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A Model of Frame Categories for Analyzing Media Discourse of Emerging Technologies

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This article presents a model of frame categories for analyzing media discourse about emerging technologies, applying it to 2 original case studies on UK news coverage of big data and generative artificial intelligence (gen-AI). The Frame Categories for Emerging Technologies (FCET) model offers 4 categories (Conceptualization, Newness, User Experience, and Evaluation) to allow researchers to identify frames inductively while affording easy and effective comparisons across studies. The empirical results demonstrate this, showing that the news included frames unique to each technology (such as Vast for big data and Human-Like for gen-AI), as well as shared frames such as Revolutionary and Important. This article contributes to the literature on media discourse of emerging technologies and offers a methodological approach to improve the quality and comparability of future studies in this area.

Keywords: framing, media discourse, emerging technologies, big data, artificial intelligence

Media discourse can have a significant impact on public perception of new technological developments, as well as their adoption and development (Asif & Gouqing, 2023; Buenaflor & Kim, 2013; Harley, 2022). In particular, studies employing framing theory to examine media coverage of technology have found that the way these developments are framed is often mirrored in readers'/viewers' opinions of those technologies (e.g., Bingaman, Brewer, Paintsil, & Wilson, 2021; Scheufele & Lewenstein, 2005). Uncovering these representations is therefore paramount in understanding how emerging technologies are socially constructed.

Since emerging technologies come with new concepts, it is important to use an inductive approach for frame identification when analyzing the media discourse about them. This means researchers are not limited to a pre-defined set of frames, which could lead to significant meaning being lost (Matthes & Kohring, 2008). However, inductive framing analyses have been criticized for their lack of replicability and comparability (de Vreese, 2005; Hertog & McLeod, 2001; Tankard, 2001). Thus, this article presents a model for analyzing the media discourse of emerging technologies (Frame Categories for Emerging Technologies; FCET). This model intends to minimize such methodological issues by providing categories within which frames can be identified. The FCET approach allows comparisons to be made across studies while offering researchers the flexibility to

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identify specific, perhaps unique, frames for each context. This enables richer and more accurate studies on the media discourse of emerging technologies. This approach was first developed in a study on media coverage of extended reality (XR)—an umbrella term for virtual, augmented, and mixed reality technologies (Graves, 2024)—and is further operationalized here by providing more detailed methodological guidance on its use and demonstrating how it can be applied to other technologies through two case studies.

As well as its methodological contribution to the literature through the FCET model, this article provides useful empirical insights into the media discourse of two related emerging technologies—big data and artificial intelligence (AI)—through the application of the FCET model. The term big data is commonly used "to describe the collection, processing, analysis and visualisation associated with very large data sets" (Emmanuel & Stanier, 2016, p. 1). It has applications in many areas, from audience insights (Anshari, Almunawar, Lim, & Al-Mudimigh, 2019) to predicting disease outbreaks (Tosi & Campi, 2020; see also Rodríguez-Mazahua et al., 2016). Relatedly, AI refers to "algorithms and techniques, often dependent on large amounts of data that perform relatively sophisticated tasks without human intervention" (Chinen, 2023, p. 1). Specifically, this article focuses on generative AI (gen-AI), a term for "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data" (Feuerriegel, Hartmann, Janiesch, & Zschech, 2024, p. 111). Gen-AI tools rapidly gained popularity after ChatGPT was released to the public at no cost in November 2022, becoming the fastest-growing application in history (Gordon, 2023). Gen-AI is strongly linked to big data since these large data sets are used to train AI systems (Teubner, Flath, Weinhardt, van der Aalst, & Hinz, 2023). Given the power of media discourse in socially constructing innovations (Brewer, Bingaman, Paintsil, Wilson, & Dawson, 2022; Scheufele & Lewenstein, 2005), applying the FCET model to these case studies provides valuable data to further our understanding of the media discourse surrounding new technologies. Two research questions inform the examination of these case studies:

RQ1. *What are the key frames that have been applied to big data and generative AI in UK news?*

RQ2. *How do the key frames applied to big data and generative AI compare to each other and to extended reality?*

In what follows, relevant literature on framing theory and previous research about media coverage of emerging technologies is discussed. The article then presents the FCET model and details its development process. This is followed by methodological guidance on how the model can be applied to examine other emerging technologies. Methodological information is then provided about the case studies of big data and gen-AI. The findings discussion is structured according to the FCET model to analyze the frames that were applied to these two technologies in UK news discourse.

Literature Review

Framing Theory

While there are many varying definitions of framing (see Cacciatore, Scheufele, & Iyengar, 2016; Linström & Marais, 2012), this article uses Entman's (1993) conceptualization of framing that centers on

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selection and salience (see also de Vreese, 2005; Gitlin, 1980; Hallahan, 1999). In Entman's (1993) oft-cited definition, he states: "To frame is to *select some aspects of a perceived reality and make them more salient in a communicating text*" (p. 52; emphasis in original). Although Cacciatore, Scheufele, and Iyengar (2016) argue that salience-based definitions of framing are "too loose to have practical value" (p. 13), Cappella and Jamieson (1997) provide a set of useful criteria for identifying a frame: It must 1) have identifiable conceptual and linguistic characteristics; 2) be commonly observed in journalistic practice; 3) be easily distinguished from other frames; and 4) have representational validity, meaning it can be recognized in ways other than through the researcher's imagination.

The concept of framing devices (Gamson & Lasch, 1983; Linström & Marais, 2012; Pan & Kosicki, 1993) strongly relates to the first criterion. Synthesizing work by other authors, Linström and Marais (2012) categorize framing devices as rhetorical and technical. Rhetorical framing devices refer to issues of language (such as word choice, metaphors, and exemplars), whereas technical framing devices refer to elements of news production (such as headlines, images, placement, and quotations). Analyzing framing devices can help researchers identify whether a frame exists, as well as the strength of that frame.

Broadly, news frames have been categorized as generic (relevant in any context) or topic-specific (D'Angelo, 2018). In relation to generic frames, Iyengar (1996) conceptualized episodic news frames, which focus on specific cases or events, and thematic news frames, which relate to the broader context of a topic. Entman (1993) also set out four generic frame types that can be identified in news discourse: problem definition, causal diagnosis, moral evaluation, and treatment recommendation. Topic-specific frames, on the other hand, "are typically observed as facets of a topic or as themes extrapolated from attributes of the topic" (D'Angelo, 2018, p. xxxii). The FCET model presented in this article focuses on assisting with the identification of topic-specific frames—precisely those related to emerging technologies. This could be a facet of a topic (such as a focus on regulation) or a theme within a topic impacting the way a technology is represented (such as revolutionary).

Furthermore, Chong and Druckman (2007) describe equivalence and emphasis framing, where equivalence frames are formed by presenting logically equivalent information in different ways, and emphasis frames are formed by emphasizing particular aspects of a story (see also Scheufele & Iyengar, 2014). Equivalence frames are also known as valence frames because of their presentation of the same information either positively or negatively (Druckman, 2004). Both equivalence and emphasis frames can be identified using the FCET model, as it prompts researchers to consider not only which aspects of the technology are given particular attention but also whether positive or negative representations are favored.

Approaches to Framing Analysis of Emerging Technologies

Framing has been a popular approach for studying media discourse of science and technology (e.g., Dimopoulos & Koulaidis, 2002; Kelly, 2009; Ricci, 2010; Rössler, 2001), including studies of emerging technologies such as XR (Deng & Matthes, 2023; Graves, 2024), AI (e.g., Brennen, Howard, & Nielsen, 2022; Freeman & Aoki, 2024; Sun, Zhai, Shen, & Chen, 2020), and—to a limited extent—big data (e.g., Nguyen, 2023; Pentzold & Fischer, 2017). Some scholars have developed typologies of frames in this area. Nisbet and Scheufele (2009) identified eight frames applicable to science-related policy debates, including

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social progress, economic development/competitiveness, morality/ethics, uncertainty, and conflict/strategy. Additionally, Weaver, Lively, and Bimber (2009) developed a set of four frames related to nanotechnology news (progress, regulation, conflict, and generic risk). However, these typologies were developed with a focus on science-based technologies. To the best of the author's knowledge, no frame category model that specifically focuses on emerging technologies or computer-based technologies has been developed aside from the one presented in this article.

Among studies of media discourse about emerging technologies, approaches to frame analysis vary greatly. Some use Entman's (1993) four frame elements to identify frames (e.g., Deng & Matthes, 2023; Köstler & Ossewaarde, 2022), while others examine Iyengar's (1996) thematic versus episodic framing (e.g., Chuan, Tsai, & Cho, 2019) or use a deductive approach based on frames identified in previous literature (e.g., Bunz & Braghieri, 2022; Kelly, 2009). On the other hand, some articles claim to have identified frames, although the result is a list of topics rather than frames (e.g., Nguyen, 2023; Nguyen & Hekman, 2024). This is particularly evident in big data research. Additionally, several articles provide very little information about how frames were identified and/or what constitutes a frame (e.g., Freeman & Aoki, 2023; Köstler & Ossewaarde, 2022; Ricci, 2010), while others broadly mention framing theory but do not identify specific frames in their studies (e.g., Dimopoulos & Koulaidis, 2002; Paganoni, 2019; Rössler, 2001). This highlights some key issues in the literature that the FCET model aims to reduce.

Media Framing of Big Data and AI

Several studies have examined the media framing of AI; however, as noted above, framing analyses of big data are more limited. Starting with AI, this research generally finds that the technology is framed both positively and negatively (Cools, Van Gorp, & Opgenhaffen, 2024; Sun et al., 2020). Examining how this changed over time in U.S. news, Chuan et al. (2019) found that coverage was typically positive but became more negative across the course of their study period (2009–2018). However, in a larger study of UK and U.S. news from 1980 to 2020, Korneeva, Salge, Teubner, and Antons (2023) found the opposite: sentiment became more positive, and articles were more likely to legitimize AI than to delegitimize it.

Positive frames tend to emphasize the economic benefits of AI (Chuan et al., 2019; Korneeva et al., 2023; Sun et al., 2020) and its potential to improve everyday life (Cools et al., 2024; Köstler & Ossewaarde, 2022). Additionally, four frames were identified by Sun et al. (2020) in their study of UK and U.S. news from 1977 to 2019: superintelligence, AI superiority, AI revolution, and strong AI, which all focus on positive aspects of AI. Identifying both positive and negative frames, Köstler & Ossewaarde (2022) found that, in German news media, AI was framed as a key to the future, a solution to a wide range of issues, beneficial to the industry, and as a black box with issues around ethics. On the other hand, risks include job losses, privacy concerns, and the threat of AI to humanity (Chuan et al., 2019; Korneeva et al., 2023).

For big data, the existing research rarely identifies specific frames. In a study of English news coverage, Paganoni (2019) found that there was a clash between two main topics that impact the framing of big data: data and information versus rights and privacy. Looking at the UK and U.S. contexts, Nguyen (2023) examined both big data and AI news. Although they claim to carry out a framing analysis, the author

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terms the results "themes" rather than frames. These themes are politics, research, big tech platforms/products, and the automated-datafied society. Nguyen (2023) also identified four main risk categories: cybercrime, misinformation, surveillance, and bias. Finally, Pentzold and Fischer (2017) examined news about the Handygate Affair (where German authorities collected and analyzed personal mobile phone data without notifying the respective individuals in 2011). They found that the news discourse included both justification and criticism frames, demonstrating the polarity of the coverage of big data in this instance. While this provides valuable insight into the framing of that event specifically, it does not explore the broader framing of big data.

By choosing these two technologies as case studies, it is possible to show how the FCET model can be applied to both well-researched and under-researched technologies. Furthermore, likely due to its recent emergence, there do not appear to be many framing analyses of gen-AI specifically, apart from those presented in Freeman and Aoki's (2023) conference paper. The current research, therefore, makes a further original contribution to the field by addressing these two gaps, in addition to presenting the FCET model.

Frame Categories for Emerging Technologies Model

The FCET model aims to provide methodological guidance for identifying media frames applied to emerging technologies, enabling easy comparison with other studies using the model. Figure 1 displays the full model as first set out in Graves (2024), based on a study of XR media discourse. Each category suggests questions that can be used to help the researcher identify frames for the technology under study. The questions and categories enable the identification of emerging frames, whether they relate to purely technological areas or to social, political, or economic issues.

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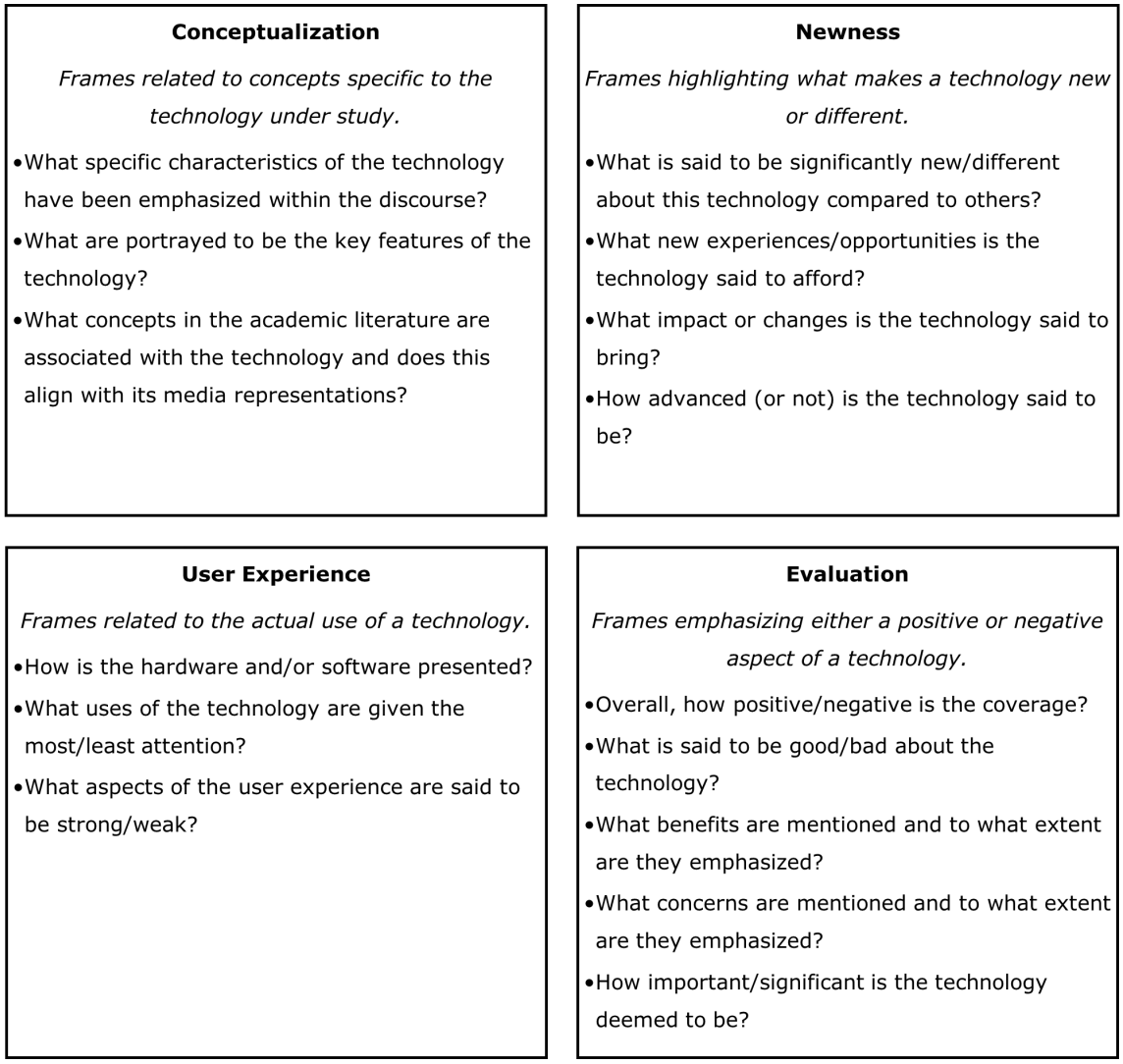

Figure 1. Frame categories for emerging technologies (FCET) (Graves, 2024).

The FCET model categories were developed based on innovation and diffusion theories (e.g., Buenaflor & Kim, 2013; Krumsvik, Milan, Bhroin, & Storsul, 2019; Rogers, 2003), as well as an empirical study of XR media discourse (Graves, 2024). To specify, as an actor in the social construction of technology, the news media play an important role in how an innovation is conceptualized (McKernan, 2013). Moreover, innovation is about change (Krumsvik et al., 2019), meaning that new concepts may emerge or become prominent in the discourse. Thus, the first category, Conceptualization, allows researchers to identify frames related to concepts specific to the technology being analyzed. This category is most likely to include unique frames compared to studies of other emerging technologies, although this does not rule out potential overlaps.

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Second, "innovation implies introducing (and implementing) something *new* into the socioeconomic system" (Krumsvik et al., 2019, p. 194; emphasis added). Therefore, it is probable that frames will be used that relate to the Newness of a technology (the second frame category). Frames in this category are likely to relate to the progress frame that appears in the typologies associated with science and technology introduced above (Nisbet & Scheufele, 2009; Weaver et al., 2009).

Third, Rogers (2003) highlights the two components of a technology: hardware and software. These two components impact the user experience of the technology, which may be a focus of frames in the media. While a discussion of ease of use (whether easy or difficult) may likely appear in media coverage of many different technologies, other frames appearing in this category may differ depending on how exactly users *experience* these technologies. For example, AI is highly unlikely to be framed as Comfortable, as a wearable component is not required for its use.

Lastly, the perception of innovations can impact their development, diffusion, and success (Asif & Gouqing, 2023; Buenaflor & Kim, 2013; Harley, 2022). Since media coverage has a significant impact on these perceptions, it is important to examine how emerging technologies are evaluated in the media, leading to the final frame category: Evaluation. On the one hand, this could involve broadly examining positive versus negative discourse and discussions of risks, concerns, benefits, and opportunities. In this way, some frames in this category could relate to either problem definition frames or moral evaluation frames (Entman, 1993). On the other hand, this could involve equivalence (or valence) frames (Chong & Druckman, 2007), positively or negatively presenting some aspect of the technology. However, that is not to say that other categories of the model *cannot* include valence frames; instead, the Evaluation category simply facilitates a broader understanding of the positive and negative evaluations of emerging technologies without being constrained by the foci of the other categories.

It is pertinent to note that there could be overlaps among frame categories, particularly between Evaluation and the other three groups. For example, the Comfortable frame that appeared in XR discourse (Graves, 2024) is a positive evaluation of the technology, meaning it links to the Evaluation category, yet it is more closely related to the use of XR, making it better placed in the User Experience category. Discussions of frames in any category can include a consideration of whether a frame presents the technology in a positive or negative light, regardless of whether it is situated in the Evaluation category.

Case Studies: Big Data and AI

Samples

The Lexis+ UK Newspaper database was used to identify print and online news articles about big data and gen-AI. To ensure a comprehensive sample was collected, all available regional and national publications were included, and the time frame was set to include all articles in the database (which starts from 1970) up until December 31, 2023. Using the Lexis+ filters, the publication type was restricted to newspapers and web-based publications to exclude content such as news transcripts and magazine articles. To ensure relevancy, a search string was used that required references to big data and gen-AI to appear in either the headline or lead, and a relevant keyword filter was used for each search (see Table 1). After removing duplicate articles, the big

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data sample consisted of 248 articles, and the gen-AI sample consisted of 240 articles. Supplemental Material 1 lists the publications in which the articles appeared for each case study.

Table 1. Search Criteria and Details of Sample Articles.

Criterion	Big Data	Gen-AI
Search string	HLEAD("big data")	HLEAD("generative artificial intelligence" OR "gen-AI" OR "generative AI")
Keyword filter	Big data	Generative AI
Number of initial results	292	320
Sample size (after duplicates removed)	248	240
Publication date of earliest identified article	June 6. 2011	March 13, 2023
Publication date of latest identified article	November 3, 2023	December 31, 2023
Number of news sources articles identified within	28	35

Data Collection and Analysis

All articles were analyzed quantitatively, and 20 articles from each sample were randomly selected (using Excel's RANDBETWEEN function) for qualitative analysis. This number was large enough to allow for meaningful themes to be identified within the articles (which could be analyzed on a greater scale quantitatively) and small enough to be manageable for the scale and scope of the project. However, it is of course possible that some meaning may have been missed as a result of not qualitatively analyzing a larger sample of articles.

Frame identification was a three-stage process conducted by the author and supported by NVivo. Using an inductive approach, qualitative analysis was first applied to the sub-sample of 40 articles. This analysis used NVivo nodes to record themes based on each FCET model category, as well as the annotation feature to record deeper analysis. After this first stage, a total of 50 nodes (representing themes) were created for the big data sample and 55 for the gen-AI sample. For each case study, all nodes were re-evaluated and consolidated into a smaller number of themes with nested nodes where there were similarities or overlaps. This resulted in a list of 11 node groups for the big data sample and 18 for the gen-AI sample.

The second stage involved quantitative analysis to examine how frequently each of the previously identified themes appeared across the samples. Word lists were created for each theme based on words found in articles reviewed during qualitative analysis that portrayed the technologies in a certain way[1], the

[1] For example, in the sentence "GenerativeAI can create images or human-like answers from text prompts" (Prescott, 2023, p. 33), the word "human-like" was recorded as it presents gen-AI as able to perform similarly to humans.

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previous study of XR media coverage (Graves, 2024), and a thesaurus for related words. In total, 235 words/phrases were searched across 14 categories (see Supplemental Material 2 for word lists), including general valence categories (e.g., positive and negative words) and theme-specific categories (e.g., advanced or easy to use). As the first stage of the analysis found several overlaps between the big data and gen-AI samples, most of the terms were searched within both samples; nine were unique to the big data sample, and 37 were unique to the AI sample. However, as the later analysis will show, some words/themes were significantly more prominent in one case study compared to the other.

NVivo's Text Search feature was used as a form of computer-assisted text analysis (CATA [Neuendorf, 2017]). CATA is beneficial as it is more accurate than manual coding, where human error could impact the data. For each search result, the word appearances were coded (with one node for each word searched) to retain a count of how many times words appeared. However, a drawback of CATA is that it does not consider the context within which a word is used, which could alter its meaning (Simon, 2001). To mitigate this, after all terms were searched, each article was then manually screened to examine the context within which words were used. Words were uncoded if the search term was 1) negated; 2) questioned; 3) not referring to either of the case studies; 4) a homonym that did not have the intended meaning; 5) used in the name of a person, business, product, etc.; or 6) not in the main body/headline/captions of the article. This ensured that the final word counts recorded in NVivo were accurate. The results of this frequency of terms analysis are displayed in Figure 2.

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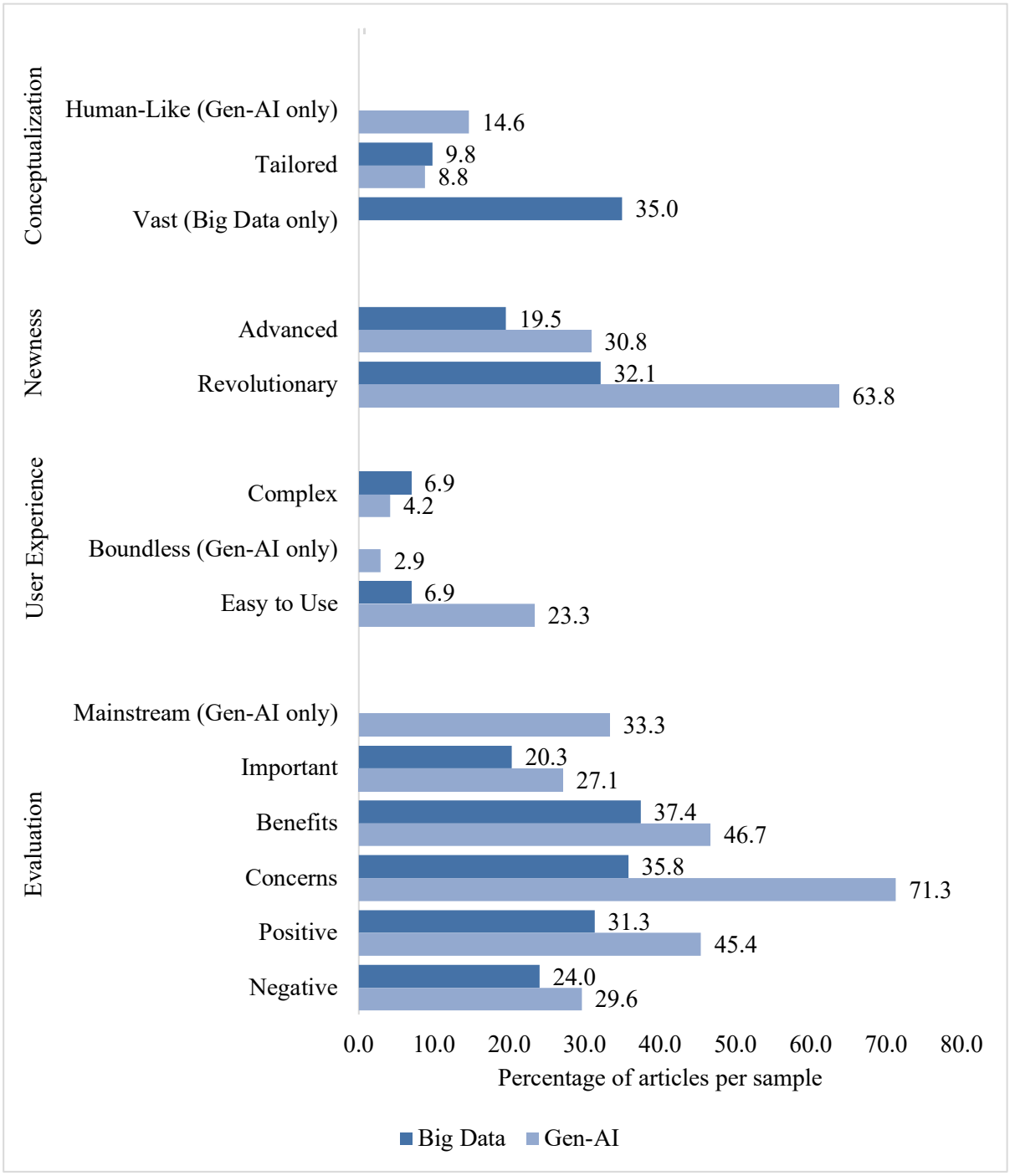

Figure 2. Percentage of articles with words from each theme.

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The third stage involved analyzing word frequency data alongside the qualitative data from step one to identify key frames within the lists of themes. This followed Cappella and Jamieson's (1997) four criteria for determining whether a frame exists (as introduced above). To meet the first criterion, framing devices and specific word usages were identified for each frame. This also supported representational validity, along with the findings discussed below. Second, based on quantitative data regarding the frequency of terms per theme, only themes appearing in a significant portion[2] of the articles were considered frames. The revisions of nodes outlined above avoided overlap before themes could be considered frames, making them distinguishable. This resulted in the list of frames presented in Table 2.

Table 2. Frames in News Coverage of Big Data and Gen-AI.

Category/ Case Study	Conceptualiza-tion	Newness	User Experience	Evaluation
Big data	Vast	Advanced; Revolutionary		Beneficial Yet Risky; Important
Gen-AI	Human-Like	Advanced; Revolutionary	Easy to Use	Beneficial Yet Risky; Mainstream; Important

Results and Discussion

Overall, there were several overlapping frames between big data and gen-AI, perhaps because of the links between the technologies. This section will therefore discuss the two case studies together, making comparisons based on word frequencies and framing devices.

Conceptualization Frames

Under the Conceptualization category, one unique frame was identified in news coverage of each technology: Vast for big data and Human-Like for gen-AI. Starting with big data, Vast was a frame that appeared in a large portion of articles (35.0 %), making it the most common frame in this sample. This frame focused on emphasizing the large size and scale of big data, which aligns with its academic definitions (Emmanuel & Stanier, 2016). One article stated: "There are about 2.7 zettabytes of data in the digital universe, where 1ZB of data is a billion terabytes (a typical computer hard drive these days can hold about 0.5TB, or 500 gigabytes)" (Arthur, 2013, p. 6). This combination of a technical framing device (use of numbers) with a rhetorical framing device (comparison with examples readers are likely to be familiar with)

[2] In this study, any theme appearing in more than 10 % of articles was considered a frame. However, a "significant portion" of articles would differ per study depending on the relative frequency of themes. For example, if several themes appeared in more than 70 % of articles, those appearing in 20 % would be less salient and perhaps not significant; however, if no theme appeared in more than 30 % of articles, those appearing in 20 % *would* likely be significant. The researcher can determine what percentage of articles is deemed significant within the context of their sample.

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puts particular emphasis on the vastness of big data. Alternatively, other articles used metaphors to demonstrate the size of big data: "To call what's happening a torrent or an avalanche of data is to use entirely inadequate metaphors. This is a development on an astronomical scale" (Naughton, 2012, p. 21). The Vast frame helps readers better understand the large scale of big data, supporting the first stage of Rogers' (2003) diffusion process—knowledge-building—thus aiding the diffusion of big data.

For AI, words relating to the Human−Like frame appeared in 14.6 % of articles, which anthropomorphized gen-AI. Some articles defined the technology by explaining that it operates similarly to a human. For example, "ChatGPT is a form of generative AI that can respond to questions in a human-like manner and understand the context of follow-up queries, much like in human conversations" (Busby, 2023b, para. 3). Additionally, Meta AI was described as "a new assistant users will be able to 'interact with like a person'" (Landi, 2023a, para. 3). The Human-Like frame contributes to presenting gen-AI as advanced, though it is also linked to concerns over AI replacing humans, highlighting some overlaps between frames across categories. This result also shows similarities with previous studies on AI news coverage (Bunz & Braghieri, 2022; Korneeva et al., 2023), which found that AI is humanized in the discourse. However, while Bunz and Bragieri (2022) argue that such framing could cover up potential ethical issues, this does not seem to have happened in this case (see below).

Newness Frames

In the Newness category, the same two frames were identified in both case studies: Advanced and Revolutionary. The Advanced frame was more common in gen-AI articles compared to big data (appearing in 30.8 % of articles versus 19.5 %). However, different framing devices were used to construct this frame in each sample. In the big data sample, one article explained how the current techniques of analyzing data are not capable of dealing with the large data sets produced in the big data realm (Naughton, 2012). This presents big data as significantly advanced because the technology needed to analyze it had not yet been developed. For gen-AI, the main framing device involved describing its capabilities as a significant improvement on previous technologies. In one article, a new AI photo editing tool (DragGAN) is said to "go beyond what Adobe's Photoshop is capable of" (Cuthbertson, 2023, para. 11), using a well-known example of existing software to support understanding. The Advanced frame overlaps with the Advanced and High-Quality frame that was identified in XR news discourse (Graves, 2024). Additionally, there are similarities with the superintelligence and superiority frames identified by Sun et al. (2020) in their study of AI news. Such frames legitimize these technologies as high-quality innovations worthy of attention.

Among the frame-based words searched, words related to the Revolutionary frame were the most common category in the gen-AI sample, appearing in 63.8 % of articles. These terms appeared less in the big data sample (32.1 %), but still indicate that it was a common frame. Aside from general words that present something as revolutionary (e.g., revolution, reinvent, transform, breakthrough), there was another key theme of progress within this frame, which aligns with the frame typologies introduced by Nisbet and Scheufele (2009) and Weaver et al. (2009). In this vein, both big data and gen-AI are said to replace previous innovations because they can perform better. For gen-AI, this appeared in headlines multiple times, placing particular emphasis on the frame, since this is the most salient part of a news article (Pan & Kosicki,

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1993). An article about the new gen-AI capabilities of the Alexa personal assistant was headlined: "Alexa gets smartened up; BOOSTED AI LOOKS SET TO MAKE AMAZON'S ASSISTANT EVEN MORE USEFUL" (Connolly, 2023a, p. 18), and another reported on the update to Google Assistant: "Tool set to be 'supercharged' like ChatGPT" (Sankaran, 2023). The use of words such as "boosted" and "supercharged" suggests that gen-AI is improving these devices/platforms.

Additionally, big data was linked to the Fourth Industrial Revolution, arguing that it can change several areas. On the topic of legal decision making, one article claimed: "The rise of Big Data and algorithms is changing all this" (Wachter, 2017, p. 14), and another posited: "the way we live will probably be shaped by these modern-era pioneers" (Arnold, 2013, p. 22). Similarly, exemplars were used as framing devices in news coverage of gen-AI to suggest its ability to revolutionize a wide range of industries, such as medicine ("6 ways," 2023) and entertainment (Coyle, 2023). Emphasizing these wide-ranging effects highlights the revolutionary capabilities of these technologies. Alongside other frames, the Revolutionary frame works to legitimize these innovations by emphasizing their profound impact.

User Experience Frames

One frame appeared in the User Experience category in news coverage of gen-AI: Easy to Use. Perhaps because big data is typically used in professional settings rather than by general consumers (who are the target audience of the news outlets in this study), little attention has been paid to the user experience of big data. Words relating to ease of use appeared in just 6.9 % of big data articles, and the same percentage included words describing big data as complex (see Figure 2), suggesting difficulty of use. As these numbers were relatively low, the themes were not considered frames, and no frames were identified under the User Experience heading for big data. Still, for gen-AI, words relating to this frame appeared in 23.3 % of articles. In terms of framing devices, word choice made gen-AI appear accessible and intuitive. Additionally, exemplars were used to argue that tasks previously considered complex can now be easily performed using AI, even by those with no prior experience. The article about DragGAN introduced above was headlined: "New AI can alter any photo with the click of a mouse" (Cuthbertson, 2023), suggesting that this is fast, simple, and easy to accomplish, with extra emphasis as the statement appears in the article headline.

While ease of use relates to one of Rogers' (2003) characteristics of innovations that increase the likelihood of success (low complexity), ease of use was not always presented positively in this sample. In some cases, it was also linked to concerns about how easily these tools can be misused, again highlighting an overlap between this frame and those in the Evaluation category. Concerning screenwriters' strike over AI, which began in May 2023, one article raised concerns over how gen-AI tools could easily be used to draft a script "with a few simple prompts" (Coyle, 2023, para. 7). Therefore, the Easy to Use frame could generate both positive and negative perceptions of gen-AI among readers. The Easy to Use frame also appeared in the previous study of XR discourse (Graves, 2024), but only in a way that positively represented the technology. This shows that the same frame can have slightly differing effects on news discourse depending on the topic studied, highlighting the importance of detailed qualitative analysis.

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Evaluation Frames

In this final category, two frames appeared in both case studies (Beneficial Yet Risky and Important), and one additional frame appeared in gen-AI coverage: Mainstream. The Beneficial Yet Risky frame presented big data and gen-AI as having both positive and negative features, sometimes in the same article. Quantitatively, this can be observed in the use of words from the "Positive" and "Negative" categories, as well as the "Concerns" and "Benefits" categories (see Figure 2). As demonstrated, both gen-AI and big data articles included more positive than negative words, although the difference was greater in gen-AI articles. This parallels Korneeva et al.'s (2023) study of AI news framing. On the other hand, gen-AI articles had substantially more focus on concerns than benefits, whereas the mention of benefits and concerns in big data news was fairly even.

In line with Chuan's (2023) review of studies on AI media framing, benefits in both big data and gen-AI coverage were typically broad (i.e., referring to "benefits" or "opportunities"), whereas several specific concerns were highlighted (see Figure 3). For big data, the main concern was data privacy, which was also identified by Paganoni (2019). In gen-AI articles, the two key concerns were misinformation and AI as an existential threat, in line with Chuan et al. (2019) and Nguyen (2023). Unlike previous studies, qualitative analysis showed that these concerns and risks were often paired together. In the gen-AI sample, one article was headlined "ChatGPT brings risks along with any rewards" (Partridge, 2023). Another reported on AI in education, quoting the UK's Education Secretary: "we need to understand the opportunities, as well as the real risks that new technology brings" (Busby, 2023a, para. 5).

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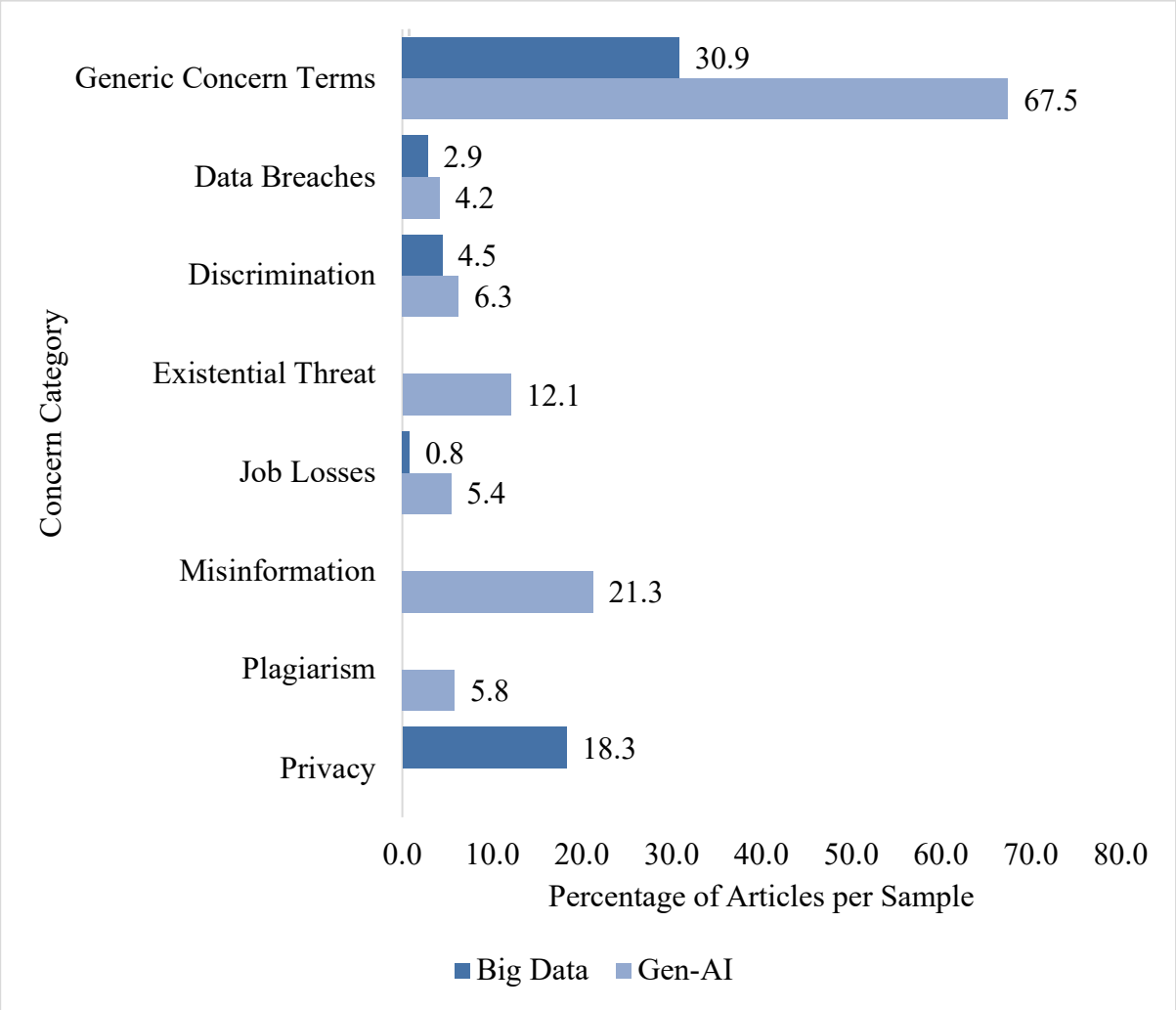

Figure 3. Percentage of articles with words relating to concerns.

Similarly, big data was presented as valuable only if used correctly. One headline argued: "Large datasets can help with long-term brand building, but the media industry needs to adapt to capitalise on this new source of insight" (Unerman, 2015). Using a metaphor as a framing device, another article termed big data "the new oil" to emphasize this point: "Data is just like crude. It's valuable, but if unrefined it cannot really be used" (Arthur, 2013, p. 6). These techniques frame the technologies as having both benefits and risks, rather than focusing on one more than the other. This frame demonstrates differences between the media coverage of these two technologies compared to the original study of XR, which found that positive discourse dominated (Graves, 2024).

The second frame shared between the two case studies in the Evaluation category was Important, which was also present in media coverage of XR (Graves, 2024). In the big data sample, 20.3 % of articles

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included words related to this frame, compared to 27.1 % of gen-AI articles. Here, both technologies were presented as significant developments with considerable impact, worthy of attention. A framing device that appeared in both data sets employed references to the large, well-known companies involved. For gen-AI, companies included Microsoft, Google, Amazon, and Meta (e.g., Landi, 2023a; Tyler, 2023). Companies in big data news coverage were much more varied, noting connections with Coca-Cola (Fildes, 2013), The Royal Bank of Scotland, Sony Mobile (Mackie, 2017), and Shell (Arthur, 2012), amongst others. Another broadly claimed that "most of the world's big corporations are making those investments [in big data] now" (Naughton, 2012, p. 21). Highlighting links with such companies indicates to readers that these technologies are of considerable value by association, thus framing them as Important. However, it should be noted that these associations could also have a negative impact on the perception of big data and gen-AI due to the reputation of such companies, although the qualitative analysis did not find much critique of the companies involved.

For big data, this importance was emphasized in some article headlines, affording the frame particular strength. For example: "Why Big Data is now such a big deal" (Naughton, 2012, p. 21) and "The Age Of Big Data" (Arnold, 2013, p. 22), where this classification connotes that big data is the most important development of the present time. Additionally, the placement of information about gen-AI contributed to enhancing its perceived importance. When articles covered more than one topic or technology, such as a roundup of technology news ("Tech that," 2023) or predictions of what would be "big news" in 2024 (Connolly, 2023b, p. 20), gen-AI typically appeared first. The presence of this content and frame in salient parts of the news articles increases the likelihood for it to impact audience perceptions. The level of perceived importance can help or hinder adoption (Maisch, Binder, Schmid, & Leifer, 2011); thus, by emphasizing the Important frame, the discourse supports the diffusion of big data and gen-AI.

Finally, the Mainstream frame appeared only in gen-AI coverage. Overall, 33.3 % of the gen-AI sample included words relating to the Mainstream frame. Specifically, this frame argues that the development of gen-AI has made AI mainstream. For instance, AI is said to have "become a much more mainstream topic too—ever since the public launch of OpenAI's ChatGPT last November" (Landi, 2023b, para. 7). Similarly, "Artificial intelligence has hit the mainstream with the popularity of generative AI programmes driven by large language models such as ChatGPT" (Farah & Ambrose, 2023, para. 2). In this case, ChatGPT is used as an exemplar to frame broader AI as Mainstream. This Mainstream frame has implications for how readers might perceive the state and success of AI—if it already seems established, they may be more likely to engage with this technology, as this improves the observability of the innovation (Rogers, 2003). An established technology (or one that is *perceived* to be established) is more likely to be adopted.

Conclusion

Based on case studies of big data and gen-AI, this article has demonstrated how the FCET model can be effectively used for analyzing media coverage of emerging technologies. It has shown how the model can guide frame identification and aid comparisons across different technologies, addressing concerns from scholars such as Hertog and McLeod (2001) on the varied results of inductive frame analyses. Both unique and overlapping frames were identified in the media discourse, with unique frames including Vast for big data and Human-Like for gen-AI, and shared frames including Revolutionary and Important, which also appeared

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in the original study of XR (Graves, 2024). Unlike the study of XR, in which news discourse was found to be strongly positive, a combination of positive and negative framing devices appeared in coverage of big data and gen-AI, with particular attention paid to concerns in gen-AI news. When new technologies emerge, it is important that the general public are made aware of both their benefits and drawbacks so that they can engage critically in discussions and make informed decisions on whether to adopt them (Chuan, 2023; Nguyen & Hekman, 2024). Therefore, this is a positive indication of the quality of UK journalism on big data and gen-AI. However, other frames, such as Easy to Use, Mainstream, Revolutionary, and Important, do benefit the interests of the corporations developing big data and gen-AI by supporting diffusion.

Limitations and Future Research

It is important to note the limitations of the case studies and the FCET model. Starting with the case studies, the sample criteria resulted in medium-sized samples for both case studies (compared to the sample sizes of other related studies [Chuan, 2023]). It is possible that a larger sample would result in the appearance of different frames or at least strengthen the evidence that these frames exist. The sample was also limited to only UK news outlets in the Lexis+ database. Future studies should examine media discourse of big data and gen-AI in different contexts to identify the similarities and differences across results. The application of the FCET model would be particularly useful for this. Additionally, the Lexis+ database includes text-only articles, meaning that the analysis could not take into account any visual elements. Such elements can act as important framing devices (Linström & Marais, 2012); thus, future studies may want to further this research by examining these visual features. However, the current case studies work effectively to demonstrate how the FCET model can be used.

The FCET model has now been used to analyze media coverage of XR, big data, and AI. Based on the results of these studies, one potential drawback to the model could be the relevance of the User Experience category to a wide range of technologies since no frames appeared in this category for the big data sample, and only one appeared in the gen-AI sample. This might indicate that the model could benefit from including other categories in the future. However, the lack of frames in this area is an important finding in itself, as it shows little attention has been paid to User Experience for these two technologies.

Both the FCET model and the data presented here offer valuable contributions to studies of science and technology, journalism, and media discourse. The methodological contribution of the FCET model helps improve the quality and comparability of future media framing analyses of emerging technologies, while the case studies provide original empirical insights into the social construction of emerging technologies. This is particularly key for big data since very little framing research has been carried out on this topic. Further research using the FCET model is encouraged to gain a deeper understanding of the role of the media in socially constructing different emerging technologies.

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