagement or abandonment. On average, participants spent 150 seconds (SD = 126) per trial in the Chatbot condition, 111 seconds (SD = 110) in the Task-based Timeline condition, 116 seconds (SD = 123) in the Text Disclosure condition, and 110 seconds (SD = 108) in the Role-based Timeline condition. Given that time spent data were non-normally distributed, an aligned rank transform (ART) repeated measures ANOVA was conducted. Results (see Table 4.1) revealed significant main effects of visualization type, $F(3, 493) = 11.15, p < .0001$ analyzed without FDR correction as this was the only main effect tested for this variable. Post hoc contrasts (see Table 4.2) showed that the Chatbot trials consistently led to longer time spent compared to all other conditions (all FDR adjusted p<.001), with mean differences of approximately 81–83 seconds. No other pairwise comparisons were significant, suggesting participants interacted longer with the Chatbot visualization while the other conditions were less time-consuming.

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$	sig.
Visualization type	11.15	3	493	<0.0001	0.06356	***

Table 4.1: ART and effect size for time spent (in seconds) per visualization type

contrast	estimate	SE	df	t.ratio	p	sig.
TD - RT	-1.56	17.28	493.07	-0.09	0.98	
TD - C	-82.91	17.28	493.07	-4.80	<0.0001	***
TD - TT	-2.06	17.28	493.07	-0.12	0.98	
RT - C	-81.36	17.31	493.00	-4.70	<0.0001	***
RT - TT	-0.50	17.31	493.00	-0.03	0.98	
C - TT	80.85	17.31	493.00	4.67	<0.0001	***

P value adjustment: FDR method for multiple comparisons

Table 4.2: Post Hoc comparisons for time spent (in seconds) between visualization types

Perceived human-AI collaboration dynamics

Figure 4.5 shows a confusion matrix of the perceived human-AI collaboration vs. the actual human-AI collaboration. The two articles with a higher human contribution are combined on the right, and the higher AI contribution articles on the left. As expected, articles created with a higher AI contribution (Articles 2 and 4) were generally perceived as such, with higher proportions of "Primarily AI-generated" and "Entirely AI-generated" responses. In contrast, the more human-written articles (Articles 1 and 3) were largely seen as "Primarily human-created.". Both article versions also show a similar number for the "human-AI blend" response indicating that the work was perceived as created with an even blend of human and AI contributions [67].

Across visualization types (Figure 4.6), subtle differences appear. For example, Role-based Timeline shows an increase towards human-AI blend for articles 1, 3 and 4. When viewing responses per article, the perception remains stable, except with Role-based Timeline, suggesting that while the visualizations may influence perceived dynamics, underlying article content also shaped participant judgments, especially in articles 1 and 3, in which three shows more responses towards entirely human-created, despite identical visualizations. However, these differences are not significant.

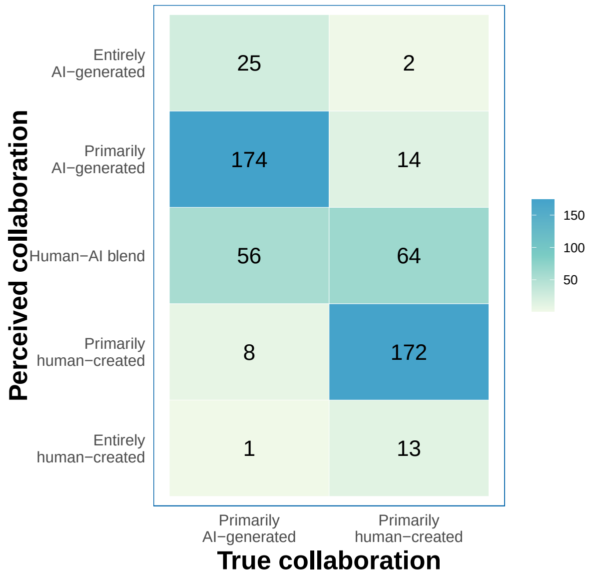


Figure 4.5: Confusion matrix of human-AI collaboration per article

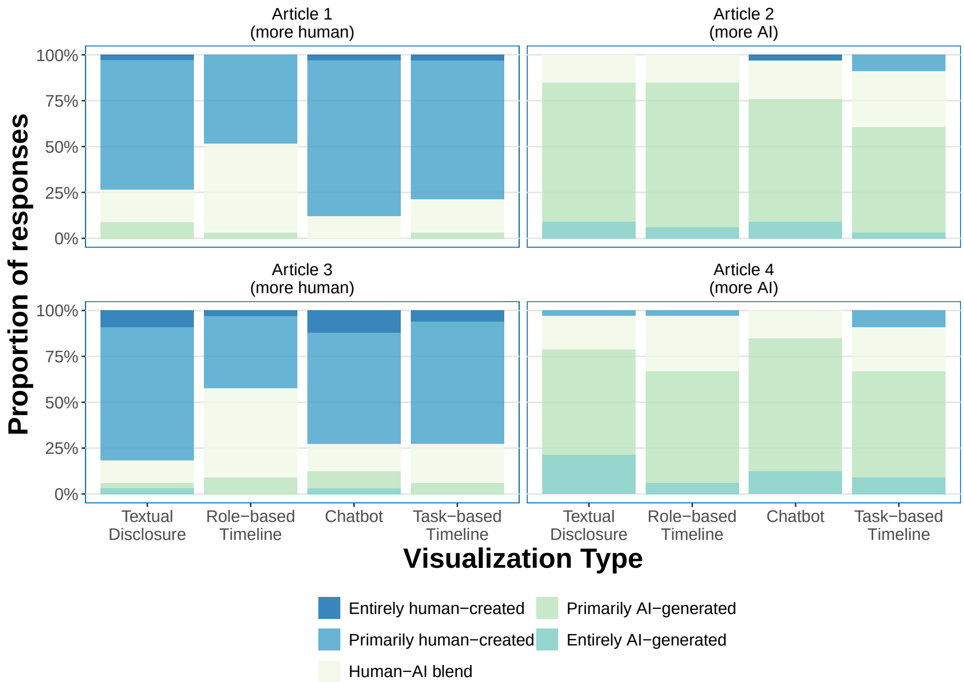


Figure 4.6: Proportion of responses of perceived human-AI collaboration per article and visualization type

Perceived role of AI per article

To explore the perceived role of AI across the trials, participants rated the extent to which AI contributed to specific tasks on a 7-point scale based on the visualization and article. This provides validity for the intended manipulation of human-AI collaboration, as participants' interpretation of the roles of AI aligned with the AI involvement indicated by the visualizations. Articles 1 and 3, designed to be primarily human-created, were perceived similarly (see Figure 4.7). Participants gave low scores for AI involvement in writing the entire article (M = 1.63 and 1.68, respectively) and writing a first draft (M = 1.51 and 1.73), while assigning higher scores to improving clarity and style (M = 6.09 and 6.27) and summarizing for headline creation (M = 5.56 and 5.94), which is in line with the AI role communicated by the disclosure visualizations. In contrast, Articles 2 and 4, with a greater AI contribution, were rated higher on writing tasks (writing the entire article: M = 5.37 and 5.34; first draft: M = 6.51 and 6.34), and a medium rating on clarity and stylistic changes (M = 3.77 and 4.09), which indicates that participants assumed stylistic changes are automatically done when AI writes an article. Similarly for fact-checking the content (M = 3.54 and 3.74) as it might be automatically done when the article is written by AI. The low rating on topic selection across all articles is also in line with the expectations, as this is not mentioned in any of the disclosures. These patterns suggest that participants were able to perceive the differences in AI contribution across trials, validating the stimulus design.

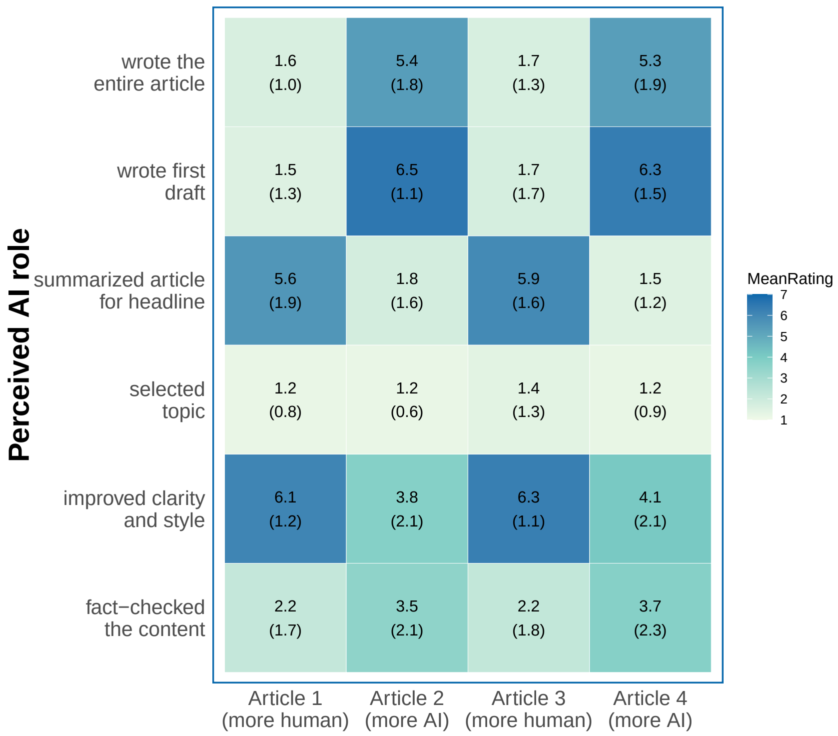


Figure 4.7: Mean rating (and SD) of perceived AI roles per article

Descriptive statistics of perception of the disclosure visualizations

Tables 4.3 and 4.4 display the descriptive statistics (mean, standard deviation, minimum, maximum) of perceived clarity and value, and perceived information per visualization type, rated on a 7-point Likert scale. Overall, scores lean more positively with means above the neutral midpoint, though the range of responses shows that some participants rated the lowest possible score as well.

Variable	Visualization Type	mean	sd	min	max
Clear	Textual Disclosure	5.06	1.70	1	7
	Role-based Timeline	6.06	1.16	3	7
	Chatbot	4.75	1.85	1	7
	Task-based Timeline	5.69	1.64	1	7
Easy to understand	Textual Disclosure	5.75	1.24	2	7
	Role-based Timeline	6.38	1.01	3	7
	Chatbot	4.53	1.93	1	7
	Task-based Timeline	6.00	1.39	2	7
Helpful	Textual Disclosure	5.31	1.35	2	7
	Role-based Timeline	5.28	1.44	2	7
	Chatbot	5.56	1.41	2	7
	Task-based Timeline	5.34	1.68	1	7
Informative	Textual Disclosure	5.06	1.63	2	7
	Role-based Timeline	5.22	1.50	1	7
	Chatbot	6.22	1.21	2	7
	Task-based Timeline	5.31	1.77	1	7
Useful	Textual Disclosure	5.06	1.58	1	7
	Role-based Timeline	5.47	1.44	2	7
	Chatbot	4.97	1.94	1	7
	Task-based Timeline	5.34	1.88	1	7

Table 4.3: Descriptive statistics of perceived clarity and value (mean, sd, min, max) by visualization type

A summary measure of *Perceived clarity and value* was constructed by taking a simple mean of the responses of the variables *Clear*, *Easy to understand*, *Helpful*, *Informative*, and *Useful* (Cronbach's α=.84, indicating good internal reliability), as they all capture aspects of the overall quality of the visualizations. For *Perceived information*, the variables were analyzed separately since they all focus on different types of communicated information.

Normality test

Shapiro-Wilk normality test indicated for all variables that the data significantly deviated from a normal distribution (see Table 4.5). Therefore, Aligned Rank Transform (ART) was performed to meet the assumptions by aligning and ranking the data before analysis [69].

Variable	Visualization Type	mean	sd	min	max
In-depth information	Textual Disclosure	3.53	1.83	1	7
	Role-based Timeline	3.66	1.73	1	7
	Chatbot	6.25	1.16	2	7
	Task-based Timeline	4.12	2.14	1	7
Overview	Textual Disclosure	5.00	1.88	1	7
	Role-based Timeline	6.03	1.18	2	7
	Chatbot	3.47	2.29	1	7
	Task-based Timeline	6.19	1.28	1	7
Sense of AI vs. human input	Textual Disclosure	5.12	1.41	2	7
	Role-based Timeline	5.19	1.71	1	7
	Chatbot	5.53	1.32	2	7
	Task-based Timeline	4.69	1.80	1	7
Understanding of specific steps in the process	Textual Disclosure	3.88	1.58	2	7
	Role-based Timeline	5.25	1.92	1	7
	Chatbot	4.84	1.67	1	7
	Task-based Timeline	6.00	1.34	1	7
Who contributed what	Textual Disclosure	5.22	1.39	1	7
	Role-based Timeline	5.38	1.68	1	7
	Chatbot	5.94	0.95	3	7
	Task-based Timeline	5.34	1.86	1	7

Table 4.4: Descriptive statistics of perceived information (mean, sd, min, max) by visualization type

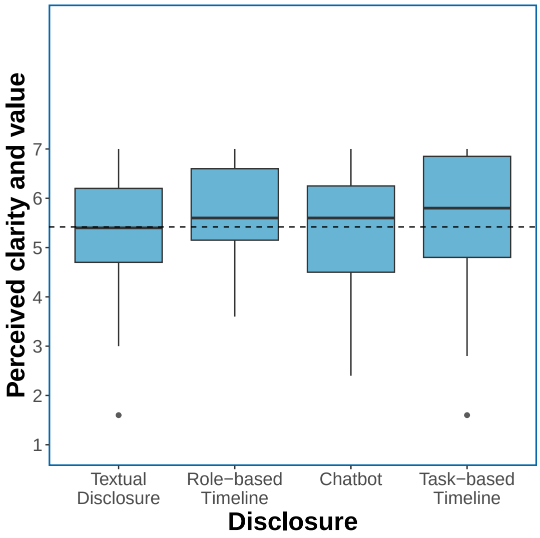
Question	W	p
Perceived clarity and value	0.93384	< 0.00001
Overview	0.81872	< 0.00001
In-depth information	0.89938	< 0.00001
Understanding of steps	0.88653	< 0.00001
Insight who contributed what	0.83883	< 0.00001
Sense of AI vs. human input	0.89862	< 0.00001

Table 4.5: Shapiro-Wilk normality tests on ANOVA residuals for each variable (N = 32)

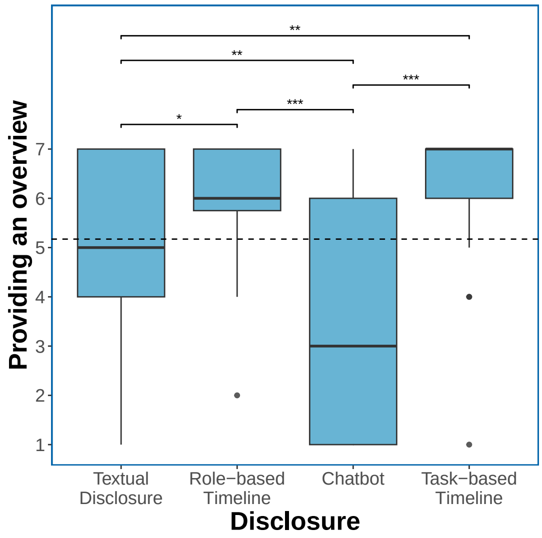
ART ANOVA analysis of perception of visualizations

The ART method was used to perform a nonparametric ANOVA for the response variables *Perceived clarity and value*, *Overview*, *In-depth information*, *Sense of AI vs. human input*, *Understanding of specific steps*, and *Who contributed what*, with FDR correction across metrics and for post hoc contrasts. Table 4.6 shows the analysis of variance for all response variables per visualization type. In addition, Figure 4.8 shows the distributions of the response variables per visualization type, including the mean rating per variable as a dashed line.

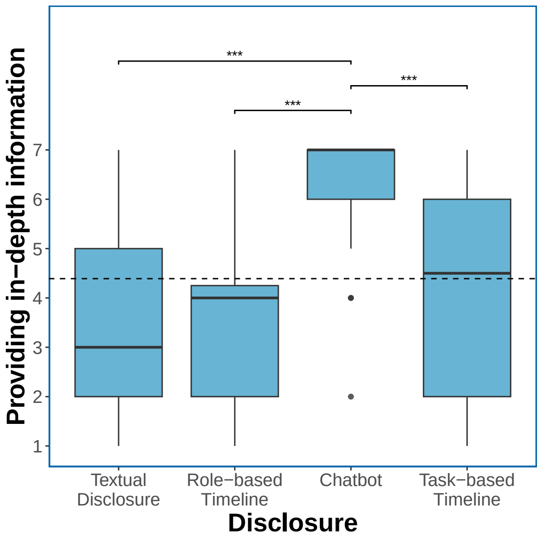
Perceived clarity and value. There were no significant main effects on perceived clarity and value per visualization type. However, with a mean=5.42 (SD=1.25) above the midpoint, it shows that the visualizations are generally perceived clearly and were



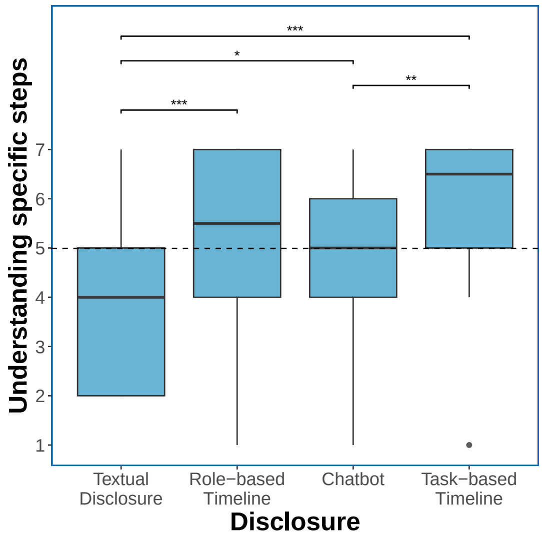
(a) Perceived clarity and value



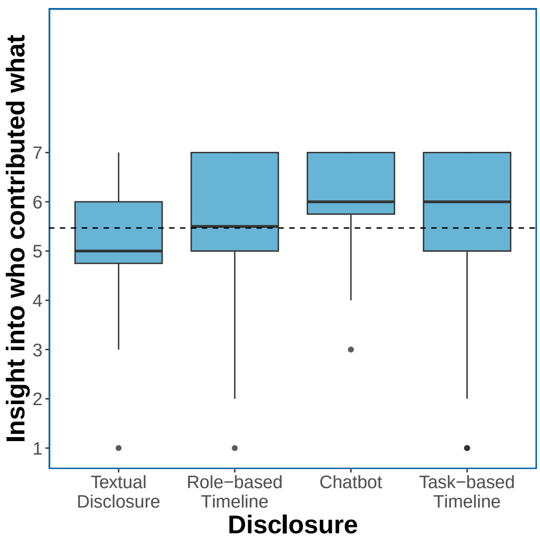
(b) Providing an overview



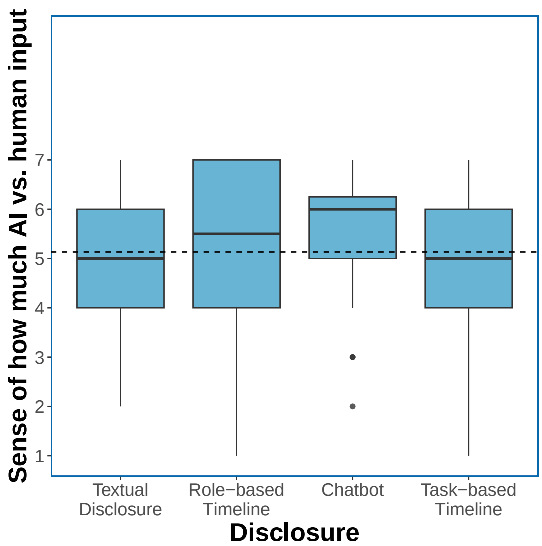
(c) Providing in-depth information



(d) Providing an understanding of specific steps in the process



(e) Providing insights in who contributed what



(f) Providing a sense of how much AI vs. human input

Figure 4.8: Plots of response variables per visualization type

Response Variable	F	df	p	$\eta^2 p$
Perceived clarity and value	1.26	3.00	0.293	0.04
Overview	15.65	3.00	$< .001$***	0.34
In-depth information	25.96	3.00	$< .001$***	0.46
Understanding of specific steps	12.10	3.00	$< .001$***	0.28
Who contributed what	1.95	3.00	0.191	0.06
Sense of AI vs. human input	1.57	3.00	0.242	0.05

Table 4.6: ANOVA results for all response variables by visualization type using Aligned Rank Transformed data. P values were adjusted with FDR corrections.

valued.

Providing an overview. ART ANOVA revealed a significant main effect of visualization type, F(3, 93) = 15.65, p < 0.001, with a partial η^2 of .34. Post hoc comparisons (FDR adjusted) showed that the other three visualizations were significantly better at providing an overview than the Chatbot. Very large effect sizes for Role-based Timeline (p<0.001, d=1.36), Task-based Timeline (p<0.001, d=1.54), and medium effect size for Textual Disclosure (p<0.05, d=.72). Furthermore, the Role-based and Task-based Timeline provided a significantly better overview than Textual Disclosure (RT: p<0.01, d=.82, TT: p=.015, d=.64), with medium to high effect sizes. The full contrast test tables of the features with significant main effects can be found in Appendix E.

Providing in-depth information. There is a significant main effect of visualization type (F(3, 93) = 25.96, p < 0.001, partial η^2=.34). Post hoc comparisons (FDR adjusted) showed that the Chatbot visualization was significantly better at providing in-depth information compared to the other three visualizations (TD p<0.001, d=1.93, RT p<0.001, d=1.85, TT p<0.001, d=1.50), all with very large effect sizes.

Providing an understanding of specific steps in the process. The ART ANOVA results for providing an understanding in specific steps in the process also revealed a significant main effect of visualization type (F(3, 93) = 12.10, p < .001, partial η^2=.28). Post hoc comparisons (FDR adjusted) showed that the Textual Disclosure performed significantly worse than all other visualizations at showing the specific steps (RT: p<0.001, d=.98, C: p=.023, d=.62, TT: p<0.001, d=1.46). Additionally, the Task-based Timeline was significantly better at showing the specific steps than the Chatbot (p=.002, d=.84).

4.2.2 Quantitative Gaze Results

This section reports the eye tracking measures recorded during each trial to assess participant's visual attention to the disclosure visualizations.

Data pre-processing
Eye tracking data was collected with the Tobii Pro Fusion eye tracker and the Tobii Lab Pro system. Event-based data was used to only include eye tracking data when the disclosure visualizations were visible. This was both during the initial display of the visualization, and while participants were answering the questionnaire, as they could glance back and forth between the visualization and question.

The built-in Tobii I-VT (Fixation) filter from Tobii Pro Lab was used to process the raw data. It classifies the data with a threshold of 30° per second, which means that gaze movement slower than 30° per second are categorized as fixations, while faster movements are classified as saccades. Additional parameters eliminated short fixations and merged adjacent fixations [72].

Tobii states that data is considered valid when at least 80% of collected gaze data is valid [73]. The data was considered valid when either the left or right eye had valid data points. The validity was calculated per participant, which caused an exclusion of 8 participants due to not enough valid data. This was followed by an evaluation of accuracy and precision. According to Tobii, good accuracy and precision of a participant is an average accuracy of less than 0.8°, and a standard deviation of precision that does not exceed 1.5° [73]. Due to the large Areas of Interest, the threshold for average accuracy was adjusted to 1.6°, to keep a total of 20 participants.

Areas of Interest (AOIs)
Three AOIs were defined to make a distinction between the regions of the stimulus layout.

- **Visualization AOI**: the human-AI disclosure visualization, located bottom left.
- **Article AOI**: the news article headline, text, and image, located on the top and middle left.
- **Questionnaire AOI**: the survey items, located on the right side.

For this analysis, only gaze data within the Visualization AOI were examined, as this region was the main focus to evaluate participants' engagement with the visualizations. Figure 4.9 shows the AOIs on top of the stimulus, and illustrates an example of a gaze pattern of one participant.

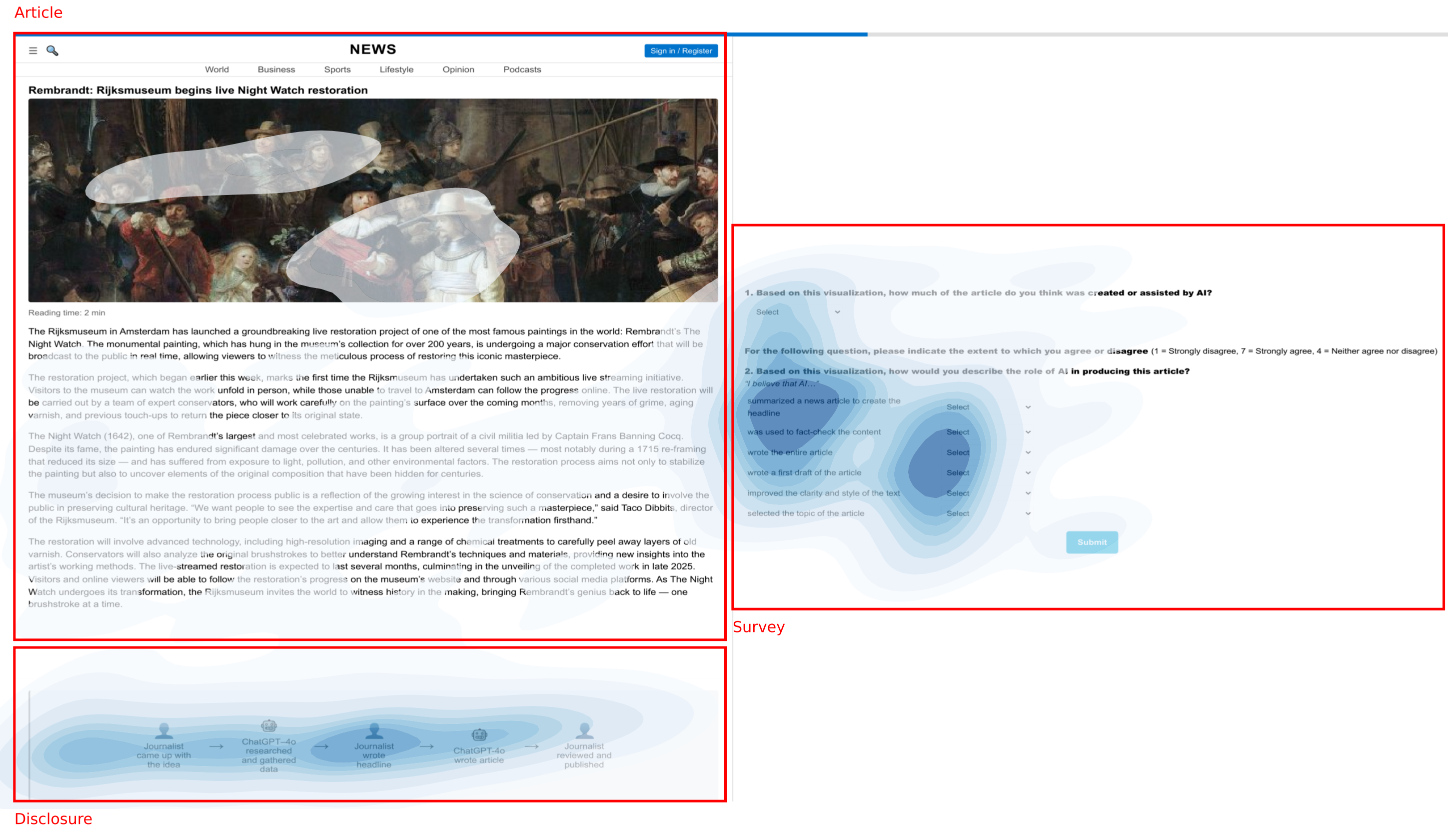


Figure 4.9: Heatmap of the gaze points of one participant on a stimulus. The red boxes indicate the predefined AOIs.

Eye tracking measures

The features that were extracted from the Visualization AOI are:

- **Gaze duration**: total accumulated time (in seconds) the participant's gaze was within the AOI, also known as dwell time [74].
- **Fixation duration**: average duration of individual fixations within the AOI, only whole fixations were used. Fixations happen when the eyes focus on a particular area. A greater duration refers to a greater level of engagement [75] [76].
- **Fixation count**: total number of fixations in the AOI.
- **Saccade count**: total number of saccades occurring within the AOI. Saccades are rapid eye movements that happen between fixations, and indicate more searching as no new information can be processed during a saccade. [76].
- **Saccade length**: mean length of saccades within the AOI.

Descriptive statistics

Table 4.7 summarizes the mean, SD, and minimum and maximum values of the features across all visualization types.

Feature	Visualization Type	mean	sd	min	max
Gaze duration (s)	Textual Disclosure	81.08	41.30	21.30	202.67
	Role-based Timeline	71.00	40.60	24.48	214.73
	Chatbot	218.44	122.47	77.60	522.93
	Task-based Timeline	74.91	37.13	11.79	153.15
Fixation duration (ms)	Textual Disclosure	215.24	36.78	133.71	280.68
	Role-based Timeline	284.94	62.68	162.56	397.84
	Chatbot	217.71	36.16	147.76	282.41
	Task-based Timeline	242.48	46.88	153.34	316.67
Fixation count	Textual Disclosure	334.50	148.40	127.00	749.00
	Role-based Timeline	226.70	111.16	141.00	638.00
	Chatbot	881.15	399.10	373.00	1698.00
	Task-based Timeline	275.65	113.42	68.00	573.00
Saccade count	Textual Disclosure	272.85	144.80	56.00	639.00
	Role-based Timeline	173.95	100.70	39.00	510.00
	Chatbot	717.55	405.68	212.00	1588.00
	Task-based Timeline	222.70	115.09	35.00	523.00
Saccade length	Textual Disclosure	0.07	0.02	0.04	0.11
	Role-based Timeline	0.10	0.03	0.05	0.16
	Chatbot	0.06	0.01	0.04	0.09
	Task-based Timeline	0.08	0.04	0.05	0.18

Table 4.7: Descriptive statistics per gaze feature and visualization type

Normality test

Normality was again checked with Shapiro-Wilk (Table 4.8). The data was not normally distributed, except for fixation duration. However, for all features ART ANOVA was used for analysis of main and interaction effects, to keep the analysis uniform, and corrected with FDR.

Feature	W	*p*
Gaze duration	0.75601	< 0.00001
Fixation duration	0.97912	0.2151
Fixation count	0.76729	< 0.00001
Saccade count	0.76568	< 0.00001
Saccade length	0.84789	< 0.00001

Table 4.8: Shapiro-Wilk normality tests for each gaze feature (N = 20)

ART ANOVA analysis

The ANOVA results with Aligned Rank Transform can be found in Table 4.9. All *p*-values were adjusted with FDR correction, across metrics and in post hoc contrasts.

Figure 4.10 shows the plots of the features per visualization type, including the mean value per feature as a dashed line. The full contrast test tables of the features can be found in Appendix E. All significant contrasts between visualization types showed large effect sizes (Cohen's $d \geq 0.8$).

Response Variable	F	df	p	$\eta^2 p$
Gaze duration	36.05	3	<0.001***	0.65
Fixation duration	34.21	3	<0.001***	0.64
Fixation count	46.19	3	<0.001***	0.71
Saccade count	44.13	3	<0.001***	0.70
Saccade length	12.53	3	<0.001***	0.40

Table 4.9: ANOVA results for all gaze features by visualization type using Aligned Rank Transformed data. P-values adjusted with FDR corrections.

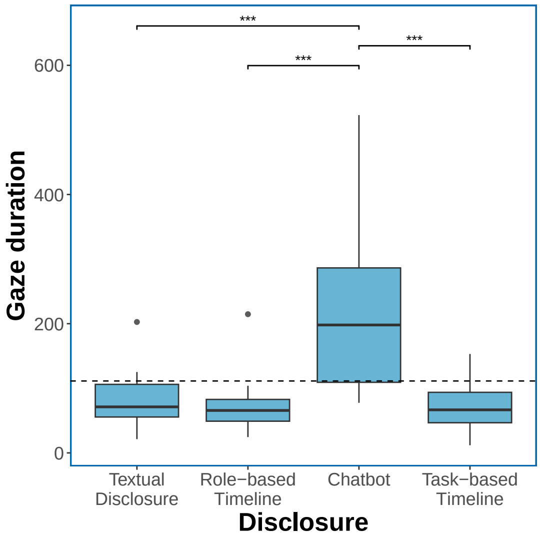
Gaze duration. ART ANOVA showed a significant main effect of visualization type, F(3,69) = 36.05, p<0.001, partial η^2=.65. Post hoc comparisons showed that the Chatbot had significantly longer gaze durations than all other visualizations (all p<0.0001), with very large effect sizes (vs. RT: d=2.93, vs. TD: d=2.37, vs. TT: d=2.64). Which is in line with the time spent on the surveys (Table 4.2).

Fixation duration. A significant main effect of visualization type was also found for fixation duration, F(3,69) = 34.21, p < 0.001, partial η^2=.64. Participants had significantly longer fixations for Role-based Timeline than all other types (all p < 0.001, vs. TD: d=2.844, vs. C: d=2.64, vs. TT: d=1.47). The fixations on Task-based Timeline were also significantly longer compared to Textual Disclosure (p < 0.001, d = 1.37), and Chatbot (p < 0.001, d = 1.18). The Chatbot did not differ significantly from Textual Disclosure.

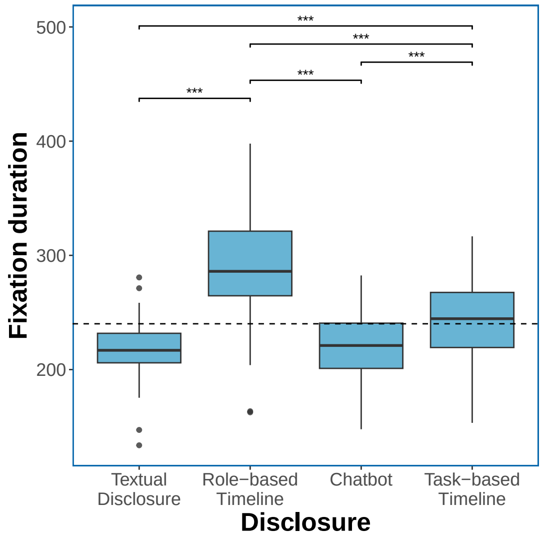
Fixation count. There was a significant main effect of visualization type for fixation count, F(3, 69) = 46.19, p < 0.001, partial η^2=.71. The Chatbot had significantly more fixations compared to all other visualizations (all p < 0.001, vs. TD: d=2.25, vs. RT: d=3.54, vs. TT: d=2.74). Furthermore, the Textual Disclosure had significantly more fixations than the Role-based timelines (p < 0.001, d = 1.30). Between the two timelines, the Task-based timeline had significantly more fixations than the Role-based Timeline (p = .017, d = .80).

Saccade count. For saccade count there was also a significant main effect found, F(3, 69) = 44.13, p < 0.001, partial η^2=.70. Similar to fixation count, saccade counts were significantly higher for Chatbot than all others (all p < 0.001, vs. TD: d=2.11, vs. RT: d=3.48, vs. TT: d=2.65). The Textual Disclosure also showed a significantly higher saccade count than Role-based Timeline ($p < 0.001$, $d = 1.37$). Between the two timelines, again, the Task-based timeline had significantly more saccade counts than the Role-based Timeline ($p = .013$, $d = .84$).

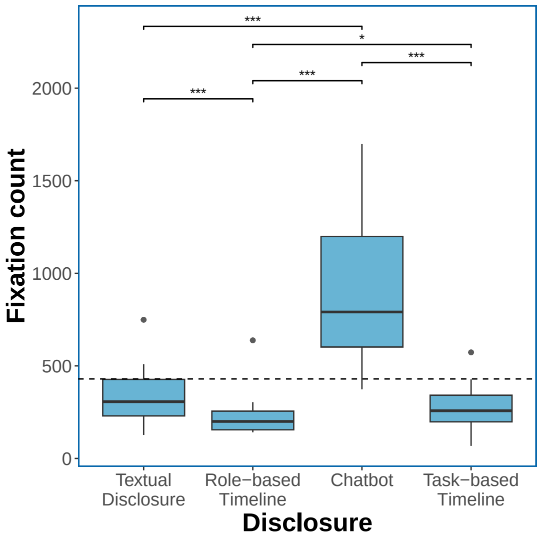
Saccade length. There was a significant main effect of visualization type, $F(3, 69) = 12.53$, $p < 0.001$, partial $\eta^2 = .40$. Post hoc test showed that Role-based Timeline had significantly longer saccades than all other visualizations (vs. TD: $p = .001$, $d = 1.15$, vs. TT: $p < 0.001$, $d = 1.44$, vs. C: $p < 0.001$, $d = 1.84$). Furthermore, the saccade length for Textual Disclosure was significantly longer compared to Chatbot ($p = .050$, $d = 1.15$).



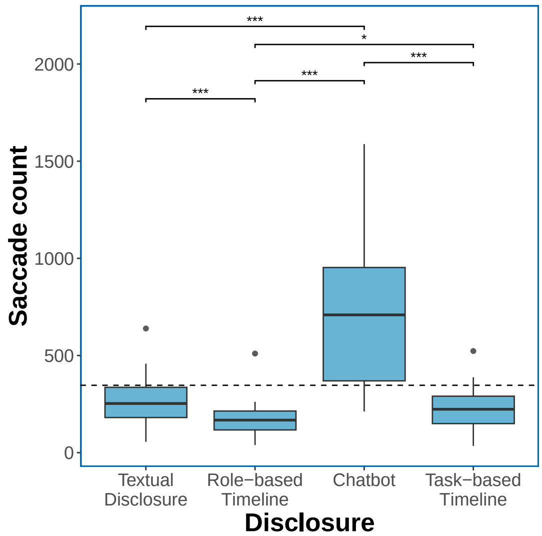
(a) Gaze duration



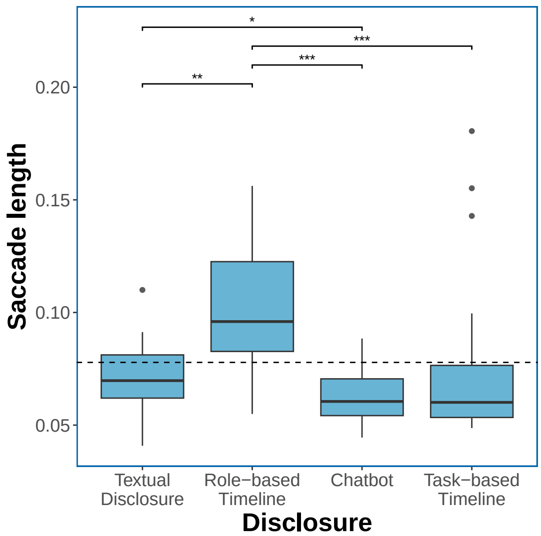
(b) Fixation duration



(c) Fixation count



(d) Saccade count



(e) Saccade length

Figure 4.10: Plots of gaze features per visualization type

4.2.3 Qualitative Results

All semi-structured interviews were conducted after participants completed the evaluation of the AI disclosure visualizations, and were transcribed with Condens[4]. A thematic analysis of the transcripts was done. The goal was to understand how users perceive and understand the human-AI collaboration disclosure visualizations. Recurring ideas across participants were noted down, but due to the semi-structured nature of the interview, it is important to mention that if a participant did not mention something, it does not mean they disagree. All participants are labeled P1–P32. Several themes emerged from the coded topics, including initial interpretations of the visualizations, preferences for different designs, reflections on interactivity and information structure, and disclosures in real-world news contexts. All these themes together offer insights into the perception and opinions surrounding AI disclosures in news media.

Interpretation of the visualizations

The initial reaction of participants on the disclosures was overall positive. They were described as "*useful and helpful for the average consumer reading the news*" [P19], and "*illustrative, functional*" [P30]. Three participants mentioned they had never seen these kinds of visualizations before "*I hadn't really seen those before, so I was kind of surprised by them. And I was just curious to see what was done by journalists and what was done by an AI tool*" [P14]. Four participants appreciated the transparency "*I think it's nice to be transparent about AI use*" [P4].

Participants also reflected on how the visualizations shaped their understanding of how the article was created. Seven said they could not initially tell AI was used "*I didn't really have an idea on what was done by AI and what was done by the journalist*" [P14]. For six others, the visualizations matched their expectations "*this is written by AI and then the visualization confirmed it for me*" [P17]. Additionally, two participants mentioned the visualizations created more nuance "*It still made me change from the opinion that this was an AI generated article to actually a blend of AI and human generated article*" [P16]. However, two other participants also expressed some doubts about the visualizations "*if it's stated like a journalist wrote an article, I'm not sure whether to believe that or not*" [P1], "*I feel like some parts were not true. Maybe it's just the wording in it*" [P9].

[4] `https://condens.io/automated-transcription/`

User preferences per visualization type

Visualization	# Ranked 1st	# Ranked 2nd	# Ranked 3rd	# Ranked 4th
Textual Disclosure	4	6	8	14
Role-based Timeline	11	10	9	2
Chatbot	5	9	8	10
Task-based Timeline	12	7	7	6

Table 4.10: Rankings of Different Types of Visualizations

Overall, the Task-based Timeline was the most frequently ranked as the top preference (12/32 participants) (Table 4.10). According to the participants, it is "*the best combination of informative, in depth and visually clear as well. So it immediately provides you an overview*" [P25]. However, nine participants mentioned they did not know they could hover, "*I didn't know [it] was interactive*" [P5], indicating that the interactive element was not always intuitively understood. Improvements were also suggested, changing the interactive element to "*a small text, above or below the small circles, and that you would be able to click on it if you wanted to dive deeper*" [P25]. There were also negative opinions about the hover "*I didn't like having to hover. I mean, if you're going to do a visualization, then, you know, just show it directly*" [P7].

Ranked highest by 11 participants, the Role-based Timeline was clear and easy to understand, participants mentioned "*the level of AI against human input is clearly stated here*" [P32], and "*the pictures make it more easy to understand*" [P27]. It also provided a "*good overview and it's to the point, you don't have to hover*" [P20]. There were also some critiques, such as "*it did not provide as much detail as the task-based timeline*" [P16], and it could be misleading "*as it gives you the idea that the roles are done half half, then you need to read it*" [P12]. This misleading element also aligns with Figure 4.6 in Section 4.2.1, where Role-based Timeline leaned more towards a human-AI blend.

The Chatbot was the most informative, which is in line with the findings in Section 4.2.1. Participants "*liked the ability to interact with it and because I have very little knowledge of what AI does anyway. I thought it was quite interesting that it could explain what it can do. It has so many possibilities to really go in depth. And I think especially with journalism, I'd like it to be very transparent and adherent to integrity.*" [P11]. Others appreciated having control over the information "*it was nice to be given the option to consume the information that you are interested in*" [P31]. In contrast, it was also mentioned by many participants that it was "*a bit too much information. I'm not sure if people are really going to read this*" [P8]. Three participants also mentioned they had trouble navigating the menu between questions. While the Chatbot was also often seen as clear and novel, it was not perceived to provide an overview.

Participants most often ranked the Textual Disclosure the lowest (16/32), describing it as "*too textual, looks like a legal disclaimer rather than an informative thing for users*" [P10], it is also easy to miss as it "*didn't grab my attention*" [P11], and too general "*it gives a bit of an idea, but it's not very detailed*" [P16]. However, seven participants did mention that it was easy to understand "*it has a short overview of all the information needed*" [P14] and they liked the simplicity.

Interaction style and information structure

Participants' preferences reflected broader design considerations: interaction style (static vs. interactive) and information structure (role-based vs. task-based). Nine participants were in favor of the interactive disclosures "*I understand the process better when it's interactive because you actively click on something and because you want to know what happened in the process. And the static ones, they don't give you that*" [P3]. The control of the information was especially appreciated, "*It's nice with the interactive ones that you can look for more information if you want it*" [P15]. In contrast, six participants favored the static disclosures, partially because they were doubting they would interact with it on a news page "*I think it's a nice thing to create, but I don't think it's really used if it would be in an article*" [P5] and the static visualizations created a better total view "*all the information already printed out in a schematic way. So it's good that you don't need to even move a finger to get other information*" [P10].

Participants were also divided in their preference of representing information role or task-based. Four participants had no preference, as both conveyed sufficient information. Fourteen participants did prefer seeing the roles, oftentimes because they were already familiar with the steps "*I was more concerned about the roles since I already knew the steps*" [P10]. On the other hand, eleven participants preferred the tasks "*I felt the process depicts a timeline better*" [P31]. Also contradicting familiarity with the steps "*Because I write articles. So then I want to know what they did and every step*" [P15]. This highlights that both design format and information representation are heavily dependent on individual preferences.

AI disclosures in real-world news environments

There were also reflections on how these disclosure visualizations would influence their engagement with news. Five participants reported that the disclosures would affect their reading behavior depending on the topic of the article "*when it would be a topic such as something political or societal, then I think it's really important that some things are properly fact checked. And then I would want to know who did what*" [P11]. Similarly, thirteen participants said disclosures would become more important in high-impact news contexts, "*It's important then, especially who has done the research*" [P8], and "*the specific steps in which AI is involved becomes way more important*" [P25]. There were also nine mentions of wanting to know more about the creation of the article: "*if it's more high-impact... then I would want to know if AI made that assumption or a person*" [P30]. There were also two participants who would not read news created with AI "*I wouldn't want to read an article that would be partly created by AI if it would be a critical article. Because I think you should think about the impact that an article can make. So then I think it is more wise to only have a journalist write it*" [P5].

In contrast, two participants had no interest in AI usage "*I don't really want to know if the AI did it or the human did it. I don't care actually*" [P2]. This is also more in line with two participants that have less interest when they know about the AI usage "*if I know it would have been written by AI I would have just scanned over it more instead of generally reading the article*".

At the same time, eight participants said it made them look at the articles more critically "*if you see how much AI has done for the article, then you might become a bit more critical or you would start paying attention to it a bit more*" [P21]. There were also two mentions that the visualizations gave them a better understanding of AI's capabilities "*it made me realize that AI could do a lot more than I thought*" [P18].

When considering the usage of the AI disclosure visualizations on a real-world news platform, fifteen participants would like to see it, saying "*transparency is really important*" [P17]. However, it also raised some skepticism among five participants, they mentioned "*It's like a romantic idea of journalism and investigative journalism still being very much primarily human based. And if I were to see an AI label, then I would probably become a bit skeptical*" [P11]. With two participants mentioning they "*would stop reading the newspaper*" [P23], and "*steer more towards other platforms or news sites if I knew that that platform uses AI*" [P5].

Regarding placement on news articles, opinions varied between showing the visualization at the beginning or at the end. Fifteen participants had a slight preference for showing the disclosure up front. *"I can imagine that maybe people would like to be aware of it because it is such a controversial topic and a lot of people seem to have an opinion about it. Then I think it's more ethical to make people aware as soon as possible"* [P11]. *"I would want to see the visualizations first and then read the article so I can be more critical of certain parts of the article instead of when I read it"* [P15].

Placement at the bottom was favored by eleven participants, *"I think it takes away from the article if you immediately show like this was generated with AI"* [P30]. Three participants also argued for making disclosures optional, leaving the control with the user whether they want to get AI disclosures. Two others mentioned showing the visualizations *"on the side just because sometimes maybe you don't finish the whole article"* [P4]. Or a combination of top and bottom was mentioned by two participants *"just maybe a small icon above the article and then the full visualization under the article"* [P25].

5. Discussion

The findings from this two-part study are discussed in this chapter to answer the two research questions. This is followed by a discussion of the limitations and possibilities for future work.

5.1 How can we visually represent the ratios of human-AI collaboration output in news production?

A primary goal of this research was to explore how human–AI collaboration dynamics in news production can be effectively communicated to readers through visual disclosures. To achieve this, the study drew on principles from HCI, Information Visualization, and involved designers and HCI experts in co-design sessions to create meaningful and usable representations of collaboration ratios (**RQ1**). 69 static and interactive design ideas were generated during the co-design sessions, which explored a wide design space to represent human-AI collaboration. Various representations were tried by designers, taking visual and textual approaches. Ratios and workflows were used to create concepts like timelines, stamps, bars with icons, and varying levels of information depth were explored ranging from simple percentages, to dynamic highlights on the article text.

There were two overarching strategies that emerged: ratio-focused and process-focused. With ratio-focused, the designers laid emphasis on showing proportions (e.g. pie-chart, bar-chart, percentages), which reflect common ratio visualization types used in media [49][50]. With process-focused the emphasis was on the steps the journalists or AI took. The process-focused approach is in line with Wittenberg et al.'s [34] framework on which this research builds for creating process-based disclosures.

The main design challenge that arose during the sessions was how to communicate "who did what" without overloading the reader with information. Therefore, designers explored various levels of information depth, ranging from simple visualizations that give an immediate overview, to elaborate multi-layered designs. They built on progressive disclosure [16] to create multiple layers to the visualizations, which can support readers with different levels of AI literacy and news engagement goals. This also aligns with Burrus et al. [37], stating that users should be informed without overwhelming them with technical details.

The findings show that there is no one-size-fits-all solution to visualize human–AI collaboration in journalism. Instead, a visualization must balance (1) a proportional representation of human and AI contributions, (2) how contributions were made in the process, and (3) a level of information detail to support readers with different goals and AI literacy levels.

5.2 Which disclosure visualizations are most effective in communicating human-AI collaboration in news media?

The four different human–AI collaboration disclosure visualizations were evaluated on user perception (**RQ2**) in a lab-based study. Participants interacted with each visualization embedded in an online news article while their eye movements were tracked and completed questionnaires and an interview, providing self-reported and behavioral measures of how they perceived and understood the disclosures.

Figure 4.6 in Section 4.2.1 shows that all four visualizations helped participants distinguish between articles with high and low AI contributions, and facilitated a more nuanced view on AI usage. This validates that disclosure visualization can be used as tools to communicate human-AI collaboration effectively. It also aligns with prior work of Zier & Diakopoulos [36], who state that showing human involvement in combination with GenAI contribution is necessary to disclose, to demystify assumptions about AI. With regard to the clarity and value of the visualizations, all four were rated positively. However, the findings also indicate that there is no single format that is the best, each visualization has strengths suited for certain purposes or contexts.

Textual Disclosure most closely resembles labels that already exist on some platforms, but with a focus on explaining the collaboration. It was easy to understand, but was often described as too general or overlooked. Eye tracking data supported this, as it had shorter fixations and more saccades than the two timelines, indicating that participants scanned rather than deeply processed information. It also performed the least in providing an understanding of the steps in the process, and less effective in creating either an overview or exploring in-depth information. For this visualization it is important to take Epstein et al.'s [43] work into account, in which they mention that language used in labels has a great influence on the perception. Although this is the most common format nowadays, these findings suggest that it is not the most effective in communicating human-AI collaboration.

The **Role-Based Timeline** was significantly better at providing an understanding of specific steps in the process. Its static format made quick scanning possible, and would therefore fit best for contexts where an overview is needed, but interaction is not possible. Eye tracking data showed that it had the longest fixation duration and longest saccades, indicating deep processing and broader eye movements, in line with creating an overview with information depth per step. However, the use of icons led the readers to perceive the collaboration as more balanced than it was in reality, indicating the need to refine the design to avoid misleading information. This risk was also stressed by Altay & Gilardi [38] the distinction between human and AI contributions should be very clear so users do not overestimate or underestimate AI's role.

With the **Chatbot** the users were able to explore in-depth information. It had the longest dwell time and most fixations and saccades, indicating high engagement, but not necessarily more information processing per element, as the fixation duration was not longer than the timelines. Its progressive disclosure design [16] gave users control, but lacked an immediate overview, and some participants found it too much to read, which could discourage engagement in a casual reading context. This is in line with Burrus et al.'s [37] warning to not include too much technical detail to not overwhelm the user. However, in real-world use, the user has the freedom to choose to interact with it, and the progressive disclosure approach of this visualization could prevent cognitive overload. For high-stake articles where the readers may want more information, this visualization could be valuable.

Task-based Timeline provided both a good overview and insight into specific steps, and was the most frequently preferred visualization. It had longer fixations than the Textual Disclosure and Chatbot, indicating more information processing, and shorter saccades than the Role-based timeline, suggesting a more narrow search pattern. These are in line with the questionnaire data, which indicated it provides a better overview. The downside was that the interactive hover elements were not always discovered.

This visualization could be expanded with even more in-depth progressive information, or simplified by removing the hover element and placing the text underneath. This again aligns with Burrus et al. [37] to inform users without too much technical detail.

Overall, the effectiveness of human-AI collaboration disclosure visualizations depends on their intended use and context. Textual disclosure is familiar, but least effective in communicating the collaboration. For high-stake articles that may require detailed information, the Chatbot is most effective. However, Task-based and Role-Based Timelines are better suited to provide an overview and insight into the specific steps of the process. To maximize transparency and usability, news organizations should adapt these visualizations according to article topic, desired information depth and the goal of reader engagement.

5.3 Limitations and future work

5.3.1 Limitations

This thesis offers insights into how visual disclosures of human-AI collaboration dynamics can be created and interpreted However, there were several limitations that should be mentioned.

First, the user evaluation was limited to four prototype designs. These were selected with criteria to create diverse visualizations, but many other design formats have not been investigated and could lead to different results. Second, the small sample size (n=32) of the user study limits the generalization of the findings to a diverse news audience. Third, the user study was conducted with a controlled web application, which made it possible to compare stimuli, but it did not fully reflect the functionalities and context of a real-world news platform. This may have influenced how participants interacted with the visualizations. Fourth, only short-term effects were explored in the study, long-term effects of repeated exposure to disclosure visualizations remain unexplored. Finally, although the eye tracking data gave insights into visual attention, unfortunately pupil diameter could not be used to evaluate cognitive load, as there was no baseline measurement collected of the pupil size of each participant.

5.3.2 Future work

Real-world implementation and long-term effects

Future research should test the disclosure visualizations on real-news platforms, preferably over a longer period of time, and with the inclusion of high-stake news articles. This will generate more insights into organic reader interactions, long-term effects and contextual factors that may influence the effectiveness. Additionally, collaborations with journalists and news organizations will be essential to evaluate workflow integration and feasibility for journalists.

Credibility, trust and bias effects

The qualitative results showed that some participants doubted the accuracy or truthfulness of the disclosures themselves. This shows a deeper trust issue, not only towards the article's content, but towards the truthfulness of the disclosure. Given that LLMs are known to hallucinate or fabricate believable but incorrect information [77], this especially raises concerns for Chatbot disclosures. A new problem arises if an AI-generated disclosure explains how AI-generated content is created: what if the explanation itself is inaccurate? It is important to prevent disclosure tools themselves from becoming new sources of false information or assurance. Therefore, disclosure tools might also need to disclose how, by whom, and with what information these disclosures were created. It would be interesting for future work to investigate how audiences evaluate the accuracy and trustworthiness of the disclosures themselves.

Concerns regarding trust are also closely related to potential bias introduced by knowing about human–AI collaboration in news production. In this study, participants were divided on where the disclosure visualizations should appear on the news webpage. While some preferred placement at the top to encourage more critical reading, others thought this would create negative bias. This aligns with previous research showing that headlines labeled "AI-generated" are perceived as less accurate and less likely to share, regardless of content quality [38][78][79]. This effect is in line with the transparency paradox, where readers want to see disclosures intended to increase trust, but this knowledge can lead to diminished trust as well [80]. The detailed human–AI collaboration visualizations may be able to mitigate these negative effects by providing a more nuanced view, but this was not directly tested. Therefore, future research should explore how these visualizations and its placement influence trust and bias.

Enhancing AI literacy

Some participants mentioned that the visualizations made them more aware of AI's capabilities, and others reporting that the disclosures made them more critical readers. These outcomes suggest that AI disclosures may function as implicit AI literacy interventions, especially for readers with little knowledge of GenAI. This aligns with Carolus et al.'s [63] Meta AI Literacy Scale framework, a multi-dimensional construct that includes many aspects like understanding, detecting, and ethical awareness. Although these meaningful disclosure visualizations were not initially designed as educational tools, repeated use could increase AI literacy in some of these dimensions. Future work could explore this potential, especially among readers with low knowledge and familiarity with GenAI.

6. Conclusion

Generative AI is increasingly being used in the journalistic workflow [1], yet readers are rarely informed about its role. This lack of transparency raises ethical concerns, particularly regarding trust [7] [8]. Research shows that readers want to be informed when AI contributed to content creation [11]. This is also supported by the EU AI ACT, mandating AI disclosure when informing the public [10]. However, these regulations remain vague about how to disclose. Existing AI disclosure approaches do not show the nuanced collaboration between humans and AI, and can be easily misinterpreted.

This thesis addresses this gap by exploring how human-AI collaboration in news production can be effectively communicated to readers through visual disclosures. Through co-design sessions with ten designers, 69 design ideas were generated. A selection process led to four diverse prototypes (Textual Disclosure, Role-based Timeline, Chatbot, and Task-based Timeline) which were evaluated in a lab-based user study with 32 participants using eye tracking, questionnaires, and a semi-structured interview. Each visualization effectively communicated human-AI collaboration in different ways, with trade-offs between clarity, information depth, and engagement.

Overall, these findings offer a practical approach on how to disclose AI usage in journalism, depending on the article topic, informational goals, and the reader engagement. By adopting these human-AI collaboration disclosure visualizations in the journalism workflow, news organizations can increase transparency, address ethical concerns towards trust, reduce misinterpretation of AI use, and potentially help normalize responsible AI use. These visualizations also have the potential to enhance the public's knowledge of AI's role in news production and stimulate more informed media consumption. As more news content is created in collaboration with AI, this research provides a foundation for designing nuanced disclosure methods that balance clarity, context and audience needs.

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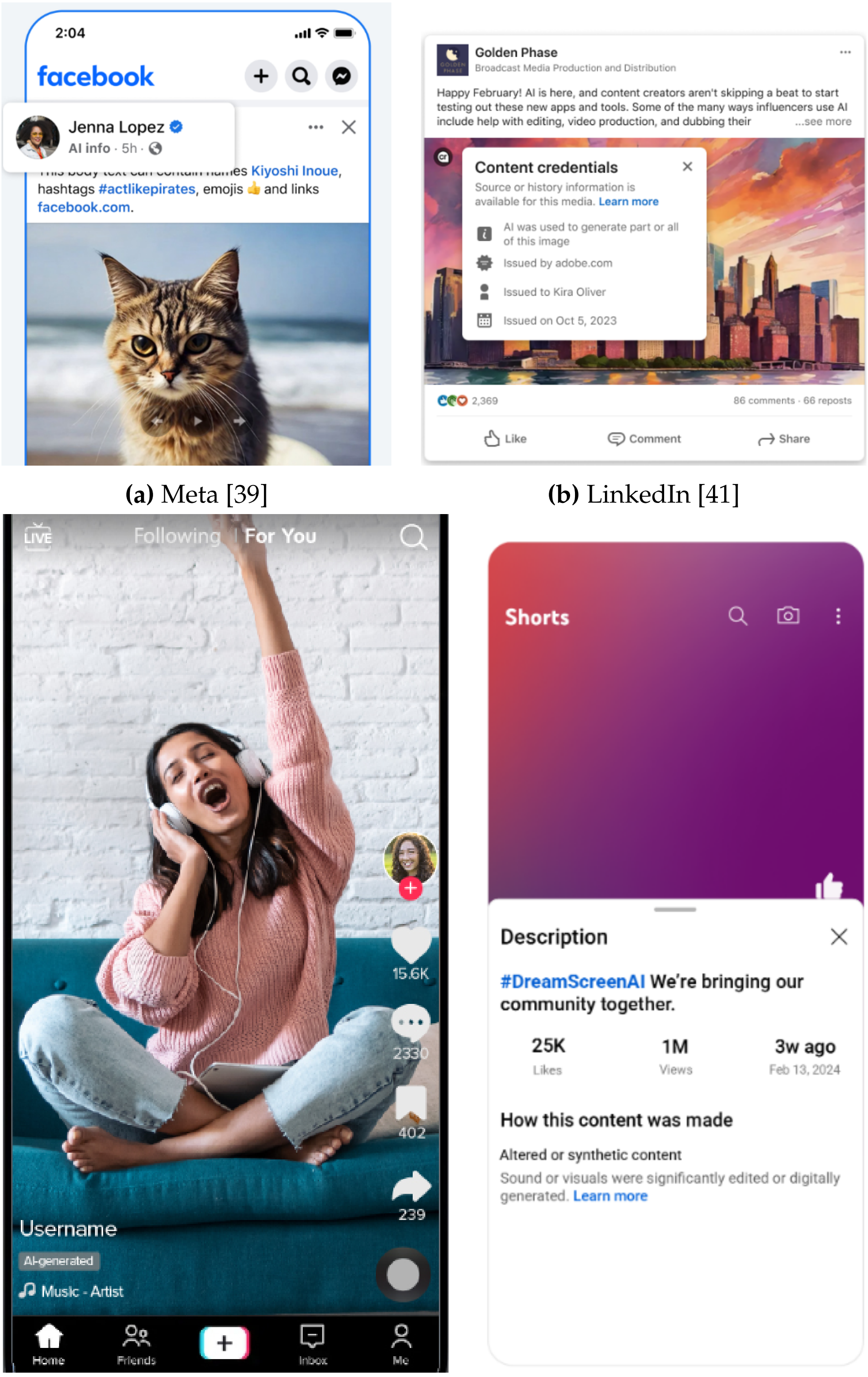
Appendix

A. Existing AI Disclosures



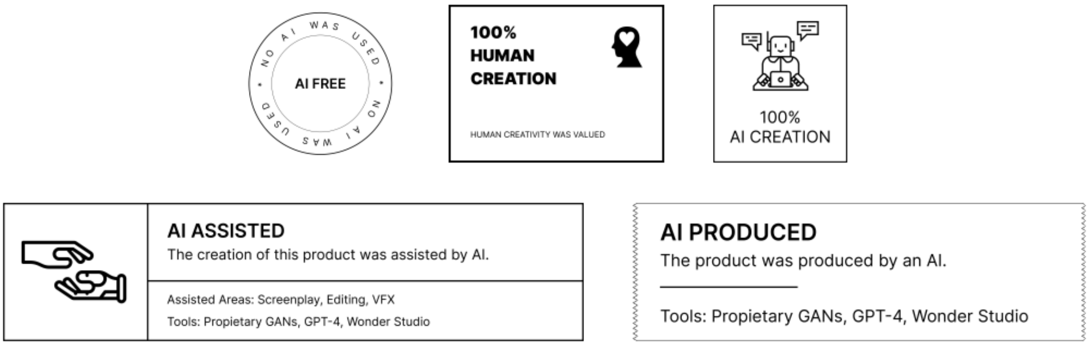
(a) Meta [39]

(b) LinkedIn [41]

(c) TikTok [81]

(d) YouTube [42]

Figure A.1: Social media AI disclosure labels

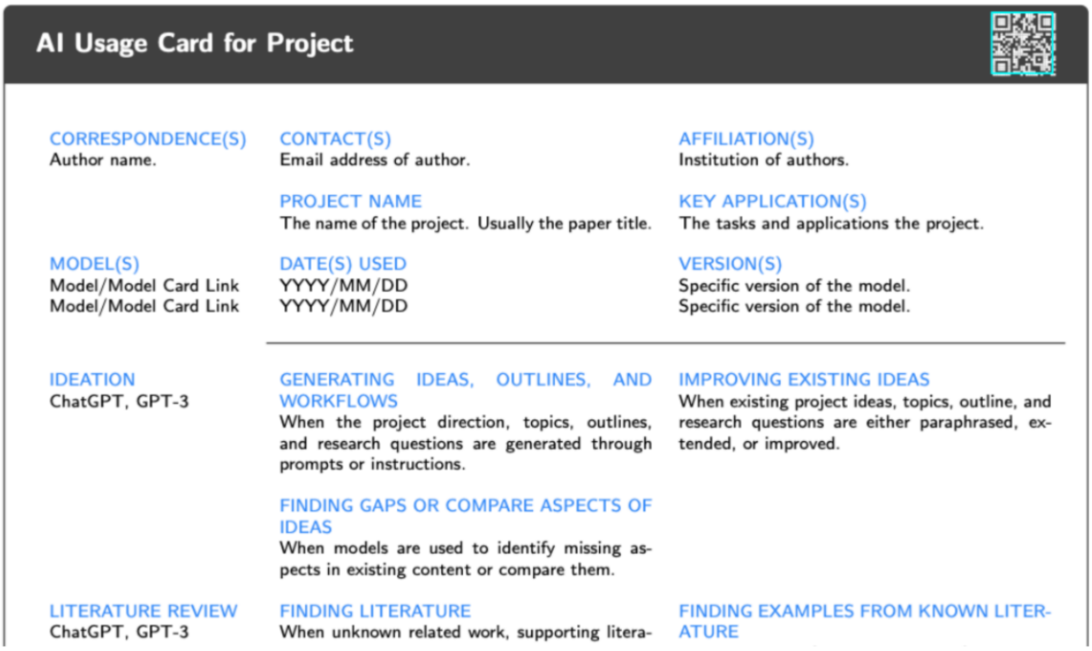


(a) Possible AI disclosure labels for different levels of AI involvement [44]

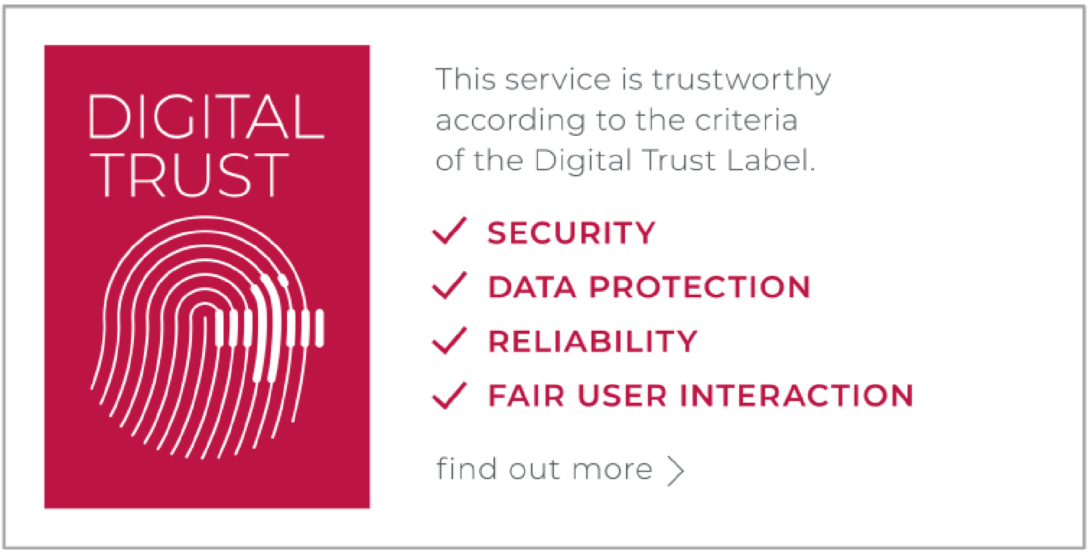
(b) "Written by artificial intelligence" stimuli [11]

(c) Two stimuli labels [46]

Figure A.2: Research AI disclosure labels



(d) AI Usage Card [15]



(e) Certification label [14]

Figure A.2: Research AI disclosure labels (cont.)

B. Co-Design Session Materials

B.1 Consent Form

Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production

Consent form for participation in the Study.

Please read the statements below carefully. By signing below, you confirm that you have read and understood the information provided and agree to participate under the stated terms.

- ☐ I confirm that the research project ***"Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production"*** has been explained to me. I have had the opportunity to ask questions about the project and have had these answered satisfactorily.

- ☐ I consent to the material I contribute being used to generate insights for the research project "***Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production".***

- ☐ I am aware that the researcher will take an audio and video recording of the session. I understand that I can request to stop these recordings. I understand that I can ask for the recording to be deleted.

- ☐ I understand that my participation in this research is voluntary, and that I may withdraw from the study at any time.

- ☐ I consent to allow the <u>fully anonymised</u> data to be used for future publications and other scholarly means of disseminating the findings from the research project.

- ☐ I confirm that I am 18 years of age or over.

- ☐ I understand that the information/data acquired will be securely stored by researchers, but that appropriately anonymised data may in future be made available to others for research purposes only.

- ☐ I understand that I can request any of the data collected from/by me to be deleted.

- ☐ I agree to take part in the above study on ***"Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production"***.

Name of participant	Date	Signature
Name of researcher	Date	Signature

Sensitizing Booklet

SENSITIZING BOOKLET

Participant: Date:

Human-AI Collaboration in Journalism

Welcome!

Thank you for participating in the study!

This sensitizing booklet is designed to prepare you for the **co-design session**.

In this booklet, you will:
- ✓ **Get familiar** with human-AI collaboration in journalism
- ✓ **Learn about generative AI** in news creation
- ✓ **Reflect on your experiences**
- ✓ Start ideating **designs**

This image was created using AI (DALL·E by OpenAI)
Prompt: *generate an image of scattered human and AI generated news articles with a questionmark overlay*

How does this work?
- **Time required:** ~20 minutes
- **No right or wrong answers!** The goal is to **learn & reflect**
- **Deadline:** Please complete it at least **one day before the session**
- **Questions? Contact me at:** amber.kusters@cwi.nl

Your work produced in this booklet will be used in the co-design session.

Please finish the booklet a day before the co-design session.

Thank you!

Click the arrow to continue

SENSITIZING BOOKLET

About Me

Before we start, tell me about yourself!

My name is

Type here

My current job (role) is

Type here

at

Type here

I have been studying/working in the design field for

Type here (e.g. 5 years bachelor's degree + 2 years in industry)

I would describe my experience with AI as

Type here (e.g. novice, no experience; expert, I developed AI systems)

My News Habits

Please fill in the post-its to finish the sentence

I read news about

e.g. politics, sports

Replace with your answers

from

e.g. BBC, Twitter

around

e.g. once a day

Click the arrow to continue

SENSITIZING BOOKLET

Generative AI

Generative AI (GenAI) is a type of artificial intellligence that can create new content based on what you ask it. This includes writing, images, music, and even code.

You may already use AI in everyday life without realizing it! Some common AI-powered tools include:

- **Spell check & autocorrect**
- **Voice assistants**
- **Photo editing & generation**

Reflection: Have you ever used any GenAI tools? If so, for which tools and which kind of tasks?

e.g. Chatgpt for rewriting an email

Examples of popular GenAI tools are:

1. **ChatGPT**: for written results
2. **DALL-E 3** and **Midjourney** for text-to-image generation,
3. **Adobe Firefly**: for both text-to-image generation and editing specific elements in an image.

Human-AI Collaboration

GenAI does not replace journalists, they work together collaboratively. The collaboration is based on:

- Ongoing back-and-forth process
- Learning from each other
- Trust
- Including transparency and ethical considerations.

Click the arrow to continue

SENSITIZING BOOKLET

GenAI & Journalism

Traditionally, journalists come up with an idea to write about, research and gather information, write, edit, and publish their articles. Now, generative AI can be used to create these articles. On the right, you can see a visualization of the news production workflow and GenAI's possible contributions.

News production stages	Possible GenAI contributions
Story Ideation	• Idea generation • Content recommendation
Research & Information Gathering	• Information gathering • Fact checking • Data processing
Content Creation	• Writing drafts, summaries and headlines • Translation • Image generation
Editing & Reviewing	• Style correction • Verification
Publishing	• Personalized feed • Customized content

Figure on news production workflow

Here are two news articles about the same topic:
- https://apnews.com/article/netherlands-golden-helmet-art-heist-romania-021895346e06db10c968d86811742af6
- https://newsgpt.ai/2025/01/31/daring-museum-heist-in-netherlands-nets-three-arrests/

Reflection: What difference do you notice between these two articles?

The usage of GenAI in journalism is a spectrum of more or less GenAI usage, as illustrated below:

Human-made — Less GenAI usage — More GenAI usage — GenAI-made

Click the arrow to continue

SENSITIZING BOOKLET

AI Disclosure

An AI disclosure tells readers whether AI was involved in creating the content. Readers prefer to have these disclosures, so they can decide for themselves how to perceive the article. In this study we will focus on disclosing the human-AI collaboration ratio.

Static disclosure
A static disclosure is something that provides all the necessary information upfront, typically visible immediately when the content is accessed. It does not change as the user interacts with it. Already at first glance the user understands the message of the disclosure.

Interactive (Progressive) disclosure
Interactive disclosure reveals information gradually, depending on how the user interacts with the content. The user might need to click, hover, or scroll to reveal more details. Used so the user is not overwhelmed.

Reflection: Have you ever encountered any type of disclosure? What comes to mind? This can be online, but also in the physical world.

Click the arrow to continue

SENSITIZING BOOKLET

Thank You!

You have completed the booklet!

When you are done, please **send an email** to:
amber.kusters@cwi.nl
to indicate that you are finished.

Session date:
You have received a zoom link invite in your email.
Please **join the zoom link 5 minutes before** the session starts.

Don't forget to set up your **drawing tablet** in advance.

Get ready for the session!
Think about how AI disclosures could look—**browse examples, sketch ideas, or note what might work.**
We'll design together, but time is limited, so a little prep helps :)

See you soon!

B.2 Co-Design Session Miro Board

Introduction

Goal: collaboratively design effective **AI disclosure representations** for **human-AI collaboration** in news production

Schedule

	Time	Duration
Introduction	09:00 - 09:05	5 min
Reflection and recap	09:05 - 09:10	5 min
Ideation Phase 1	09:10 - 09:25	15 min
Guidelines	09:25 - 09:35	10 min
Ideation Phase 2	09:35 - 09:50	15 min
Voting	09:50 - 10:00	10 min
Closing	10:00	- min

Teams

Name	Personal Code	Team
XXXX	A	1
XXXX	B	
XXXX	C	2
XXXX	D	

Reflection

Recap

Human-made — Less GenAI usage — More GenAI usage — GenAI-made

News production stages	Possible GenAI contributions
Story Ideation	• Idea generation • Content recommendation
Research & Information Gathering	• Information gathering • Fact checking • Data processing
Content Creation	• Writing drafts, summaries and headlines • Translation • Image generation
Editing & Reviewing	• Style correction • Verification
Publishing	• Personalized feed • Customized content

Static disclosure

A static disclosure is something that provides all the necessary information upfront, typically visible immediately when the content is accessed. It does not change as the user interacts with it. Already at **first glance** the user understands the message of the disclosure.

Interactive (Progressive) disclosure

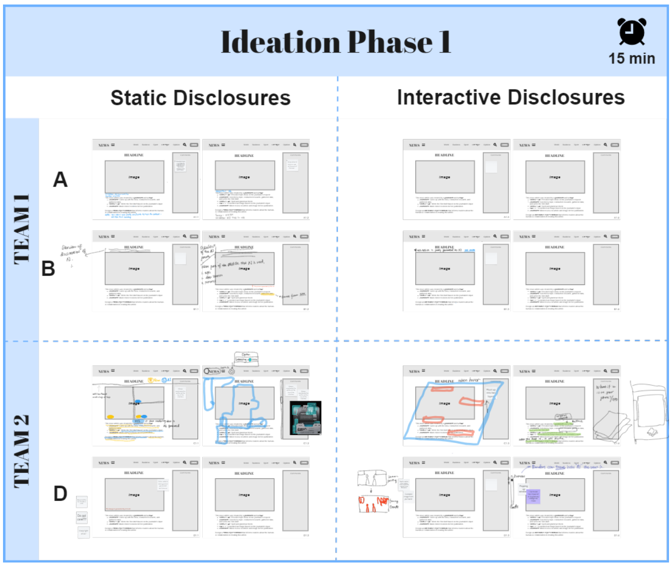
Interactive disclosure reveals information gradually, depending on how the user **interacts with the content**. The user might need to click, hover, or scroll to reveal more details. Used so the user is not overwhelmed.

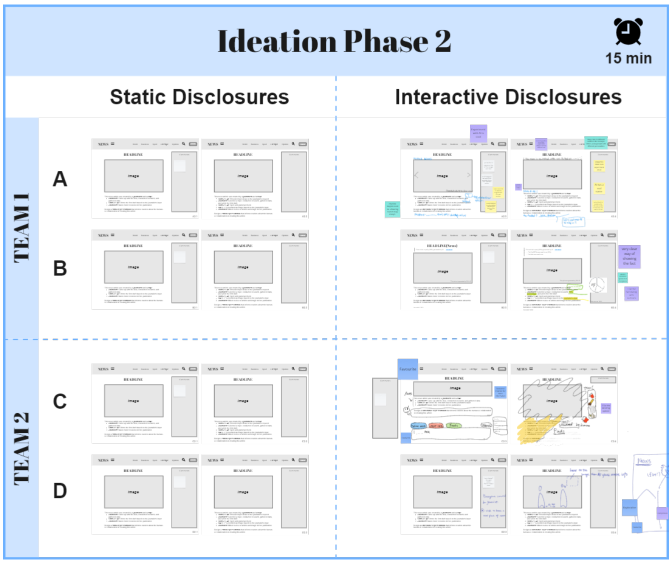
Feedback & Voting

Favourite

Suggestions

Compliment



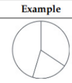
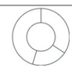
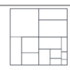


Requirements

Principle	Description	Related Heuristic
Simplicity	The design should be clear, free from unnecessary elements, and immediately understandable.	Aesthetic and Minimalist Design [53]
Cognitive Load Management	Users should be able to grasp the AI-human ratio without needing to remember prior information or interpret complex details.	Recognition Rather than Recall [53]
User-Centered Approach	The visualization should align with user expectations and avoid unnecessary technical complexity.	Match Between System and the Real World [53]

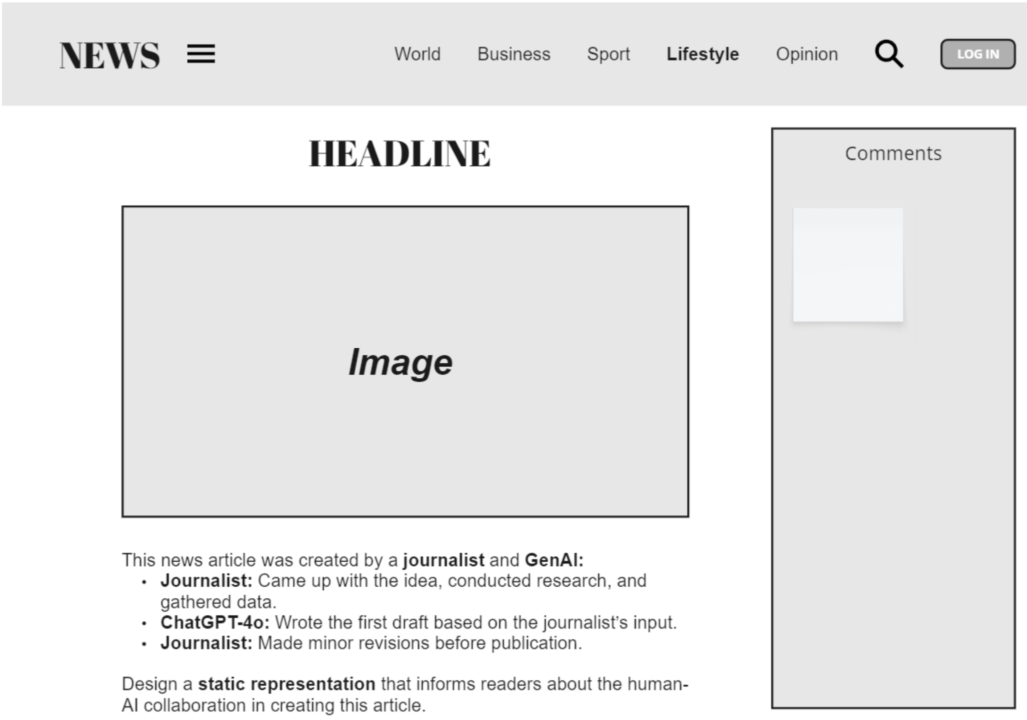
You can also choose your own requirements!

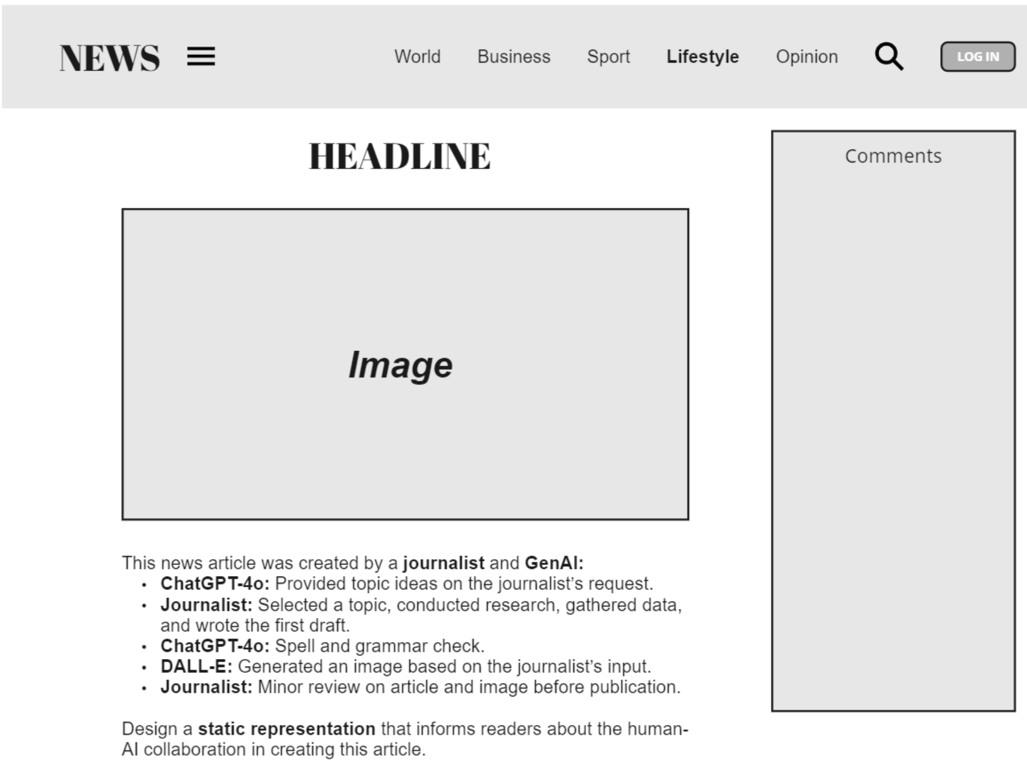
Information Visualizations Methods

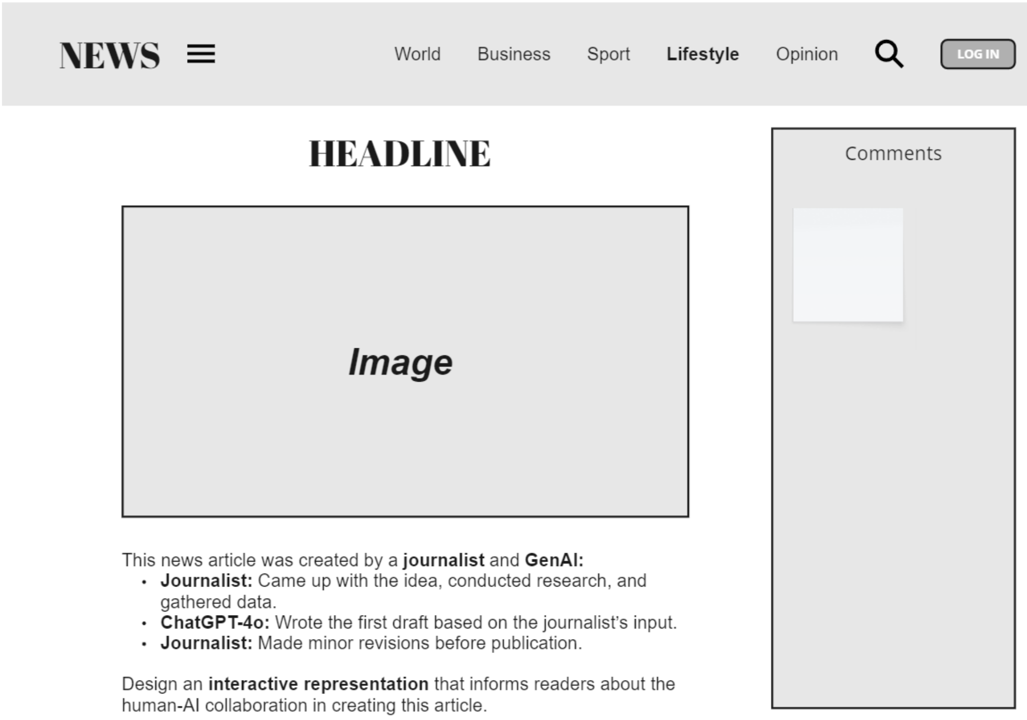
Visualization Type	Description	Example
Pie Chart	Divides a circle into proportional slices.	
Donut Chart	Similar to a pie chart, but with a central hole.	
Stacked Bar Chart	Uses segments within a bar to represent proportions.	
Tree Map	Represents hierarchical data using nested rectangles.	
Waffle Chart	Uses a grid of squares to show proportions.	
Numerical/Textual	Directly states proportions (e.g., "75% AI, 25% Human").	

Many other options possible!

B.3 Co-Design Session Scenarios






NEWS
World
Business
Sport
Lifestyle
Opinion
LOG IN
HEADLINE
Image
Comments
This news article was created by a **journalist** and **GenAI:**
• **Journalist:** Came up with the idea, conducted research, and gathered data.
• **ChatGPT-4o:** Wrote the first draft based on the journalist's input.
• **Journalist:** Made minor revisions before publication.
Design an **interactive representation** that informs readers about the human-AI collaboration in creating this article.


NEWS
World
Business
Sport
Lifestyle
Opinion
LOG IN
HEADLINE
Image
Comments
This news article was created by a **journalist** and **GenAI:**
• **ChatGPT-4o:** Provided topic ideas on the journalist's request.
• **Journalist:** Selected a topic, conducted research, gathered data, and wrote the first draft.
• **ChatGPT-4o:** Spell and grammar check.
• **DALL-E:** Generated an image based on the journalist's input.
• **Journalist:** Minor review on article and image before publication.
Design an **interactive representation** that informs readers about the human-AI collaboration in creating this article.

C. Co-Design Session Results

Disclosure type	Category	Placement	Textual/ Visual	Ideas
Static	Labels / Icons / Stamps	Headline	Visual	**AI label/stamp** showing "AI" was used, above headline
Static	Labels / Icons / Stamps	Headline	Visual	Fixed top part with **icon/persona** of author and AI next to headline (highlighting who did what with yellow/blue), and credibility score under image
Static	Labels / Icons / Stamps	Headline	Textual	**[Human-AI] stamp** or simple imaged based disclosure right under headline, and at the bottom (right) detailed information on what the journalist created and what ChatGPT created.
Static	Labels / Icons / Stamps	Headline	Visual	**Stamp** right at the end of the headline, e.g., a person with a check mark / people and (AI) icon
Static	Labels / Icons / Stamps	Image	Textual	**Description Label AI/Human** (!), also acknowledgment in the caption via a statement. Bottom left of image
Static	Labels / Icons / Stamps	Image	Visual	**Cloud-like icon** with AI in upper left or human in top right corner
Static	Labels / Icons / Stamps	Image	Visual	**(AI) stamp/icon** bottom right of image
Static	Labels / Icons / Stamps	Image	Textual	**Smiley face** top left next to image: "Grammar corrected by AI for your comfort"
Static	Labels / Icons / Stamps	Bottom / footer	Visual	**Icon of person/robot** [person $\rightarrow$ robot $\rightarrow$ person] to show division of work, with more details at end
Static	Textual	Headline	Textual	Text disclosure under headline

Continued on next page

Disclosure type	Category	Placement	Textual/Visual	Ideas
Static	Textual	Headline	Textual	Text disclosure under headline **(AI) icon + "AI assisted the creation of this article"** (high impact news)
Static	Textual	Headline	Textual	Text disclosure under headline overview of AI usage including what part of the article used AI in **list form**
Static	Textual	Headline	Textual	**Human % | AI %** under headline
Static	Textual	Image	Textual	Text disclosure under image
Static	Textual	Image	Textual	Text disclosure under image **(AI) icon + "AI assisted the creation of this article"** (low impact news)
Static	Textual	Image	Textual	Text disclosure under image "**Co-editor**: AI Tools Partly in use, Reporter: Name", at end of article: "NOTE: This article was partly created with AI tools for xxx tasks, NOT FOR fact checking"
Static	Textual	Image	Textual	Text disclosure under image "**Reporter**: name" and at the end of the article: "source: xxx, co-editor: AI tools used"
Static	Textual	Image	Textual	**Watermark** bottom right of image: "Generated with DALL-E"
Static	Textual	Image	Textual	**"! *this picture is generated by DALL-E"** in red
Static	Textual	Image	Visual	Bottom left of image: **"The image is generated by AI tools" + color coding** to distinguish AI generated and human
Static	Textual	Image	Textual	Bottom of article: **author description + add ChatGPT-model description**
Static	Elaborate	Image	Visual	Right side of image: **potion glass** showing AI/human layers with different colors
Static	Elaborate	Image	Visual	**Meter** (from human to AI): trust/bias meter, bottom right of image

Continued on next page

Disclosure type	Category	Placement	Textual/Visual	Ideas
Static	Elaborate	Body	Visual	On the left **a bar with icons** and an asterisk referring to the legend at the bottom
Static	Elaborate	Bottom / footer	Textual	**Section** (bottom or right): detailed explanation of what AI vs journalist did
Static	Elaborate	Body	Textual	**Add data source** where data came from
Static	Elaborate	Body	Visual	On the left a bar that moves with the page, which has the different steps of the workflow with icons of human/robot to indicate the collaboration
Static	Elaborate	Bottom / footer	Visual	Bottom right a **small bar** with human (green) and AI (red) to show how much was done by which, details at the bottom of the article
Static	Elaborate	Headline	Textual	Under headline: "This news is co-worked with our AI tech to . . . . :)". Under image left: **Name of AI** (it's more personal, later on different AI has different tone?). Underneath article: Any feedback? name@email.com and a block underneath to explain "why we need AI to help us?"
Interactive	Sliders / Adjustable	Body	Visual	**Contribution Spectrum or Layers**: Semi-transparent bar fixed on side, one color = human generated, one color = AI generated, and one color = mix of both. Include legend (left side of page), similar to VS Code left-side highlight.
Interactive	Sliders / Adjustable	Body	Visual	**A dynamic bar or pie chart** representing the percentage of human vs. AI contribution in different aspects of the article (e.g., research, drafting, editing). Users can **adjust sliders** to see how the balance shifts and how it affects perceived credibility/authenticity.

Continued on next page

Disclosure type	Category	Placement	Textual/Visual	Ideas
Interactive	Sliders / Adjustable	Body	Visual	**A layered visualization** with highlights or overlays indicating AI-generated vs. human-written content (e.g., AI-written text in blue, human-edited in green). **A toggle or slider** reveals different layers, showing the evolution of the article.
Interactive	Sliders / Adjustable	Body	Textual	**Slider** on the page (left to right), with author **annotations** revealed as the user moves the slider.
Interactive	Sliders / Adjustable	Body	Visual	**Up-down slider** on left from human → AI scale, toggling the **disclosure level**.
Interactive	Click / Toggle	Headline	Visual	**Cloud-like AI** icon at top right, **highlighting AI** text on click.
Interactive	Click / Toggle	Headline	Textual	Right of headline: simple **info icon [i]** to click.
Interactive	Click / Toggle	Headline	Visual	Right of headline: **(AI) icon** to click; pop-up lists tasks with link for AI model details.
Interactive	Click / Toggle	Headline	Visual	Right of headline: **button with person and robot illustration**; clicking highlights human/AI elements with descriptions.
Interactive	Click / Toggle	Headline	Visual	Left of headline: **button to show info layer** (auto-pops for 10s, visual layer appears) indicating AI collaboration, plus additional visualization.
Interactive	Click / Toggle	Headline	Textual	Under headline: "**See more**" link reveals task + model details.
Interactive	Click / Toggle	Headline	Textual	Under headline: "**See more**" link reveals task + model details and % AI involvement with model usage details. e.g. This article is partly (xx%) generated by AI See more" when clicked, "The ChatGPT-4o was used for xxx (20%), The DALL-E was used for xxx"

Continued on next page

Disclosure type	Category	Placement	Textual/Visual	Ideas
Interactive	Click / Toggle	Headline	Visual	**Settings icon** near hamburger menu; click toggles “interesting” mode showing a **layered who-did-what interface.**
Interactive	Click / Toggle	Headline	Visual	**Potion bottle** icon with “**mix me**” bubble; click reveals more info.
Interactive	Click / Toggle	Image	Textual	**Text/button** at bottom right of image, “**Who created**?” – on click, shows creator statement.
Interactive	Click / Toggle	Image	Visual	Eye icon (closed/open with AI in iris) **toggles semi-transparent highlight** and % AI-generated info.
Interactive	Click / Toggle	Image	Visual	**Blurry image** requires click to reveal, informing AI involvement.
Interactive	Click / Toggle	Image	Visual	**Toolkit** on right side to adjust AI usage level, possibly via annotations.
Interactive	Click / Toggle	Image	Visual	**Clippy**-like (or star) figure on left; click shows text bubble with AI contribution info.
Interactive	Hover / Reveal	Headline	Visual	Left of headline: **author picture and AI icon**; hover shows list of tasks done by each.
Interactive	Hover / Reveal	Body	Visual	**3D layer**: on hover, content floats up highlighting AI involvement; could dissolve AI content to show original.
Interactive	Hover / Reveal	Body	Visual	Highlighted words show **pie chart** or data source on hover.
Interactive	Hover / Reveal	Body	Visual	Left-side **stack of icons**; hover reveals **info bubbles** (e.g., speech bubbles).
Interactive	Hover / Reveal	Body	Textual	Bottom of article: **timeline** (idea → research → draft → final); hover over steps for details.
Interactive	Hover / Reveal	Image	Textual	Hover on image shows **disclosure box**.
Interactive	Hover / Reveal	Image	Visual	**Switch between human and AI** image on hover.
Interactive	Hover / Reveal	Image	Textual	**AI info** appears on hover over image.

Continued on next page

Disclosure type	Category	Placement	Textual/Visual	Ideas
Interactive	Hover / Reveal	Image	Visual	**Image-only news**; hover shows AI-generated text, exploratory style.
Interactive	Pop-up	Body	Textual	**On page load, center pop-up**: human generated [x%], AI generated [x%], AI used in specific tasks.
Interactive	Pop-up	Image	Visual	**Pie chart** at image corner; pop-up shows human vs AI contribution.
Interactive	Pop-up	Body	Textual	**Cookie-like** disclosure pop-up.
Interactive	Pop-up	Body	Textual	**Intro screen**: choice between **quick summary** (icons highlight contributions while scrolling) or **detailed walkthrough** with more information.
Interactive	Pop-up	Body	Textual	Basic pop-up: "**Want to know more news**? [Click!]".
Interactive	Scroll / Floating	Body	Visual	**Small persona icon scrolls** with text, showing content creator type.
Interactive	Scroll / Floating	Body	Visual	**Parallax effect** updates **icon** based on author vs AI.
Interactive	Scroll / Floating	Body	Textual	Option: **solo mode**, or **assisted reading**, highlighted text as you scroll, click for a pop up text window with an icon specifying the workflow stage and who did it. (shouldn't be detailed, should be explicit)
Interactive	Scroll / Floating	Body	Textual	**Row of squares** on right in different colors. At the end: "xx% Thanks for AI's help in draft".
Interactive	Chat	Bottom / footer	Textual	**Speech bubble** at bottom right: "Check what I helped with" $\rightarrow$ chatbot displays tasks/models, then allows questions.
Interactive	Chat	Body	Textual	Author's name and collaboration details, scroll images to see AI vs original, **chatbot** button always on page.
Interactive	Chat	Bottom / footer	Textual	**Chatbot** underneath article to ask how it was created.

D. User Study Materials

D.1 Stimuli News Article Versions

Article 1 (More Human)

Rijksmuseum Begins Live Restoration of Rembrandt's Night Watch
The Rijksmuseum has begun the most extensive restoration ever of Rembrandt's famous painting The Night Watch and is inviting the public to watch the work unfold live. The 1642 masterpiece has been placed inside a specially designed glass chamber, allowing viewers to observe the restoration process in real-time. The museum is also streaming updates online for art enthusiasts.

The celebrated painting, last restored more than 40 years ago after it was slashed with a knife, is considered Rembrandt's most ambitious work. It was commissioned by Frans Banning Cocq, the mayor and leader of Amsterdam's civic guard, who wanted a group portrait of his militia company. Nearly 4 meters tall and 4.5 meters wide (12.5 x 15 feet), the painting weighs 337 kilograms (743 pounds). Famous for its dramatic lighting and movement, The Night Watch has become one of the most iconic works in Western art.

However, experts at the Rijksmuseum are concerned that some aspects of the masterpiece are deteriorating. One example is the fading of a small dog in the composition. The museum said the multi-million-euro restoration project, which includes extensive research, aims to provide a clearer understanding of the painting's condition. "This detailed study is necessary to determine the best treatment plan and will involve imaging techniques, high-resolution photography, and advanced computer analysis," the museum said in a statement. "We will create a detailed picture of the painting—not only of the painted surface but of every layer, from varnish to canvas."

This is the first major restoration of The Night Watch since 1975, when a man armed with a bread knife slashed the painting after fighting off a museum guard. The attacker, who said he "did it for the Lord," caused significant damage, but the painting was later repaired. It had also been attacked with a knife in 1911 and sprayed with a chemical in 1990, though the damage in those instances was relatively minor.

Taco Dibbits, general director of the Rijksmuseum, explained that the decision to allow the public to view the project—dubbed Operation Night Watch—was made because the painting "belongs to us all." "More than two and a half million people come to see it each year. It belongs to everyone, whether they live in the Netherlands or anywhere in the world," Dibbits said at the project's launch on Monday."

Article 2 (More AI)

Rembrandt: Rijksmuseum begins live Night Watch restoration
The Rijksmuseum in Amsterdam has launched a groundbreaking live restoration project of one of the most famous paintings in the world: Rembrandt's The Night Watch. The monumental painting, which has hung in the museum's collection for over 200 years, is undergoing a major conservation effort that will be broadcast to the public in real time, allowing viewers to witness the meticulous process of restoring this iconic masterpiece.

The restoration project, which began earlier this week, marks the first time the Rijksmuseum has undertaken such an ambitious live streaming initiative. Visitors to the museum can watch the work unfold in person, while those unable to travel to Amsterdam can follow the progress online. The live restoration will be carried out by a team of expert conservators, who will work carefully on the painting's surface over the coming months, removing years of grime, aging varnish, and previous touch-ups to return the piece closer to its original state.

The Night Watch (1642), one of Rembrandt's largest and most celebrated works, is a group portrait of a civil militia led by Captain Frans Banning Cocq. Despite its fame, the painting has endured significant damage over the centuries. It has been altered several times — most notably during a 1715 re-framing that reduced its size — and has suffered from exposure to light, pollution, and other environmental factors. The restoration process aims not only to stabilize the painting but also to uncover elements of the original composition that have been hidden for centuries.

The museum's decision to make the restoration process public is a reflection of the growing interest in the science of conservation and a desire to involve the public in preserving cultural heritage. "We want people to see the expertise and care that goes into preserving such a masterpiece," said Taco Dibbits, director of the Rijksmuseum. "It's an opportunity to bring people closer to the art and allow them to experience the transformation firsthand."

The restoration will involve advanced technology, including high-resolution imaging and a range of chemical treatments to carefully peel away layers of old varnish. Conservators will also analyze the original brushstrokes to better understand Rembrandt's techniques and materials, providing new insights into the artist's working methods. The live-streamed restoration is expected to last several months, culminating in the unveiling of the completed work in late 2025. Visitors and online viewers will be able to follow the restoration's progress on the museum's website and through various social media platforms. As The Night Watch undergoes its transformation, the Rijksmuseum invites the world to witness history in the making, bringing Rembrandt's genius back to life — one brushstroke at a time."

Article 3 (More Human)

Researchers Unveil First Glimpse of Denisovan Appearance
Researchers have unveiled the first reconstruction of what Denisovans, an ancient group of humans, may have looked like. Denisovan remains were discovered in 2008, and experts in human evolution have been fascinated by this group, which went extinct around 50,000 years ago. One of the biggest questions surrounding the Denisovans has been their appearance, as no full sketches had previously been created. Now, a team of researchers has produced reconstructions based on DNA analysis.

Who Were the Denisovans?
Around 100,000 years ago, several different human groups, including modern humans, Neanderthals, and Denisovans, coexisted. "In many ways, Denisovans resembled Neanderthals, but in some traits, they resembled us and, in others, they were unique," said Prof. Liran Carmel, a researcher at the Hebrew University of Jerusalem. Denisovans are believed to have lived in Siberia and eastern Asia. Evidence suggests Denisovans lived at high altitudes in Tibet, passing on a gene that helps modern humans cope with similar elevations. It is still unclear why they went extinct.

The Denisovans only gained attention after archaeologists investigated remains in a cave in Siberia a little more than a decade ago. So far, the only Denisovan remains discovered include three teeth, a pinky bone, and a lower jaw. Studies indicate about 5% of the ancestry of people from Oceania can be traced to Denisovans.

What Do the New Reconstructions Tell Us?
The reconstructions—based on DNA analysis of Denisovans, Neanderthals, chimpanzees, and humans—reveal that the Denisovan skull was likely wider than that of modern humans or Neanderthals. They also appeared to lack a chin. Experts predict many Denisovan traits were similar to Neanderthals, including a sloping forehead, long face, and large pelvis. Other traits, however, were unique, such as a large dental arch.

Prof. Carmel expressed excitement over the confirmation of some of their predictions following the discovery of a Denisovan jawbone by separate researchers. "The jawbone was reported, and we were thrilled to see how it matched. It was an independent confirmation of our method," he said. Carmel added that the reconstructions are just the beginning of Denisovan research. "They were humans very similar to us, so pointing out the differences between us is critical for understanding what makes us human and what led to the way we adapted to the world," he said."

Article 4 (More AI)

Denisovans: Face of long-lost human relative unveiled
For years, the Denisovans—a mysterious and long-lost branch of the human family tree—have been known only through their DNA. But now, thanks to a groundbreaking new study, scientists have unveiled what may be the first-ever depiction of a Denisovan face, offering a tangible glimpse into the appearance of our ancient relatives.

The Denisovans were first identified in 2008, when genetic material from a finger bone found in the Denisova Cave in Siberia was sequenced. Since then, scientists have used genetic evidence to learn that these hominins lived in Eurasia between 50,000 and 300,000 years ago. Despite their genetic footprint, fossil evidence of Denisovans remains scarce, making it difficult to piece together their physical characteristics. But thanks to advances in genomic technology and 3D facial reconstruction techniques, researchers have been able to create a face that bridges the gap between the known and the unknown.

The breakthrough, led by an international team of researchers, used DNA extracted from Denisovan fossils to generate a detailed facial reconstruction. By comparing Denisovan genetic data with the faces of modern humans and Neanderthals, scientists applied a computational model that predicts the likely physical traits of the species. The result is a lifelike rendering of a Denisovan individual, with features that suggest they were likely stockier and more robust than modern humans, with a broader face and prominent brow ridges, reminiscent of Neanderthals.

While much about the Denisovans remains elusive, the study provides a critical visual link to an ancient population that shared common ancestors with both Neanderthals and modern humans. It's also a reminder of the complex web of human evolution, where multiple hominin species coexisted, interacted, and even interbred with one another. In fact, many people of non-African descent today carry traces of Denisovan DNA in their genomes, a testament to the genetic legacy left behind by these ancient relatives.

This new portrait of the Denisovans also has broader implications for the study of human history, shedding light on the migration patterns and lifestyles of early human populations. "By reconstructing the face of the Denisovans, we're not just putting a face on an ancient species," said Dr. Katerina Harvati, a paleoanthropologist involved in the project. "We're also uncovering the deep and rich history of humanity itself."

Though this reconstructed face is not the final word on Denisovan appearance, it marks an important step forward in understanding the diverse branches of human evolution—and the lost relatives that once walked the Earth alongside us."

D.2 Consent Form

INFORMED CONSENT FORM

Participation in research on AI disclosure visualizations in news media

Conducted by Centrum Wiskunde & Informatica (CWI) and Utrecht University

Thank you for participating in this study, which explores how people interpret visual disclosures of collaboration between humans and generative AI in online news articles.

The experiment involves reading short news articles, viewing different disclosure designs, and answering questionnaires. Eye-tracking and interaction data will be collected during this task, followed by a short interview. All materials produced in this session may be used for research publications.

The collected data

- [Demographic data]: Age, gender, education will be processed in raw format.
- [News and AI literacy data]: Self-reported news habits and (generative) AI experience
- [Questionnaire responses]: Perception of the disclosure visualizations
- [Eye-tracking data]: Gaze direction, fixations, pupil diameter
- [Mouse interactions]: Clicks and hovers
- [Audio recording]: A brief post-session interview, which will be transcribed for thematic analysis. The raw audio recording will be deleted after transcription.

Data Use and Publication

All data will be pseudonymized: your name is replaced with a code, and only the research team holds the key. Your identity will remain confidential and secure.

Please note that all data will be processed and stored at an individual level. The raw eye-tracking data will be processed to extract characteristics or relevant features in relation to the study. The processed eye-tracking and interaction data, demographic data, questionnaire answers and audio transcriptions will be analysed at a group level. The results of the analyses will be made available to the public as scientific publications and presentations for advancing science, including visualizations and selected anonymous quotes. Some individual examples may be shown, but never linked to your name or identity. The personal data (captured in paper: use of lenses, name and contact information) will be always kept separated from the other data.

These research results may be shared within and outside Europe. While your data is pseudonymized, data protection standards may differ outside the EU.

Your rights

You can exercise your rights, including the right to withdraw your consent, according to the personal data protection laws by contacting the researcher (amber.kusters@cwi.nl) or supervisor (aea@cwi.nl). When we receive your consent withdrawal, we will delete your data that only CWI holds. However, it is important to note that despite our best efforts to delete your data, some data that has been previously shared or published may remain in the public domain for a longer period. You can obtain more information about your privacy rights at https://www.cwi.nl/en/about/privacy/.

Consent Form

- ☐ I confirm that the research project ***"Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production"*** has been explained to me. I have had the opportunity to ask questions about the project and have had these answered satisfactorily.
- ☐ I consent to the material I contribute being used to generate insights for the research project "***Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production".***
- ☐ I am aware that the researcher will take an audio recording of the interview. I understand that I can request to stop these recordings. I understand that I can ask for the recording to be deleted.
- ☐ I understand that my participation in this research is voluntary, and that I may withdraw from the study at any time.
- ☐ I consent to allow the fully pseudonymized data to be used for future publications and other scholarly means of disseminating the findings from the research project.
- ☐ I give specific consent for the processing of my eye-tracking and interaction data as described.
- ☐ I confirm that I am 18 years of age or over.
- ☐ I understand that the information/data acquired will be securely stored by researchers, but that appropriately anonymised data may in future be made available to others for research purposes only.
- ☐ I understand that I can request any of the data collected from/by me to be deleted.
- ☐ I understand that withdrawal post-publication only removes my data from CWI's systems.
- ☐ I agree to take part in the above study on ***"Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production"***.
- ☐ OPTIONAL: I agree that my image may be exposed in scientific publications illustrating the environment of the experiment

Participant ID	Email Address	
Name of participant	Date	Signature
Name of researcher	Date	Signature

Participant Visual Information

Please complete the information below after signing the informed consent form.

Participant ID: ___________________________

Do you wear glasses or contact lenses?

☐ No
☐ Yes, I am wearing them right now
☐ Yes, I am not wearing them right now

Do you have any known visual impairments (e.g., color blindness, low vision)?

☐ No
☐ Yes, please specify: ____

D.3 Pre-task Questionnaire

Demographics

1. What is your age? *(Open-ended)*
2. What is your gender?
   (Male, Female, Non-binary, Prefer not to say, Other: ___)
3. What is the highest level of education you have completed?
   (Less than high school degree, High school degree or equivalent, Bachelor's degree, Master's degree, Doctorate)

News Consumption

4. How often do you consume news?
   (Multiple times a day, Daily, A few times per week, Weekly, Rarely, Never)
5. Where do you primarily get your news?
   (News websites, TV, Social media, Newspapers, Podcasts, Other: ___)
6. Have you ever encountered AI-generated news articles? *(Yes, No, Not sure)*

Experience with AI

7. How experienced are you with using ChatGPT (or other Generative AI tools)?
   (7-point Likert scale: 1=Never used, 2=Very little experience, 7=Very experienced) [31]
8. In the following, you will read descriptions of different abilities that one can have when dealing with artificial intelligence (AI). These abilities can be more or less pronounced.
   Please rate yourself: How pronounced are your abilities?
   - 0 means that an ability is not at all or hardly pronounced
   - 10 means that an ability is very well or (almost) perfectly pronounced

   Select the number that best matches your ability.
   - I know the most important concepts of the topic "artificial intelligence".
   - I can assess what the limitations and opportunities of using an AI are.
   - I can assess what advantages and disadvantages the use of an artificial intelligence entails.
   - I can tell if I am dealing with an application based on artificial intelligence.
   - I can distinguish technology that uses AI from technology that does not.
   - I can weigh the consequences of using AI for society.
   - I can incorporate ethical considerations when deciding whether to use data provided by an AI.
   - I don't let AI influence me in my everyday decisions.
   - I can prevent an AI from influencing me in my everyday decisions.
   - I realize if artificial intelligence is influencing me in my everyday decisions.

   Shortened and adapted version of Carolus et al. AI literacy questionnaire [63].

D.4 Human-AI Collaboration Questionnaire

1. Based on this visualization, how much of the article do you think was created or assisted by AI? *(Multiple-choice)* [67]
   - Entirely AI-generated
   - Primarily AI-generated
   - A blend of human and AI
   - Primarily human-created
   - Entirely human-created

2. Based on this visualization, how would you describe the role of AI in producing this article?
   (7-point Likert scale: 1=Strongly disagree, 7=Strongly agree, 4=Neither agree nor disagree) Adapted version of Altay et al. [38]
   "I believe that AI..."
   - summarized a news article to create the headline
   - was used to fact-check the content
   - wrote the entire article
   - wrote a first draft of the article
   - improved the clarity and style of the text
   - selected the topic of the article

D.5 Disclosure Evaluation Questionnaire

For the following questions, please indicate the extent to which you agree or disagree

1. I found this visualization to be...
   (7-point Likert scale: 1=Strongly disagree, 7=Strongly agree, 4=Neither agree nor disagree) Adapted version of Wittenberg et al. [46]
   - Clear
   - Informative
   - Helpful
   - Easy to understand
   - Useful

2. I found that this visualization gave me...
   (7-point Likert scale: 1=Strongly disagree, 7=Strongly agree, 4=Neither agree nor disagree)
   - an overview
   - in-depth information
   - an understanding of specific steps in the process
   - insight into who contributed what
   - a sense of how much AI vs. human input there was

D.6 Semi-Structured Interview

1. What was your overall preference for AI disclosure design, please rank, and tell me why?
2. What thoughts came to mind when you first saw the disclosures?
3. Did your initial thoughts on how the article was created, match what the visuals portrayed?
4. Were there any elements of the disclosure visualization that you found confusing? How would you improve it?
5. How did you perceive the interactive visualizations compared with the static ones?
6. In what ways do you think the disclosures would affect how you read an article?
7. Some visualizations focussed more on the roles of humans and AI, some more on the tasks, which did you find more important and why?
8. Suppose it was a different article, with more high-impact or critical news, would you feel differently about the disclosure visualizations?
9. Where do you think the visualization should be placed on the page?
10. What would your thoughts be if you came across these disclosures on a real news platform?
11. What other visualizations would you have liked to see?
12. Any other comments?

E. Quantitative Data Analysis Tables

Providing an overview

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	15.65	3	93	<0.001	0.34

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	-17.937500	7.045880	93	-2.546	0.0151	-0.636453	*
Textual Disclosure - Chatbot	20.437500	7.045880	93	2.901	0.0070	0.725158	**
Textual Disclosure - Task-based Timeline	-23.062500	7.045880	93	-3.273	0.0030	-0.818297	**
Role-based Timeline - Chatbot	38.375000	7.045880	93	5.446	<.0001	1.361611	***
Role-based Timeline - Task-based Timeline	-5.125000	7.045880	93	-0.727	0.4688	-0.181844	
Chatbot - Task-based Timeline	-43.500000	7.045880	93	-6.174	<.0001	-1.543455	***

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Providing in-depth information

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	25.96	3	93	<0.001	0.46

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	-2.093750	6.332598	93	-0.331	0.7417	-0.082658	
Textual Disclosure - Chatbot	-48.968750	6.332598	93	-7.733	<.0001	-1.933202	***
Textual Disclosure - Task-based Timeline	-10.875000	6.332598	93	-1.717	0.1339	-0.429326	
Role-based Timeline - Chatbot	-46.875000	6.332598	93	-7.402	<.0001	-1.850544	***
Role-based Timeline - Task-based Timeline	-8.781250	6.332598	93	-1.387	0.2026	-0.346669	
Chatbot - Task-based Timeline	38.093750	6.332598	93	6.016	<.0001	1.503875	***

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Providing an understanding of specific steps in the process

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	12.10	3	93	<0.001	0.28

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	-29.625000	7.591454	93	-3.902	0.0005	-0.975604	***
Textual Disclosure - Chatbot	-18.781250	7.591454	93	-2.474	0.0228	-0.618500	*
Textual Disclosure - Task-based Timeline	-44.343750	7.591454	93	-5.841	<.0001	-1.460318	***
Role-based Timeline - Chatbot	10.843750	7.591454	93	1.428	0.1565	0.357104	
Role-based Timeline - Task-based Timeline	-14.718750	7.591454	93	-1.939	0.0667	-0.484714	
Chatbot - Task-based Timeline	-25.562500	7.591454	93	-3.367	0.0022	-0.841818	**

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Gaze duration

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	36.05	3	69	<0.001	0.65

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	6.900000	3.934954	57	1.754	0.1273	0.554510	
Textual Disclosure - Chatbot	-29.500000	3.934954	57	-7.497	<.0001	-2.370732	***
Textual Disclosure - Task-based Timeline	3.400000	3.934954	57	0.864	0.3912	0.273237	
Role-based Timeline - Chatbot	-36.400000	3.934954	57	-9.250	<.0001	-2.925242	***
Role-based Timeline - Task-based Timeline	-3.500000	3.934954	57	-0.889	0.3912	-0.281273	
Chatbot - Task-based Timeline	32.900000	3.934954	57	8.361	<.0001	2.643969	***

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Fixation duration

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	34.21	3	69	<0.001	0.64

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	-29.000000	3.228030	57	-8.984	<.0001	-2.840930	***
Textual Disclosure - Chatbot	-2.000000	3.228030	57	-0.620	0.5380	-0.195926	
Textual Disclosure - Task-based Timeline	-14.000000	3.228030	57	-4.337	0.0001	-1.371483	***
Role-based Timeline - Chatbot	27.000000	3.228030	57	8.364	<.0001	2.645003	***
Role-based Timeline - Task-based Timeline	15.000000	3.228030	57	4.647	<.0001	1.469446	***
Chatbot - Task-based Timeline	-12.000000	3.228030	57	-3.717	0.0006	-1.175557	***

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Fixation count

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	46.19	3	69	<0.001	0.71

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	16.925000	4.123717	57	4.104	0.0002	1.297896	***
Textual Disclosure - Chatbot	-29.300000	4.123717	57	-7.105	<.0001	-2.246874	***
Textual Disclosure - Task-based Timeline	6.475000	4.123717	57	1.570	0.1219	0.496536	
Role-based Timeline - Chatbot	-46.225000	4.123717	57	-11.210	<.0001	-3.544770	***
Role-based Timeline - Task-based Timeline	-10.450000	4.123717	57	-2.534	0.0169	-0.801360	*
Chatbot - Task-based Timeline	35.775000	4.123717	57	8.675	<.0001	2.743410	***

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Saccade count

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	44.13	3	69	<0.001	0.70

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	16.025000	3.687336	57	4.346	0.0001	1.374312	***
Textual Disclosure - Chatbot	-24.600000	3.687336	57	-6.671	<.0001	-2.109708	***
Textual Disclosure - Task-based Timeline	6.275000	3.687336	57	1.702	0.0942	0.538147	
Role-based Timeline - Chatbot	-40.625000	3.687336	57	-11.017	<.0001	-3.484020	***
Role-based Timeline - Task-based Timeline	-9.750000	3.687336	57	-2.644	0.0127	-0.836165	*
Chatbot - Task-based Timeline	30.875000	3.687336	57	8.373	<.0001	2.647855	***

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

Saccade length

Term	F	Df	Df.res	Pr(>F)	$\eta^2 p$
Visualization type	12.53	3	69	<0.001	0.40

contrast	estimate	SE	df	t.ratio	p	d	sig.
Textual Disclosure - Role-based Timeline	-19.300000	5.290740	57	-3.648	0.0011	-1.153562	**
Textual Disclosure - Chatbot	11.550000	5.290740	57	2.183	0.0497	0.690344	*
Textual Disclosure - Task-based Timeline	4.750000	5.290740	57	0.898	0.3731	0.283908	
Role-based Timeline - Chatbot	30.850000	5.290740	57	5.831	<.0001	1.843906	***
Role-based Timeline - Task-based Timeline	24.050000	5.290740	57	4.546	0.0001	1.437470	***
Chatbot - Task-based Timeline	-6.800000	5.290740	57	-1.285	0.2447	-0.406436	

Degrees-of-freedom method: kenward-roger
P value adjustment: FDR method for comparing a family of 4 estimates

F. Ethics Quick Scan

Response Summary:

Section 1. Research projects involving human participants

P1. Does your project involve human participants? This includes for example use of observation, (online) surveys, interviews, tests, focus groups, and workshops where human participants provide information or data to inform the research. If you are only using existing data sets or publicly available data (e.g. from X, Reddit) without directly recruiting participants, please answer no.

- Yes

Recruitment

P2. Does your project involve participants younger than 16 years of age?

- No

P3. Does your project involve participants with learning or communication difficulties of a severity that may impact their ability to provide informed consent?

- No

P4. Is your project likely to involve participants engaging in illegal activities?

- No

P5. Does your project involve patients?

- No

P6. Does your project involve participants belonging to a vulnerable group, other than those listed above?

- No

P8. Does your project involve participants with whom you have, or are likely to have, a working or professional relationship: for instance, staff or students of the university, professional colleagues, or clients?

- Yes

P9. Is it made clear to potential participants that not participating will in no way impact them (e.g. it will not directly impact their grade in a class)?

- Yes

Informed consent

PC1. Do you have set procedures that you will use for obtaining informed consent prior to collecting data from all participants, including (where appropriate) parental consent for children or consent from legally authorized representatives? (See suggestions for information sheets and consent forms on the website.)

- Yes

PC2. Will you tell participants that their participation is voluntary?

- Yes

PC3. Will you obtain explicit consent for participation?

- Yes

PC4. Will you obtain explicit consent for any sensor readings, eye tracking, photos, audio, and/or video recordings?
- Yes

PC5. Will you tell participants that they may withdraw from the research at any time and for any reason?
- Yes

PC6. Will you give potential participants time to consider participation?
- Yes

PC7. Will you provide participants with an opportunity to ask questions about the research before consenting to take part (e.g. by providing your contact details)?
- Yes

PC8. Does your project involve concealment or deliberate misleading of participants?
- No

Section 2. Data protection, handling, and storage

The General Data Protection Regulation imposes several obligations for the use of **personal data** (defined as any information relating to an identified or identifiable living person) or including the use of personal data in research.

D1. Are you gathering or using personal data (defined as any information relating to an identified or identifiable living person)?
- No

Section 3. Research that may cause harm

Research may cause harm to participants, researchers, the university, or society. This includes when technology has dual-use, and you investigate an innocent use, but your results could be used by others in a harmful way. If you are unsure regarding possible harm to the university or society, please discuss your concerns with the Research Support Office.

H1. Does your project give rise to a realistic risk to the national security of any country?
- No

H2. Does your project give rise to a realistic risk of aiding human rights abuses in any country?
- No

H3. Does your project (and its data) give rise to a realistic risk of damaging the University's reputation? (E.g., bad press coverage, public protest.)
- No

H4. Does your project (and in particular its data) give rise to an increased risk of attack (cyber- or otherwise) against the University? (E.g., from pressure groups.)
- No

H5. Is the data likely to contain material that is indecent, offensive, defamatory, threatening, discriminatory, or extremist?
- No

H6. Does your project give rise to a realistic risk of harm to the researchers?
- No

H7. Is there a realistic risk of any participant experiencing physical or psychological harm or discomfort?
- No

H8. Is there a realistic risk of any participant experiencing a detriment to their interests as a result of participation?

- No

H9. Is there a realistic risk of other types of negative externalities?

- No

Section 4. Conflicts of interest

C1. Is there any potential conflict of interest (e.g. between research funder and researchers or participants and researchers) that may potentially affect the research outcome or the dissemination of research findings?

- No

C2. Is there a direct hierarchical relationship between researchers and participants?

- No

Section 5. Your information.

This last section collects data about you and your project so that we can register that you completed the Ethics and Privacy Quick Scan, sent you (and your supervisor/course coordinator) a summary of what you filled out, and follow up where a fuller ethics review and/or privacy assessment is needed. For details of our legal basis for using personal data and the rights you have over your data please see the University's privacy information. Please see the guidance on the ICS Ethics and Privacy website on what happens on submission.

Z0. Which is your main department?

- Information and Computing Science

Z1. Your full name:

Amber Kusters

Z2. Your email address:

a.k.kusters@students.uu.nl

Z3. In what context will you conduct this research?

- As a student for my master thesis, supervised by::
  Abdallah el Ali

Z5. Master programme for which you are doing the thesis

- Human-Computer Interaction

Z6. Email of the course coordinator or supervisor (so that we can inform them that you filled this out and provide them with a summary):

a.elali@uu.nl

Z7. Email of the moderator (as provided by the coordinator of your thesis project):

graduation.hci@uu.nl

Z8. Title of the research project/study for which you filled out this Quick Scan:

Disclosing Collaboration: Visualizing Human-AI Collaboration in News Production

Z9. Summary of what you intend to investigate and how you will investigate this (200 words max):

This thesis explores how to visually represent human-AI collaboration ratios in news production. With generative AI (GenAI) increasingly used in journalism, there is a need for clear disclosure representations that inform readers about AI's role in content creation. Existing AI disclosures, such as labels and watermarks, often fail to convey the dynamic relationship between GenAI and humans, leading to misinterpretations. To address this, the study will develop and evaluate AI disclosure representations for news media. The research consists of two phases: (1) a design phase, where co-design sessions with designers will generate prototype visualizations, and (2) a user study, where an online survey will assess the effectiveness of these prototypes in communicating AI-human collaboration to news readers. The study will analyze how different disclosure types (static vs. interactive) and AI literacy levels impact user comprehension and perception of the disclosure representations. By bridging the gap in AI disclosure research, this thesis aims to provide insights into designing more effective and user-centered disclosure representations for GenAI usage in journalism.

Z10. In case you encountered warnings in the survey, does supervisor already have ethical approval for a research line that fully covers your project?

- Not applicable

Scoring

- Privacy: 0
- Ethics: 0
