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Going with the Mainstream: Exploring GPT Representation of Journalistic Culture

Abstract

As generative AI becomes increasingly integrated into journalism, questions about its implications for journalistic practice grow more urgent. Despite the rise of AI systems, news organizations often lack informed understanding of how these systems operate, potentially undermining journalists' capacity to exercise agency in AI-assisted news production. This study explores how large language models (LLMs), such as ChatGPT, can reflect journalistic value systems. It does this by prompting the GPT-4o model to respond to survey items from the Worlds of Journalism Study that measure journalistic role perceptions, epistemologies, and ethics. These responses were compared to actual survey data from the US, UK, and Germany. Our findings suggest that GPT-4o's outputs correspond most strongly to the survey responses of politically centrist, full-time journalists whose employers have a TV background, while showing less alignment with right-leaning, part-time, and non-degree-holding journalists. These propensities were most pronounced in the German dataset. While we do not assert that GPT-4o's cultural orientation directly translates to its journalistic applications, the results reveal which groups of journalists' perspectives the LLM is more—or less—likely to reflect. By mapping this alignment, the study offers an empirical point of departure for guiding how journalists can maintain agency in their use of LLMs, and thereby contributes to ongoing discourse about the ethical, epistemological, and institutional dimensions of AI in journalism.

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As attempts to integrate generative AI into newsrooms continue to grow (see Silver, 2025, May 7), concerns about its influence on journalism are intensifying (Beckett & Yaseen, 2023; Thompson et al., 2025). While the use of generative AI tools has not yet become "taken-for-granted" in journalists' day-to-day work, many journalists report that limited understanding of how these systems operate is a key risk in journalism's turn towards AI (Minnesota Journalism Center, 2025, April 24). The concerns reflect epistemic constraints within the journalistic field, with anxieties about AI's "potential impact on journalistic autonomy, such as algorithmic biases and the loss of editorial control" (Cools & De Vreese, 2025, p. 1) persisting.

These "reasonably foreseeable risks" (Kieslich et al., 2024, p. 2) have prompted a growing consensus around the need for ethical frameworks tailored to AI's role in journalism. Scholars propose measures that range from the labeling of AI-generated content to more robust editorial guidelines for human–machine collaboration (Paik, 2023; Piasecki et al., 2024). However, beyond technical or regulatory fixes, the integration of generative AI, such as large language models (LLMs), raises deeper questions about journalistic culture.

Recent studies suggest that journalists perceive LLMs not only as a tool but as a force that challenges their occupational identity (Van Dalen, 2024). In response, journalists' interactions with generative AI often reflect what Wu (2024) calls a "value-motivated use", where adoption is guided by the perceived compatibility of AI outputs with journalistic values. Rather than striving to automate tasks, journalists tend to position AI as an assistant—one whose outputs must be verified, edited, and evaluated (Van Dalen, 2024; Thäsler-Kordonouri & Koliska, 2025). This reflects what field theory describes as boundary work (Bourdieu, 2005): journalists seek to reassert their professional jurisdiction by maintaining control over AI-engaged practices (Carlson & Lewis, 2019).

Such so-called "human-in-the-loop" approaches are, however, constrained by the platform nature of AI systems, which yield variable outputs depending on algorithmic architectures typically hidden from end users such as journalists (Ronanki et al., 2024). Although journalists engage in post hoc moderation to adjust AI outputs in line with journalistic standards (Wu, 2024), the limited intelligibility of these systems continues to constrain journalists' capacity to exercise power over the trajectories of AI integration (Jones et al., 2022).

To safeguard journalistic agency amid the "institutionalization" of generative AI (Thäsler-Kordonouri & Koliska, 2025), journalism must be equipped with domain-specific knowledge of how these systems reflect journalistic culture (Hepp et al., 2023). Such knowledge may enable journalists to evaluate the representational tendencies embedded in algorithmic outputs during their interactions with AI. Although the sources of the socio-cultural tendencies embedded in LLMs are inherently difficult to *trace*, users, such as journalists, can *steer* these tendencies based on systematic identification of them (Narayanan & Kapoor, 2023; Santurkar et al., 2023); that is, such identification may allow the journalism field to navigate shifting boundaries and develop practices that maximize AI's technological utility while safeguarding journalists' professional legitimacy (Arguedas & Simon, 2023).

To this end, we analyzed how GPT-4o reflects the value systems of different journalistic groups. Using survey items from the Worlds of Journalism Study (WJS), we prompted the model to respond to items measuring three central dimensions of journalistic culture: role perceptions, epistemologies, and ethical orientations (Hanitzsch, 2007). We then compared these responses with surveys of actual journalists from the US, UK, and Germany. In other words, just as we previously asked journalists, we then asked ChatGPT and compared the answers.

Our findings reveal that responses generated by GPT-4o align[1] more closely with journalists who identify as politically centrist, work full-time, and whose employers have a TV background. By contrast, the model exhibits weaker alignment with right-leaning, part-time, and non-degree-holding journalists. Cross-country comparisons further suggest that GPT-4o's responses are most closely aligned with the response distributions of German journalists overall. These findings suggest that the cultural representativeness of LLMs may not follow a singular tendency but instead varies depending on domain specificity and cultural contexts (Argyle et al., 2023).

However, we do not claim that GPT-4o's representativeness of journalistic culture directly translates into its journalistic applications. Rather, our study aims to identify which journalistic value systems are more—or less—reflected in the model configuration within the context of journalistic culture. By comparing latent patterns that exist between targeted algorithmic outputs and human responses, the study provides initial evidence for advancing the intelligibility of AI within the journalism field (Amigo & Porlezza, 2025; Hepp et al., 2023; Jones et al., 2022; Van Dalen, 2024).

Theory and Literature review

This study builds on a theorization of journalistic culture and probes at the ability of AI systems to meaningfully represent journalistic culture. The study treats an LLM as a *synthetic journalist* and explores how this synthetic journalist aligns with and within journalism cultures in three countries – the US, UK, and Germany.

Journalistic Cultures across Media Systems

[1] Throughout this paper, the terms "align" or "alignment" refer specifically to the degree to which LLM survey simulations resemble the response distributions of given human participant groups. Specifying this terminological usage is essential given that in computer science—where the term "alignment" originates—the terms carry multiple connotations, ranging from output personalization to prompt responsiveness to simulation accuracy.

Hanitzsch (2007) theorizes journalistic culture "as a particular set of ideas and practices by which journalists, consciously and unconsciously, legitimate their role in society and render their work meaningful for themselves and others" (p. 369). He suggests a conceptual structure that incorporates three major areas in which journalism cultures are commonly articulated: journalism's institutional roles; epistemologies; and ethical ideologies. The area of institutional roles relates to the normative and actual functions of journalism in society; epistemologies relate to the accessibility of reality and the nature of acceptable evidence; and ethical ideologies relate to journalists' responses to ethical dilemmas. The theoretical dimensions of journalistic roles include interventionism (active-passive), power distance (adversarial-loyal), and market orientation (consumer-citizen). Journalistic epistemology includes objectivism (correspondence-subjectivity) and empiricism (empirical-analytical) dimensions, and ethical orientations vary along poles of idealism (means-outcomes) and relativism (contextual-universal). Differences among journalists on these dimensions, then, represent differences in normative commitments about journalism's place and practice in society.

Journalism cultures develop within local, regional, and national contexts, where they are responsive to unique social contexts and opportunity structures (Hanitzsch, et al., 2011). Even so, evidence suggests journalism cultures around the world bear a resemblance with one another—valuing similar roles and ethical outlooks, for example (Hanitzsch, et al., 2019). Variations among journalism cultures, however, are not inconsequential. Neither are variations within journalism cultures, where cross-cutting cleavages can form along demographic and medium differences. Thus, approaches to interventionism, objectivism, and idealism, for example, can and do vary within a journalism culture and across cultures.

Hanitzsch's (2007) conceptualization has been widely applied in numerous empirical studies, serving as the conceptual backbone for the first wave of the Worlds of Journalism Study (e.g., Hanitzsch et al., 2011; Koroma, 2023). This three-dimensional model was also employed in the most recent, third wave of the study, conducted between 2022 and 2024 in 75 countries around the globe. This inquiry provides a nuanced perspective on the variations in journalism culture across diverse countries.

Relatedly, the sociology of news (e.g., Shoemaker & Reese, 2014, Shoemaker & Vos, 2009) points to the ways in which journalism cultures manifest in news content—shaping what becomes news, how news stories are framed, and how prominently news is placed, distributed, and amplified. Different journalistic roles, epistemologies, and ethics lead to different kinds of news content—both within and between countries. For instance, US journalists who embrace a traditional monitorial role, rather than other roles, engage in "practices of relying on elite sources, limiting the diversity of political perspectives, and showing deference and trust for certain authoritative institutions," often to the detriment of citizen and non-elite sources and perspectives (Wolfgang et al., 2021, p. 1353).

Enter LLMs. Much attention has been focused on their ability—or inability—to shape news content in ways that reflect journalistic judgments that would typically flow from journalists embedded in the dominant journalistic culture—a culture that values autonomy and objectivism (Cools & De Vreese, 2025; Wu, 2024). What is heretofore largely unknown, however, is whether LLMs can produce an intelligible picture of journalism. That is, can LLMs describe the nuances of journalism culture—including journalistic roles, epistemologies, and ethics—in ways that comport with journalists' own understandings of journalism culture? Before

pursuing this question, we turn to what research to date has been able to tell us about AI as synthetic journalists.

AI Intelligibility in Journalism

We define generative AI as *algorithmic systems that simulate and scale human intellectual capabilities* (Hancock et al., 2020; Mitchell, 2019; see also Simon, 2024). A prominent example is large language models (LLMs), which process natural language stochastically and demonstrate the ability to generate text that is linguistically comparable to human-written content in literacy-driven tasks (Kroon et al., 2024).

Due to these capacities, LLMs are increasingly being deployed in knowledge production domains such as journalism (e.g., Beckett & Yaseen, 2023; Thompson et al., 2025). However, the growing exploration of LLMs' journalistic utility raises concerns about potential perils (Møller et al., 2024). Studies highlight multiple discourses within journalism communities about AI's possible risks throughout the journalistic value chain—encompassing news gathering, production, and distribution (BBC, 2024; EBU, 2024a). A common thread among the discourses is journalists' loss of control and autonomy (Cools & De Vreese, 2025; Van Dalen, 2024).

As algorithmic systems become a foundational infrastructure of public information technologies (Thurman et al., 2019), platform companies are emerging as central players in the news industry. This shift in status has widened the structural gap between platform companies and news organizations in terms of control over AI systems. In Simon's (2024) interview study of news workers in the US, UK, and Germany, this situation is attributed to the benefits of AI technologies, including "efficiency, ease of use, stability, scalability, and longevity" (p. 159). While these benefits come with the "hidden costs of platform partnerships" (Paik, 2023),

journalists lack viable alternatives to counter the structural advantages held by platform companies.

Jones et al. (2022) frame this asymmetric power dynamic as *the intelligibility issue of AI in journalism*: that is, "journalists' ability to understand and engage with AI in ways that do not compromise journalistic norms and values" (p. 1731). The limited AI intelligibility restricts journalists in their critical assessments of AI outputs, thereby undermining their ability to control their own AI applications.

Epistemic Challenges for Journalism in the Era of Generative AI

In pursuit of economic benefits, the journalism field continues to explore whether professional tasks—such as news judgment or creative writing—can be automated by LLMs (Thompson et al., 2025). For instance, Diakopoulos (2023, Mar 6) demonstrates that in evaluating the newsworthiness of scientific abstracts published on a pre-print server, ChatGPT exhibited a high correlation with human expert judgments, suggesting its utility in news discovery. Similarly, Spencer (2025, Mar 20) addresses the capacity of LLMs to unearth overlooked health scandal cases from vast collections of medical documents. Such cases challenge the long-held belief that journalism is insulated from automation and have prompted journalists to state that their "sense of security has disappeared" (Van Dalen, 2024, p. 8).

Developments such as these have led the journalism field to articulate a defensive discourse that questions the feasibility of automating news production (Amigo & Porlezza, 2025; Wu, 2024). Two primary rationales underlie this view. First, LLMs function as stochastic simulators of human communicative practices rather than autonomous agents (Kok et al., 2021; see Messeri & Crockett, 2024), rendering them incapable of fulfilling journalism's normative commitments (Porlezza & Ferri, 2022). Second, the presence of latent algorithmic biases and the

error of hallucination risk undermining the transparency and factual reliability essential to journalistic integrity (Lin, 2022). In turn, these two positions question the legitimacy of the algorithmic systems as journalistic actors (Dörr & Hollnbuchner, 2017).

Journalistic Agency and the Human-in-the-Loop Principle

This skepticism about LLMs serves to reaffirm journalists' status as the "story's authoritative agent" (Carlson, 2017) while acknowledging the pragmatic imperative to harness the benefits of AI systems (Thäsler-Kordonouri & Koliska, 2025). Central to this position is the assertion that human oversight must be preserved within journalist–AI collaboration in order to uphold the principles of "good journalism" (Wu, 2024; see Kovach & Rosentiel, 2021). As professional journalism continues to constitute the *gold standard* for news quality, the utility of generative AI outputs is rendered contingent upon human editorial judgment (Ulken, 2022).

As such, studies observe that *human-in-the-loop* practices are emerging as ideal principles in the face of the institutionalization of AI journalism. For instance, Wu (2024) describes journalists' use of generative AI as "value-motivated use", a term that encapsulates how the human-oversight principles are performed in the field. This involves three key strategies: (1) refraining from taking AI output at face value, (2) and consistently verifying and editing AI-generated content, (3) which thereby upholds core journalistic values. These resonate with what Thäsler-Kordonouri and Koliska (2025) conceptualize as the "hybrid scenario" of AI implementation: human actors and AI systems engage in a collaborative relationship that is marked by mutual influence yet remains under persistent supervision by human judgment.

However, this normative demand for human supervision acknowledges that AI systems can function as a synthetic actor (or a supervisee) within the journalistic field. While AI lacks *autonomous agency*, it comes to share in human agency through interaction (Latour, 2005); that

is, humans tend to *project* agency onto AI systems, thereby experiencing them as a collective actor. Hepp et al. (2023) explain that this "hybrid agency" gives rise to communicative practices that are distinct from those in newsrooms that have not adopted AI systems (p. 51).

While LLMs do not autonomously possess journalistic socio-cultural orientations, collaborating with these models compels journalists to *evaluate* the values projected onto the models' outputs. How such evaluations are carried out, in turn, can shape the dynamics of the news ecosystem (Simon & Isaza-Ibarra, 2023). Accordingly, if journalists are not "capable of assuming agency" in evaluating LLM outputs, then it is hard to guarantee the responsible use of journalistic AI, placing structural constraints on journalists' ability to delineate their own professional domain (Helberger et al., 2022, p. 1615).

Power Dynamics within AI Journalism

If AI journalism is understood as a relationship between human journalists as inherent actors and AI systems as technological actants (Latour, 2005), then the social construction of this practice is contingent upon the power dynamics embedded within that relationship (van Rooyen, 2013). As Lewis and Westlund (2015) note, the diffusion of power between human and technological agents is manifested in how their respective contributions shape the collaboration's outcome. One expression of these power dynamics is the structural gap between platform companies and news organizations (Jones et al., 2022; Simon, 2024). As LLM outputs vary depending on training data, user prompts, and model architecture—which vectorizes the data and user queries in different ways—journalists' limited understanding of such systems further exacerbates the unpredictability of human–AI collaboration (Ronanki et al., 2024).

Research indicates that journalistic AI outputs are neither value-neutral nor guaranteed to be accurate (e.g., Breazu & Katsos, 2024; Kuai et al., 2025; Vijay et al., 2024). In turn, if

journalists lack *prior* awareness of which voices may be over- or under-represented at the generative stage, it becomes difficult to assume that *post* moderation alone can comprehensively redress such imbalances (Li & Sinnamon, 2024). If journalists lack awareness of AI's relative representativeness, it becomes difficult to claim that they will adequately address the biases allegedly embedded in the AI systems that they seek to control.

Journalists' Normative Understanding of LLMs and AI Practices

Studies report that journalists project both their understanding and personal experiences onto their use of LLMs, particularly the perception that LLM outputs do not reflect journalistic values by default (Thompson et al., 2025). They often presume that generative AI systems are inherently biased and, as such, fail to reflect core journalistic values. The studies suggest that while the cultural outlook embedded in an LLM may not directly translate into its journalistic application, user perception of the model can nonetheless shape the user's communicative practices—that is, how they interact with AI systems (Hepp et al., 2023).

The issue here, however, is that these understandings of AI systems primarily rely on knowledge produced outside the journalism field. Despite discourses on the effective adoption of responsible AI in journalism (e.g., Dodds et al., 2024) and the formation of AI-related actor networks (e.g., Nordics AI Journalism Network), there is still a need for a systematic establishment of empirical benchmarks within the journalism context; that is, algorithmic biases identified in other domains *should not* be automatically presumed to represent those present in journalistic applications (see Messari & Crockett, 2024 for a conceptual review).

Furthermore, when journalists for whom AI have limited intelligibility attempt to exercise oversight over LLM operations, they may have a false sense of how much agency they have, engendered by an "overconfidence in their expectations of the technology" (Van Dalen,

2024, p. 14). At the organizational level as well, when newsroom AI policies lack an evidence-based foundation, they may produce unintended adverse effects by hindering the effective calibration of bias (Bommasani et al., 2025). These possibilities further underscore the need for systematic investigation into LLM algorithmic biases within journalism contexts.

Algorithmic Bias, Fidelity, and Journalistic Value Systems

Bias is broadly defined as "a systematic error in judgments" (Mayson, 2019). Operationally, this definition allows social biases in algorithmic outputs to be measured as the degree to which a model's predictions about specific opinions or attitudes diverge from actual targets. In LLMs—and especially in modeling the cognitive and behavioral mechanisms of social groups—bias emerges when systems "are more representative of one class than the other" (Glickman & Sharot, 2024, p. 345). This suggests that algorithmic bias is not limited to overt prejudice (e.g., structural racism) but also encompasses how LLMs' representational stance toward social constructs aligns with or departs from specific group-level opinion distributions.

Argyle et al. (2023) thus define algorithmic bias as "a complex reflection of the many various patterns of association between ideas, attitudes, and contexts present among humans." This definition contrasts with perspectives that treat bias as "a singular, macro-level feature of the model" that generates normatively or ethically wrongful outputs (pp. 337–338). Indeed, a growing body of research demonstrates that LLMs reflect multiple interwoven socio-cultural predispositions rather than a single, unified bias (see Kuai et al., 2025).

For an overview, Santurkar et al. (2023) investigate the extent to which LLM responses align with public opinion distributions from Pew Research Center's American Trends Panel (ATP). Their findings indicate that OpenAI's language models tend to more closely mirror the views of liberals (see also Hartmann et al., 2023; Perez et al., 2022). Notably, the level of

alignment differs by topic: although liberal perspectives are prevalent, the models sometimes reflect conservative views, particularly on issues such as religion. The studies illustrate that algorithmic bias in LLMs is deeply embedded in socio-cultural context and varies depending on the intersection of topical domains and task-specific prompts.

However, computational analyses of how these context-sensitive dynamics manifest within the journalism context require further exploration. Although studies report that LLMs may exhibit cultural variation in how they assess newsworthiness (Diakopoulos, 2023), as well as demonstrating ideological biases in news summarization (Vijay et al., 2024), headline generation (Breazu & Katsos, 2024), and fact-checking (Kuznetsova et al., 2023) (see also Bang et al., 2024; Fang et al., 2024; Trhlik & Stenetorp, 2024), evaluating such biases in AI *applications* does not equate to assessing a model's *representations* of journalistic value systems.

In particular, the validity of using LLMs to simulate a social group's ideas, attitudes, or behaviors hinges on users' ability to control for the model's algorithmic biases (Argyle et al., 2023). Understanding how an LLM reflects the values of particular journalistic cohorts is therefore pivotal to prompting it in ways that more effectively uphold professional norms.

AI and Journalistic Cultures

The literature on LLMs as synthetic journalists points to several considerations relevant to their ability and desirability to represent journalistic cultures and how they might align with national journalism cultures or cultures built around cross-cutting cleavages. First, the intelligibility issue highlights the centrality of "norms and values" (Jones et al., 2022, p. 1731) in assessing the efficacy of AI. Second, as stochastic simulators, LLMs present epistemic shortcomings, such that normative commitments may go unrealized (Porlezza & Ferri, 2022). Third, the responsible use of LLMs must reflects journalists' awareness of, and control of, their

institutional autonomy (Helberger et al., 2022). Fourth, journalists' limited insight into AI's representational tendencies may cause their boundary work (intended to maintain initiative within power dynamics) to falter. Fifth, through the feedback loops of human–AI interaction, a misperception may allow users' own biases to persist while reducing their ability to detect algorithmic biases (Glickman & Sharot, 2024). Finally, what remains largely unknown is which journalistic groups' cultural orientations are echoed most (or least) closely by an LLM's representation of journalistic value systems.

In this paper, we operationalize the relative distance between an LLM's representations and those of different journalist groups as the algorithmic bias of the LLM's journalistic culture. Detecting such bias is critical, as recognizing representational tendencies is essential for preserving human agency in interactions with technological actants. The limited awareness of the journalistic cultural orientations that are present in LLMs may restrict journalists' ability to evaluate collaborative outputs in relation to journalistic values: At the input stage, such limitations in AI intelligibility can create uncertainty about how to design prompt engineering or model fine-tuning strategies to mitigate algorithmic bias (see Bloomberg, 2023); at the post hoc editorial stage, they may render the evaluation of outputs overly reliant on journalists' subjective value judgments, thereby hindering the detection of bias (Glickman & Sharot, 2024).

This dual constraint, operating both before and after model generation, undermines claims that journalists can secure outcomes aligned with their role perceptions, epistemologies, and ethical orientations. Being able to predict the nature of LLM outputs is, therefore, vital: it enables journalists to assert professional authority and exercise oversight over AI systems in ways that are grounded in their lived experience and normative commitments. Simply put, such agency allows journalists to guide the model in a "value-motivated" manner (Wu, 2024). While

tracing the sources of socio-cultural orientations embedded in LLMs remains inherently challenging, systematic steering becomes more feasible once such model configurations are identified (Narayanan & Kapoor, 2023; Santurkar et al., 2023). Accordingly, the identification of these configurations may serve as an empirical benchmark for human actors exercising normative oversight over the models.

Representation of Surveys and Representativeness of LLM Outputs

Just as journalists tend to evaluate AI-generated news content using "upmarket publications as the gold standard" (Van Dalen, 2024, p. 13), social science research that employs LLMs to simulate human cognition often relies on actual human performance—such as expert text annotations—as the *ground truth* (Bail, 2024; Karjus, 2023; Moser et al., 2024; Ziems et al., 2024). Consistent with this approach, the degree to which AI-generated survey responses resemble those of actual humans often serves as an indicator of an LLM's capacity to model social phenomena within a specific domain (Argyle et al., 2023). The present study adopts such a methodological framework for the first time in the journalism context. Specifically, we prompted an LLM to complete a survey battery derived from the Worlds of Journalism Study (WJS). We then assessed the extent to which the LLM responses aligned with the value orientations reported by actual journalists in the most recent wave of the WJS dataset (see Data and Methods).

Given that journalistic cultures vary both within and across national contexts (Shoemaker & Reese, 2014), our analysis operates on two levels: within-country variation—based on demographic, professional, and ideological profiles—and cross-national variation among equivalent subgroups. To structure this inquiry, we adopted a Most Similar Systems Design (Przeworski & Teune, 1970) and focused on three advanced democracies: Germany, the United Kingdom, and the United States. Although these countries differ in their media systems (Hallin

& Mancini, 2004), they share key institutional features, including judicial systems, ideological diversity, public sphere configurations, and the level of economic development. These shared attributes provide a meaningful basis for cross-national and subgroup comparisons.

Moreover, Simon (2024) shows that journalists in these three countries have responded similarly to AI innovations, reflecting institutional isomorphism—the tendency for organizations in a field to converge over time by mimicking successful cases to navigate uncertainty (Napoli, 2014; Caplan & boyd, 2018). However, such homogenization may obscure cultural specificities; that is, if algorithmic bias is not well contextualized, convergent AI adoption strategies may risk decontextualizing its journalistic applications—especially where culturally specific assumptions are embedded in practices (Hovy & Prabhumoye, 2021; Kroon et al., 2023). These concerns underscore the imperative of assessing LLM cultural representativeness both within and across national contexts. Accordingly, we pose the following research questions:

RQ1. How does an LLM represent different groups of journalists in terms of their journalistic cultures—namely, role perceptions, ethics, and epistemologies?

RQ2. How does the LLM's representation of journalistic cultures—based on the journalist subgroup profiles—vary across the US, UK, and Germany?

RQ3. Which country's journalists—from the US, UK, or Germany—are most closely represented by the LLM in terms of their journalistic cultures?

Data and Methods

Survey data

Data collection in the three countries followed a common methodological design within the context of the third wave of the WJS (2022–24). The survey was carried out between September 2022 and February 2023 in Germany, between June and November 2023 in the US, and between September and November 2023 in the UK. Samples were of comparable size

(Germany: N = 1221; UK: N = 1130; US: N = 1326). Probability samples in the US and UK were drawn from lists of journalists, while the German team extracted a stratified proportional random sample of organizations from which they drew a quota-based random sample of journalists. Data collection was carried out through online surveys in the US and UK; Germany used a mix of telephone and online interviews. Response rates were highest in Germany (15.5%) and somewhat lower in the US (8.2%) and UK (9.0%).

Journalistic Culture Measures

The WJS survey includes blocks of question batteries that cover three dimensions of journalistic culture, all measured on five-point scales. The role perceptions battery consists of 24 items that measure how important journalists think it is to fulfil particular roles (such as educating the reader or scrutinizing political leaders). The ethical orientation battery consists of four items that measure journalists' agreement with appropriate responses to ethical dilemmas. The epistemological beliefs battery consists of five global-mandatory and six country-optional questions that measure journalists' levels of agreement with statements about the nature of reality and knowledge. The US and German data include both epistemology batteries (global and optional), while the UK data includes only the mandatory global battery (Table S1).

Adapting the Survey to the LLM Prompt

Using the OpenAI API, we prompted OpenAI's flagship model, *gpt-4o-2024-08-06*. A total of 39 survey items were adapted into a standardized prompt format for LLM question-answering tasks. The prompt template replicated the exact original wording of the WJS survey items, and each question was paired with its corresponding Likert-scale response options (see

Hendrycks et al., 2020; Liang et al., 2022 for a methodological overview).[2] To preserve baseline accuracy in journalism contexts (Heseltine & Clemm von Hohenberg, 2024), a universal context of WJS was provided once before the start of the template prompting: "Assume you are a journalist, and the survey was conducted in 2023." No additional prompt was engineered that might substantially shift the context relative to human news workers' responses in WJS surveys (Santurkar et al., 2023; see also Lee et al., 2024; Törnberg, 2023).[3]

Furthermore, we conducted a series of additional simulations—varying the system prompt to include generic journalist roles, specific national contexts (US, UK, Germany), and no-context baselines—to confirm whether the findings were substantially influenced by the specific wording of the universal context. These tests demonstrate that the model's representational patterns remain consistent across minor prompt variations and are not merely

[2] A common concern with the QA-template approach is that a language model may retrieve memorized information rather than process queries stochastically. This risk is minimal here. The WJS third-wave data remains under embargo and is not publicly available, making it highly unlikely that GPT-4o was trained on it. Even if earlier WJS waves or related studies had been included in training, any resemblance in output cannot be attributed directly to such exposure. Our templates excluded WJS-specific keywords, further reducing this possibility. In short, the study relied on non-public data and an established API-based method designed to avoid methodological circularity and to elicit the model's algorithmic propensities rather than memory retrieval.

[3] All prompt engineering was conducted in English, with no country-specific information included during response generation or analysis. This reflects English's role as the "[g]lobal lingua franca, the default language of the [GPT-4] model" (Kuai et al., 2025, p. 9), and the model's original training on corpora rooted in Anglophone socio-cultural contexts (Buyl et al., 2025). The study seeks to identify the journalistic cultural orientations represented by GPT-4o. Introducing other languages or country codes during prompting might obscure this baseline in the journalsm contexts by adding additional linguistic variables. Nevertheless, such inputs are essential for assessing the model's capacity to simulate journalistic values specific to different cultural or national contexts—particularly those expressed in non-English languages (Santurkar et al., 2023). In this study, German serves as such a case. We therefore conducted a supplementary survey simulation using German-language prompts and performed a comparative analysis with the WJS German data. The results based on German prompting were overall highly similar to those from English prompting (Krippendorff's $\alpha = .85$). The pattern of GPT representativeness for German journalists likewise aligned with the main analysis, although subtle quantitative differences were observed for certain items. Detailed results are reported in the Supplementary Materials (S6).

artifacts of specific contextual cues. This step ensures that the simulation maintains high fidelity to the intended setting while remaining robust to the nuances of prompt engineering.[4]

The *temperature* parameter, which determines the model's randomness or creativity, was set to 0.7 in accordance with prior research (e.g., Argyle et al., 2023; Lee et al., 2024). To handle transient errors, the *max retries* parameter was set to its default value of 3. Lastly, following Heseltine and Clemm von Hohenberg's (2024) recommendation, we repeated the prompts to assess the inter-rater reliability of the model's outputs (Krippendorff's α = .92).

Evaluating LLM Representativeness

Following Santurkar et al. (2023), the degree to which LLM responses represented the actual survey responses of a group of journalists was assessed using the inverted Wasserstein distance (IWD). The Wasserstein distance offers a measure of how closely the model's prediction aligns with the broader pattern of human responses, allowing for a nuanced understanding of how *off* the prediction is in a distributional sense (Peyré & Cuturi, 2019). The IWD provides an optimal value—ranging from 0 to 1—that is comparable across different distributions, quantifying the *cost* of transforming one distribution into another (Villani, 2009).

We first computed the Wasserstein distance between the GPT response and the response distribution of each subgroup for each question. The WJS's original profiling items used to compute the subgroup distributions included political view, gender, employment status, main employer's background, and highest education level (see Table S2 for measurement details). Additionally, individual datasets for the US, UK, and Germany were each profiled as separate subsamples, and the response distributions for each country were computed accordingly.

[4] Detailed descriptions of these five system prompt variations, the results of the additional simulations, and the corresponding inter-coder reliability (ICR) scores are provided in Supplementary Materials (S7 and S8).

Subgroups with sample sizes of 30 or fewer were excluded from statistical comparisons. For cross-national comparisons, the following groups were excluded: "Other" gender, "Other" employment status, "Telecommunications" or "Other" backgrounds, "Not completed high school," "Completed high school," and "Doctorate". In within-country comparisons, exclusion groups varied by each nation's sample configuration. The "Other" gender category was excluded from the analyses for the UK and Germany but was retained for the US (N = 35). Similarly, the "Completed high school" group was included in analyses for the UK (N = 56) and Germany (N = 238), while the doctorate group was included only in Germany's analysis (N = 37).

We then operationalized *representativeness* by subtracting the normalized Wasserstein distance from 1 (i.e., IWD). For instance, a larger IWD for an item indicates a smaller gap between the LLM response and the central tendency of a subgroup's response distribution, increasing the representativeness.

Results

We began by analyzing the representativeness of GPT-4o's responses across all 39 journalistic items. Next, we conducted a more detailed analysis of the ten items that showed the highest variabilities in the Wasserstein distance between the subgroup response distributions; the larger variability indicates a more pronounced algorithmic bias toward specific subgroups.[5] Depending on the scope of analysis, the subgroups were extracted from either the combined sample of the three countries or individual country samples. All code for the analysis is available (Supplementary Materials).

RQ1: How does GPT-4o represent different groups of journalists in terms of their journalistic culture?

[5] Variability was calculated using the coefficient of variation (CV), defined as the standard deviation divided by the mean, within the normalized Wasserstein metric (Reed et al., 2002).

Figure 1 illustrates substantial variation in the model's representativeness across different subgroups. In the compound analysis across all three dimensions, GPT-4o's responses aligned closely with the distributions of groups identifying as centrist, full-time contract workers, employed by outlets with a TV background, and individuals holding a BA degree. In contrast, the model showed weaker alignment with responses from right-leaning individuals, part-time contract workers, those whose main employer has a news agency background, and individuals without a formal degree. No notable gender differences were observed.

[Figure 1 here]

A more detailed analysis of each dimension revealed additional differences. With regard to epistemological beliefs, GPT-4o's responses most closely aligned with the distributions of journalists identifying as left-leaning, those with a female gender identity, and those whose main employer had an internet-native background. In the ethical orientation battery, the model's centrist bias became more pronounced, and its responses aligned more closely with those of part-time workers than those of full-time workers. In the role perception dimension, the results were broadly consistent with those observed in the compound analysis (Figure 2).

[Figure 2 here]

Subsequently, we examined the Wasserstein distances across all items to identify the ten items with the highest coefficient of variation in representativeness between subgroups (Figure 3). The item with the highest variability was role_Q ("Convey a positive image of political leaders"). GPT-4o's responses were mostly aligned with those of left-leaning and internet-native background groups, while showing greater distance from those of right-leaning and no formal degree groups. The second-highest variability was observed for epist1_D ("Things are either true

or false, there is no in-between"), where GPT-4o's responses aligned most closely with the centrist subgroup's distributions.

[Figure 3 here]

RQ2: How does GPT-4o's representativeness vary across the US, UK, and Germany?

We conducted country-specific analyses and identified unique patterns that were not apparent in the combined dataset (Table S4 and S5). With the US sample, a three-dimensional compound analysis revealed that GPT-4o responses closely aligned with male journalists but poorly aligned with journalists identifying as "Other" gender. Unlike in the combined dataset, GPT-4o's representativeness was higher for responses from journalists whose main employer had a news agency background than for those whose main employer had a magazine background. The centrist bias persisted in the dimension compound analysis, but for epistemological beliefs and ethical orientations, GPT-4o's representativeness was higher for left-leaning groups than for centrist or right-leaning groups. Additionally, variability in representativeness between groups was most pronounced for role_Q ("Convey a positive image of political leaders"; CV = 0.375). Notably, the top nine items with the highest variability were from the role perception battery.

With the UK sample, the compound analysis showed a pronounced left-leaning bias (IWD for left-leaning: 0.80, centrist: 0.77, right-leaning: 0.75) across all three batteries. In particular, high representativeness for the TV background group was more evident than in the combined dataset. With regard to variability analysis, role_Q exhibited the highest variability in the UK sample, just as it did in the US sample. Another noteworthy item was role_P ("Support government policy"), which had the second-highest variability. GPT-4o's responses aligned least with the distribution of right-leaning groups.

The analysis of the German sample showed the strongest centrist bias in GPT-4o's responses among the three countries: In the ethics dimension, the representational gap between centrist and right-leaning groups exceeded 10.8% in IWD. Moreover, GPT representativeness for the TV background group in Germany was less pronounced than in the UK and US, while response distributions for MA degree holders showed notable alignment. In contrast to the three-country combined or US and UK analyses, the item with the highest variability for German dataset was epist_D ("Things are either true or false, there is no in-between"). For this item, GPT-4o's responses aligned least with the right-leaning group (IWD for left-leaning: 0.91, centrist: 0.93, right-leaning: 0.80). That is, GPT representation of epistemological perception on dichotomous fact-judgments was closest to that of left-leaning journalists in Germany.

RQ3: Which country's journalistic cultures are most closely represented by GPT-4o?

After conducting country-specific analyses, we returned to the combined dataset for a cross-country comparison. Using the *country* code as a grouping factor, we computed the inverted Wasserstein distances (IWDs) to assess the alignment between GPT-4o responses and the country-aggregated response distributions.

[Figure 4 here]

As illustrated in Figure 4, GPT-4o's responses showed the closest alignment with German journalists across dimensions. While the German sample exhibited narrow differences in IWDs when compared with the UK in the epistemology dimension and the US in the role perception dimension, it demonstrated substantially higher GPT-4o representativeness than both the UK and US data in the ethics dimension. Collectively, the three-dimensional compound analysis indicated that GPT-4o's responses to the journalistic culture battery aligned most closely with the response distributions of German journalists (bottom pane).

Discussion

Recent scholarship has shown that journalists are constructing discourses to reassert their professional authority amid the rise of generative AI (Van Dalen, 2024; Amigo & Porlezza, 2025). Central to these discourses are concerns that, while generative AI might ostensibly perform conventional journalistic tasks, its outputs lack core journalistic values (Thompson et al., 2025; Porlezza & Ferri, 2022). These concerns have contributed to the growing emphasis on *human-in-the-loop* practices, which assert the necessity of human oversight over AI-generated content (Thäsler-Kordonouri & Koliska, 2025; Wu, 2024).

However, calls for human oversight also expose the fact that AI systems have limited intelligibility for journalists (Jones et al., 2022; Simon, 2024); that is, journalistic engagement with AI often remains constrained to practices that rely on post hoc edits or prompts that fail to sufficiently reflect journalistic contexts (Nishal & Diakopoulos, 2024). Limited AI intelligibility, in turn, may constrain journalists' capacity to critically assess LLM outputs. Such structural constraints on oversight capacities raise the possibility that if the institutionalization of AI journalism unfolds in a way that sees technological actants primarily shape initial outputs while human agents are relegated mainly to ex-post oversight roles, then asymmetries in human–AI power dynamics could persist (Latour, 2005; Lewis & Westlund, 2015). These power asymmetries can be particularly problematic given it is still the journalist who bears the editorial responsibility for content produced with the support of AI tools.

This study addresses the challenge posed by these asymmetries by offering insight into how GPT-4o reflects journalistic culture. Using LLM simulations based on survey questions asked in the Worlds of Journalism Study (WJS), we measured GPT-4o's alignment with journalist subgroups across three dimensions: role perceptions, epistemological beliefs, and

ethical orientations (Hanitzsch, 2007). Our analysis revealed consistent alignment with politically centrist, full-time, and TV-background journalists, with the strongest overall alignment found in the German dataset.

These patterns suggest that GPT-4o does not represent a singular cultural orientation but rather reflects intertwined configurations of journalistic values in various contexts (Argyle et al., 2023). This highlights the need for localized strategies in practicing value-motivated uses of AI (Wu, 2024). While LLMs tend to *go with the mainstream* (Bender et al., 2021), the groups associated with those major views can vary across societies. Our findings show that centrist groups in Germany culturally align more closely with left-leaning groups in the US and UK. That is, a society's journalistic cultural landscape must be considered when advocating for the integration of diverse perspectives into LLM uses, as such advocacy depends on which groups are positioned as "mainstream" within that specific media system. Despite the growing institutional isomorphism in journalists' responses to AI across Germany, the UK, and US (Simon, 2024), this study illustrates that cultural nuances remain vital for assessing LLMs' journalistic feasibility.

As such, these findings offer empirical evidence for concerns about potential algorithmic biases embedded in AI—within journalistic contexts (Cools & De Vreese, 2025). Specifically, GPT-4o's representational tendencies were in line with ideological skews observed not only in other domains but also in several journalistic applications (e.g., Bang et al., 2024; Fang et al., 2024; Trhlik & Stenetorp, 2024). Moreover, the model's closer alignment with majority groups—such as television journalists and full-time workers—points to the need for continued vigilance among human journalists regarding the potential systematic omission of minority perspectives in LLM outputs.

Accordingly, this study emphasizes the importance of the journalism field recognizing the cultural configurations embedded in LLMs as a means of ensuring ethical AI practices (Arguedas & Simon, 2023). At the same time, it provides a rationale for human-in-the-loop approaches—from prompt design to post-editing.

The study also yields evidence-based policy implications (Bommasani et al., 2025). News organizations and journalism education institutions should incorporate AI literacy—particularly with respect to the mainstream-driven orientations of LLMs—within both organizational policy frameworks and the design of training programs. Understanding which journalistic cultures are more—or less—reflected in LLMs and how such algorithmic biases can be steered (Narayanan & Kapoor, 2023) should be the basis for editorial guidelines and ethical standards.

Limitations and Conclusion

Several limitations must be acknowledged. First, the WJS data is based on quota or probability samples rather than on a full census. Although they offer rigorous approximations of national journalist populations (Wahl-Jorgensen & Hanitzsch, 2019), the generalizability of subgroup-level findings should be interpreted with care due to small sample sizes for some groups (e.g., regarding education and employer background). Second, the analysis was based on an explorative implementation of a specific configuration of GPT-4o. Given that LLM output is contingent on fine-tuning and training data (Ouyang et al., 2022), alignment levels with journalistic cultures may vary between model versions and types (Buyl et al., 2025). This calls for longitudinal tracking through repeated benchmarking (Messeri & Crockett, 2024).

Relatedly, it is necessary to articulate the scholarly position of the analysis, given the inherent variability of LLM architectures and their outputs (Barrie et al., 2024). We recognize that the outputs of our LLM-driven survey simulation are subject to variation due to multiple

technical factors (e.g., prompt engineering, parameter settings, model specification). Although significant inter-coder reliability between the outputs was observed across five additional simulation variants (see Notes 3 and 4), this does not indicate that variability in model reproduction can be fully controlled.

However, it is equally important to recall that the validation of LLM-based research tools remains unconsolidated within broader social science scholarship (Peng & Yang, 2025). In text annotation, for example, researchers have experimented with Monte Carlo techniques (Tolochko et al., 2025), averaging multiple outputs (Zhao et al., 2025), and leveraging double execution (Heseltine & Clemm von Hohenberg, 2024) to validate the LLM coding outputs. Each of these approaches has distinct strengths and limitations, yet the field has not reached a consensus on establishing a common standard. Adjudicating among them lies beyond the scope of this study.

That said, this indeterminacy does not constitute a reason to avoid the scholarly use of LLMs in addressing our research questions. Rather, we contend that the value of this study lies in serving as a *catalyst* for academic discourse on algorithmic bias in journalistic applications. That is, we position our study as a demonstrative application of algorithmic bias identification rather than a confirmatory test. Our LLM survey simulation was deliberately designed to emulate journalist groups at large. The objective herein is not to consolidate GPT responses with a fixed standard, but to observe potential patterns in which journalist groups' perspectives align more—or less—closely with model outputs, under hypothetical conditions of integration into journalistic AI practice. The present analysis thus furnishes such "what if" scenarios and, in doing so, supports counterfactual reasoning about journalistic collaboration with LLMs.

Aligning with our position, scholars increasingly contend that in the scientific use of LLMs, these models should be viewed not only as methodological tools but also as conceptual

resources for abductive theorization (Bail, 2024). This perspective resonates with Margolin's (2019) argument that computational social science ought to privilege theoretical plausibility over generalizability in order to generate novel insights into established research programs, while strategically pursuing targeted analyses (see also Davidson & Karell, 2025).

Likewise, the purpose of our analysis is not to produce universally replicable simulations but to demonstrate possible model patterns when models are applied to inquiries into journalistic culture. In doing so, the study highlights potential group-specific interactions that might emerge if LLMs were incorporated into newsroom practice. The theoretical proposition that we advance—that variation in model–user alignment may shape divergent news production outcomes—offers a basis for subsequent empirical testing within established research traditions.

One promising future avenue would be to test whether journalists' prompting strategies change when they are informed about a model's representational tendencies. Researchers could then measure how this awareness affects both prompting and post-editing practices. Another extension involves panel designs using multiple LLMs (e.g., Mistral based in Europe and DeepSeek based in China) to compare cross-model representations. This is all the more important given that journalistic practice increasingly involves multiple model comparisons (EBU, 2024b). Combined with WJS data, such an approach could become a powerful benchmarking tool for journalism studies (see Buyl et al., 2025; Santurkar et al., 2023).

Ultimately, this study highlights the fact that effective AI integration in journalism requires more than technical safeguards. It demands a social understanding of how journalistic cultures and practices are encoded, reproduced, and disrupted by generative systems. In this regard, it is worth referencing Messeri and Crockett (2024), who emphasize the need for

cognitive and demographic diversity among those evaluating AI outputs, and warn against a monoculture that privileges a singular (major/mainstream) perspective.

This principle is equally vital to journalism, which should serve as a pluralistic lens in democratic societies (Porto, 2007). Therefore, assessment of AI's role in journalism must move beyond the balancing of efficiency against risk. It requires a critical rethinking of how journalistic authority and cultural plurality can be sustained amid algorithmic shifts. Key to this effort is evaluating the alignment between the perspectives that newsrooms aim to present and those that AI systems are likely to *re*present. By mapping these socio-technical configurations, this study aims to inform journalistic communities as they navigate and shape the evolving landscape of AI-driven news ecosystems.

Disclosure of interest

The authors report there are no competing interests to declare.

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Figure 1. GPT-4o representativeness for subgroups within the combined dataset

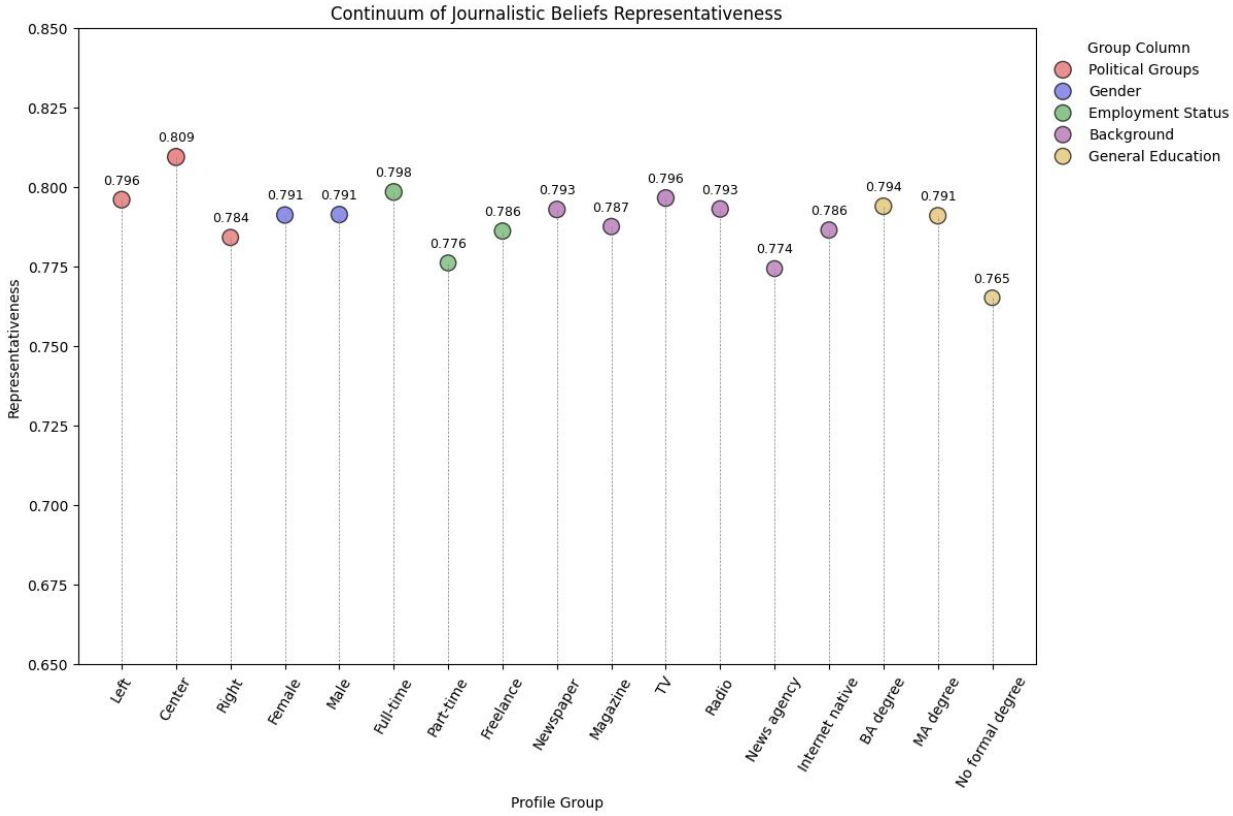


Figure 2. GPT-4o representativeness across belief dimensions within the combined dataset

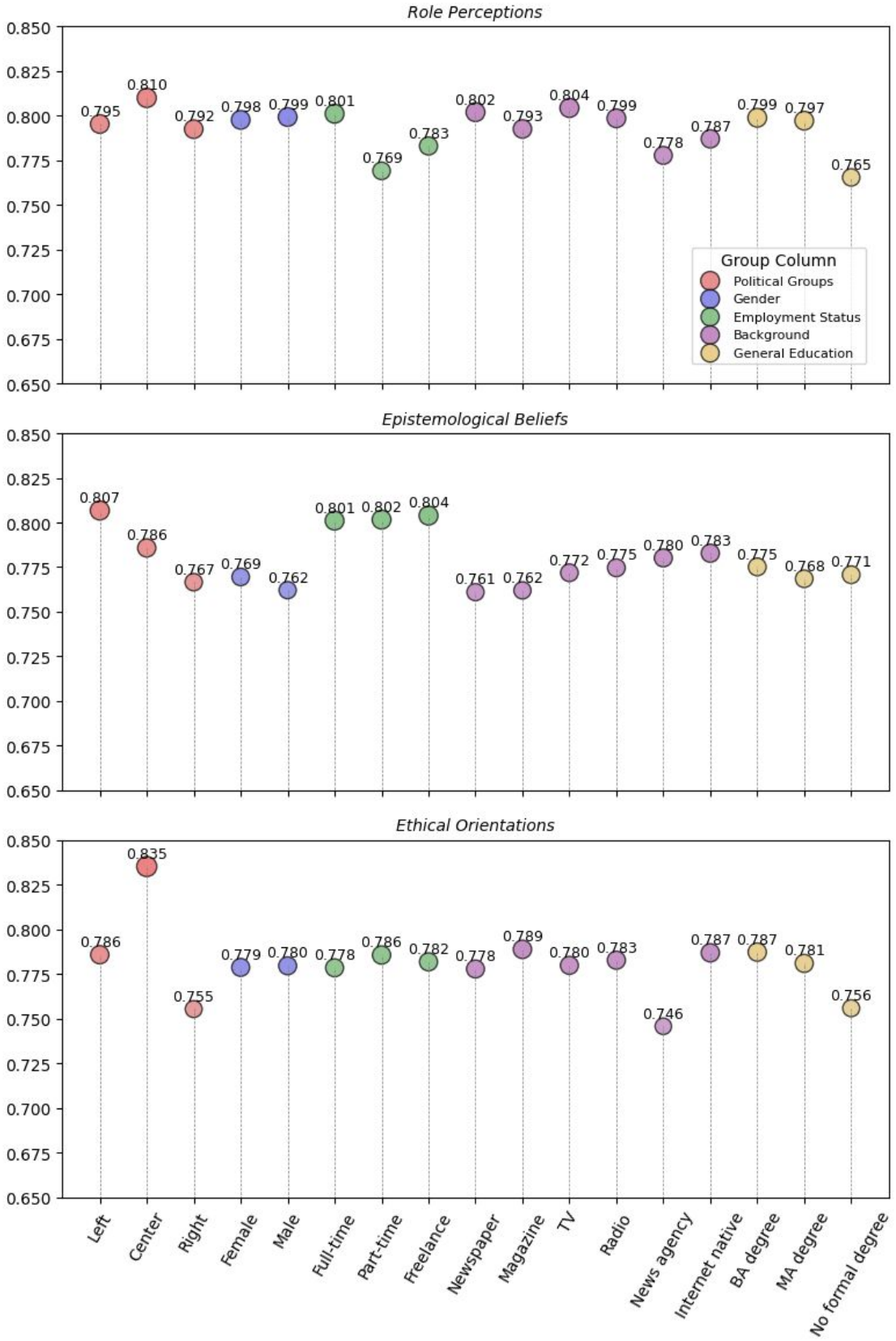
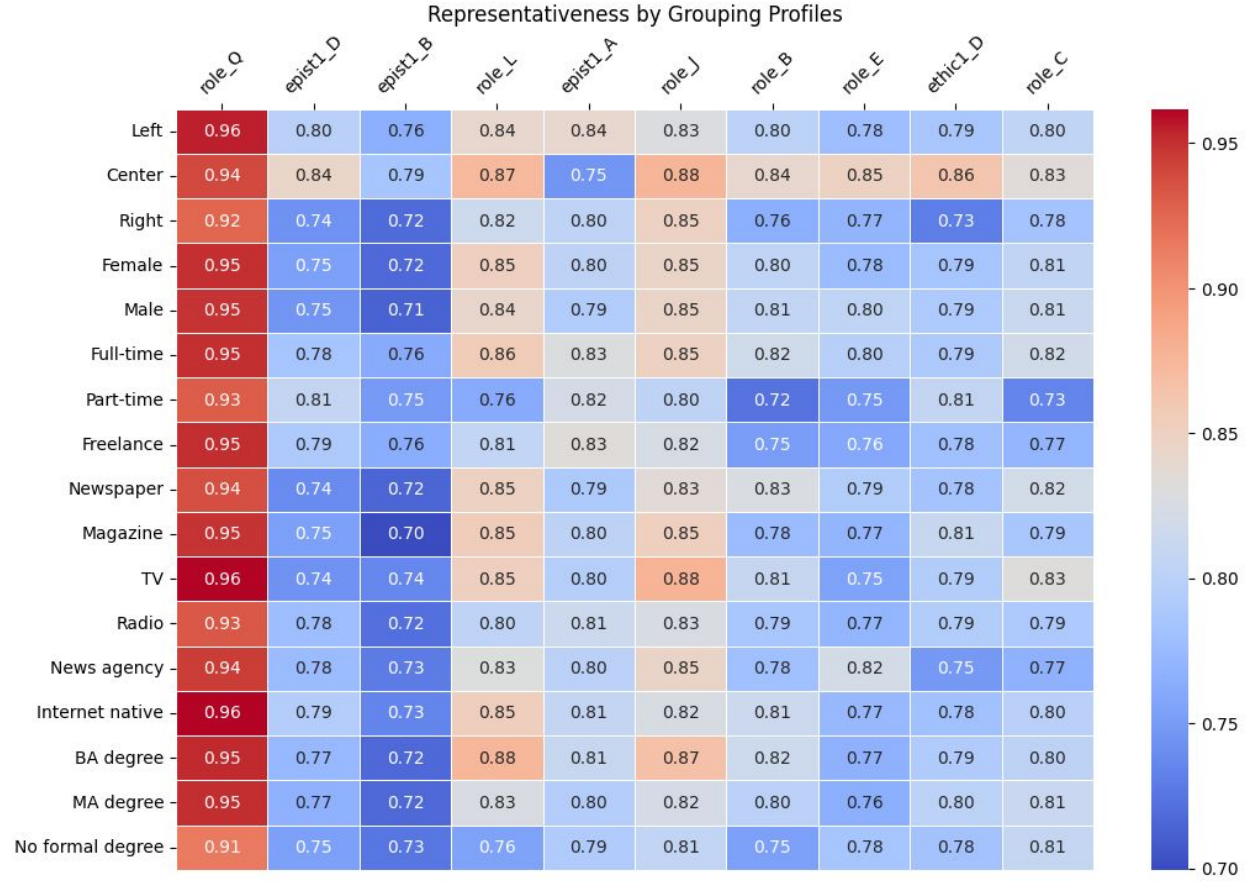


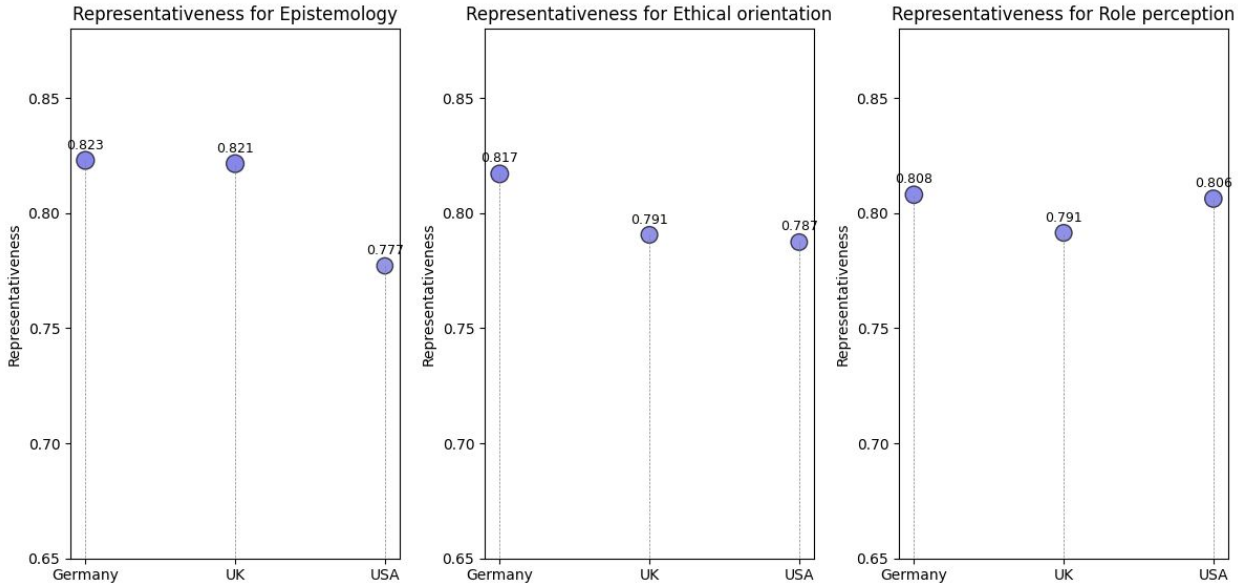
Figure 3. Top 10 high variability item comparisons within the combined dataset

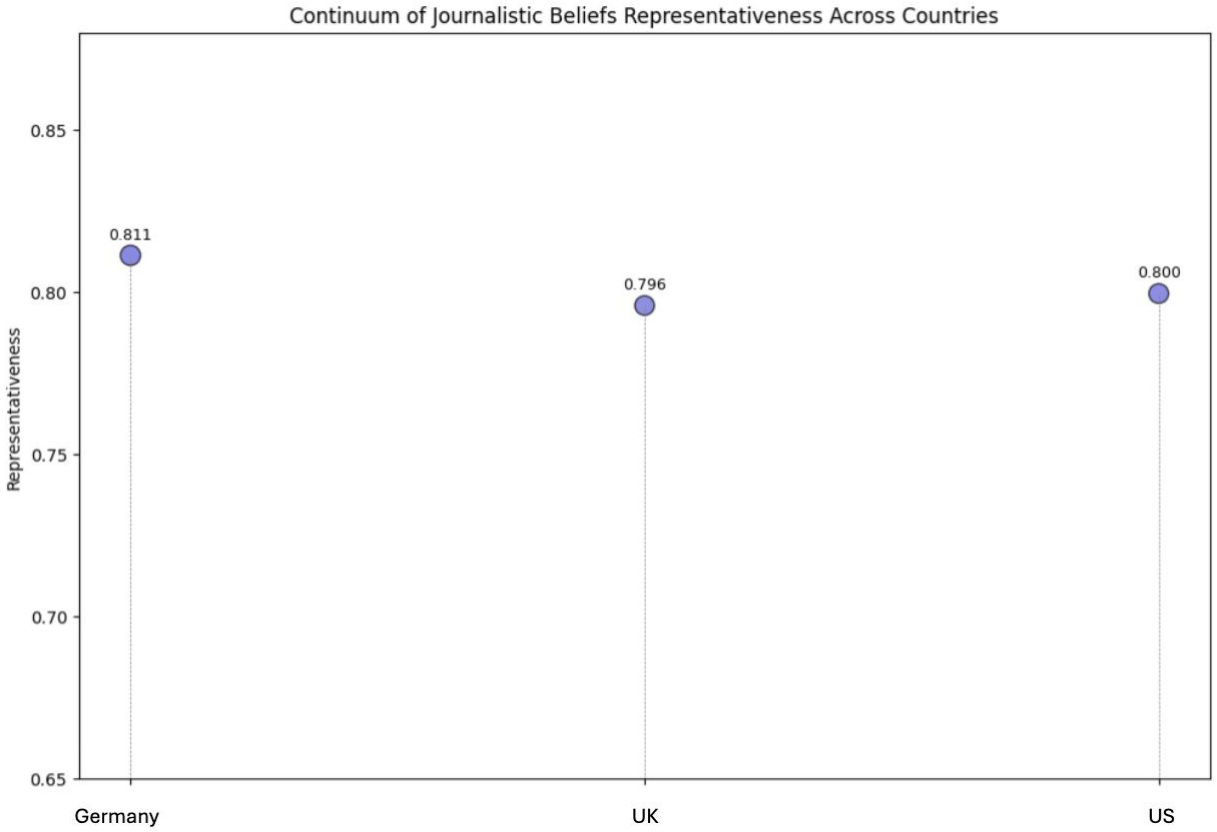


#.	1	2	3	4	5	6	7	8	9	10
	role_Q	epist1_D	epist1_B	role_L	epist1_A	role_J	role_B	role_E	ethic1_D	role_C
CV	0.458	0.308	0.284	0.282	0.260	0.254	0.245	0.242	0.241	0.238

Note. CV = coefficient of variation.

Figure 4. GPT-4o representativeness across belief dimensions in the three countries





Supplementary Materials

Our code and survey template are available at https://github.com/casllmproject/wjs_llm_project

S1. Journalistic Belief Scales in the World of Journalism Study

Variable label	Question
Role	*Please tell me how important it is to... in your daily work. (1 = Not at all important; 2 = Slightly important; 3 = Moderately important; 4 = Very important; 5 = Extremely important)*
role_A	Be a detached observer
role_B	Monitor and scrutinize those in power
role_C	Shine a light on society's problems
role_D	Motivate people to participate in politics
role_E	Provide analysis of current affairs
role_F	Let people express their views
role_G	Provide information people need to form political opinion
role_H	Advocate for social change
role_I	Influence public opinion
role_J	Set the political agenda
role_K	Promote peace and tolerance
role_L	Educate the audience
role_M	Point toward possible solutions to society's problems
role_N	Speak on behalf of the marginalized
role_O	Support national development
role_P	Support government policy
role_Q	Convey a positive image of political leaders
role_R	Provide entertainment and relaxation
role_S	Provide the kind of news that attracts the largest audience
role_T	Provide advice, orientation and direction for daily life
role_U	Tell stories that emotionally move the audience
role_X	Support efforts to protect public health
role_Y	Counteract disinformation
role_V	Discuss future implications of current events.

Ethics	*The following statements describe different responses journalists may have to ethical problems. Please tell me how strongly you agree or disagree: (1 = Strongly disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Strongly agree)*
ethic1_A	What is ethical for journalists should always be determined by professional standards regardless of situation and personal judgment
ethic1_B	What is ethical for journalists should be determined by professional standards unless extraordinary circumstances require disregarding them
ethic1_C	What is ethical for journalists should depend on each specific situation
ethic1_D	What is ethical for journalists should be a matter of personal judgment
Epistemology *(epist1: mandatory, epist2: optional)*	*The following statements deal with beliefs related to how journalists know what they know. Please tell me how strongly you agree or disagree: (1 = Strongly disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Strongly agree)*
epist1_A	Interpretation is necessary to make sense of facts.
epist1_B	Truth is inevitably shaped by those in power
epist1_C	It is impossible for journalists to withhold their personal beliefs from reporting
epist1_D	Things are either true or false, there is no in-between
epist1_E	It is possible to represent objective reality in reporting
epist2_A	Journalists should trust their instincts in deciding what's true and what's not
epist2_B	Journalists should intuitively know what the final story will be
epist2_C	Journalists should let the facts speak for themselves
epist2_D	Journalists should be part of a community to portray it accurately
epist2_E	Journalists should make their standpoint transparent in their work
epist2_F	Journalists should alert audiences when a source's claim is untruthful

S2. Subgroup Sizes across US, UK, and Germany datasets

Profile	Subgroup	US (n=1326)	UK (n=1130)	Germany (n=1221)	Total (n=3677)
Political view	Left leaning	820	718	566	2104
	Centrist	92	113	483	688
	Right leaning	231	110	94	435
Gender	Female	529	509	515	1778
	Male	754	503	651	1683
	Other	35	6	2	43
Employment	Full-time permanent contract	995	681	768	2444
	Part-time permanent contract	21	58	66	145
	Full-time fixed-term contract	182	29	120	331
	Part-time fixed-term contract	4	7	22	33
	Freelance or self-employed	32	316	239	587
	Other	85	39	3	127
Background	Newspaper	617	268	433	1318
	Magazine	40	280	243	563
	TV	368	98	205	671
	Radio	132	64	204	400
	News agency	51	67	42	160
	Internet native	93	146	37	276
	Telecommunications	11	1	2	14
	Other	9	94	19	122
Education	Not completed high school	1	2	25	28
	Completed high school	19	56	238	313
	Bachelor's degree or equivalent	948	483	148	1579
	Master's degree or equivalent	278	423	653	1354
	Doctorate	9	27	37	73
	Undertook some university studies, but no degree	69	37	92	198

Note. Subgroup sums may differ from the total due to missing data.

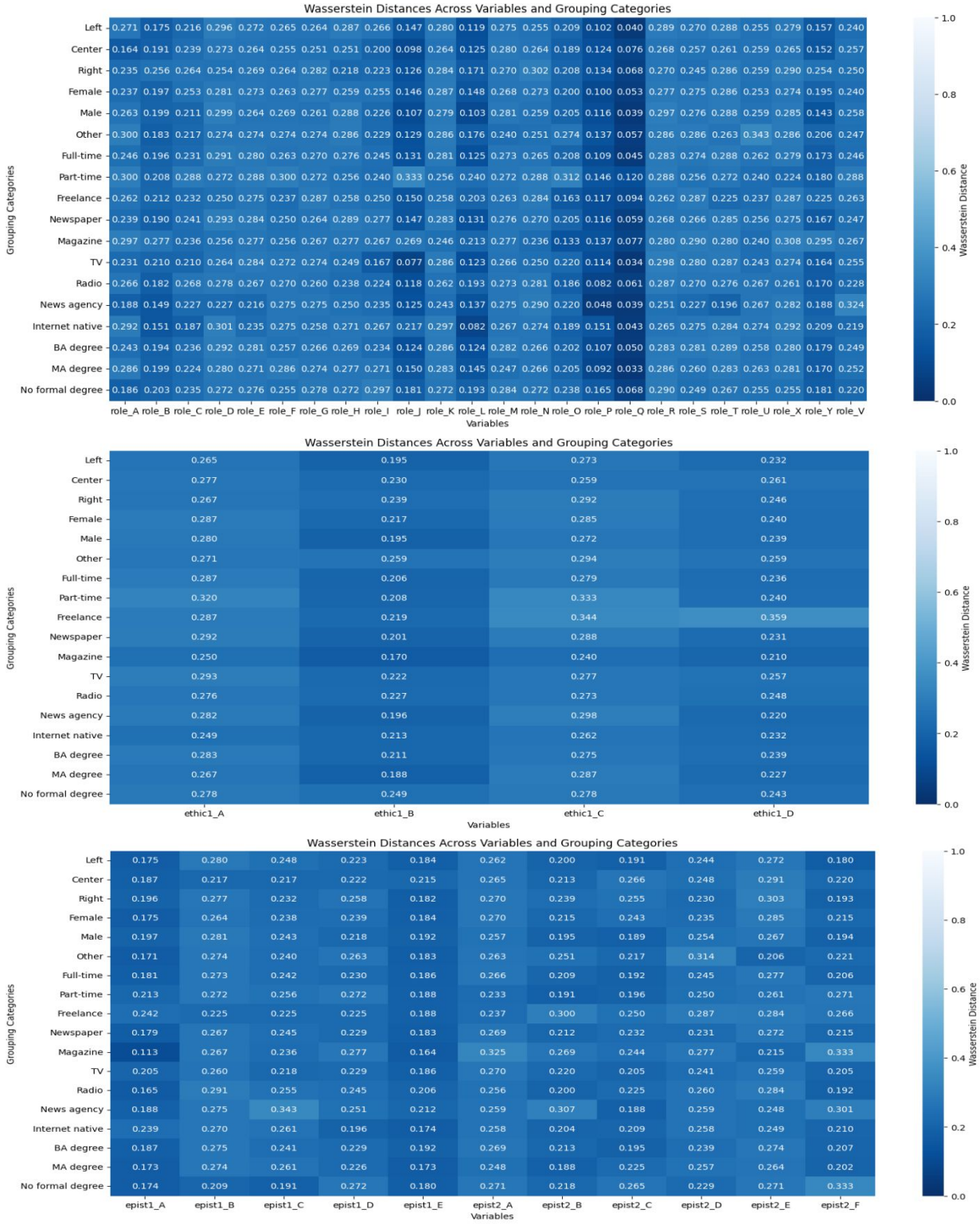
S3. Descriptives for Journalistic Belief Items across the US, UK, and Germany datasets

Variable	US		UK		Germany	
	M	*SD*	*M*	*SD*	*M*	*SD*
role_A	3.80	1.237	3.93	1.067	4.16	0.919
role_B	4.05	1.242	3.78	1.300	3.52	1.390
role_C	3.97	1.135	3.78	1.300	4.09	1.078
role_D	2.64	1.333	2.20	1.212	3.23	1.121
role_E	3.58	1.283	3.45	1.391	4.27	0.933
role_F	3.66	1.154	3.58	1.193	3.55	0.982
role_G	3.54	1.383	2.95	1.497	4.34	0.828
role_H	2.40	1.249	2.72	1.365	2.58	1.139
role_I	2.20	1.201	2.65	1.314	2.39	1.010
role_J	1.56	0.927	2.13	1.246	1.90	1.026
role_K	2.89	1.302	2.77	1.394	3.67	1.014
role_L	4.58	0.703	4.41	0.799	3.96	0.987
role_M	3.45	1.243	3.16	1.337	3.81	1.006
role_N	3.55	1.241	3.14	1.394	3.48	1.012
role_O	1.94	1.121	2.32	1.270	2.16	1.001
role_P	1.44	0.826	1.34	0.759	1.39	0.682
role_Q	1.19	0.578	1.18	0.531	1.28	0.611
role_R	2.79	1.242	3.07	1.400	3.13	1.268
role_S	3.21	1.198	2.93	1.267	3.54	1.137
role_T	2.57	1.251	2.37	1.317	3.67	0.986
role_U	3.80	1.065	3.25	1.311	3.49	1.182
role_X	3.42	1.290	2.66	1.406	2.81	1.167
role_Y	4.24	1.083	3.94	1.245	4.38	0.885
role_V	3.78	1.118	3.60	1.231	3.81	0.938
ethic1_A	3.23	1.215	3.59	1.083	4.34	0.881
ethic1_B	3.66	1.014	3.71	0.983	2.51	1.348

ethic1_C	2.94	1.228	3.01	1.180	2.40	1.398
ethic1_D	2.23	1.039	2.37	1.099	1.74	1.081
epist1_A	3.86	0.876	4.01	0.748	3.33	1.068
epist1_B	2.92	1.086	3.27	1.031	1.95	1.065
epist1_C	2.63	1.070	2.69	0.971	2.35	1.113
epist1_D	2.55	1.074	2.49	1.006	1.41	0.787
epist1_E	3.82	0.930	3.68	0.868	3.55	1.022
epist2_A	2.74	1.046	-	-	1.94	0.969
epist2_B	2.35	0.913	-	-	2.23	1.034
epist2_C	4.05	0.807	-	-	3.84	0.908
epist2_D	3.55	1.065	-	-	1.82	0.976
epist2_E	2.75	1.159	-	-	2.93	1.325
epist2_F	4.39	0.685	-	-	4.40	0.801

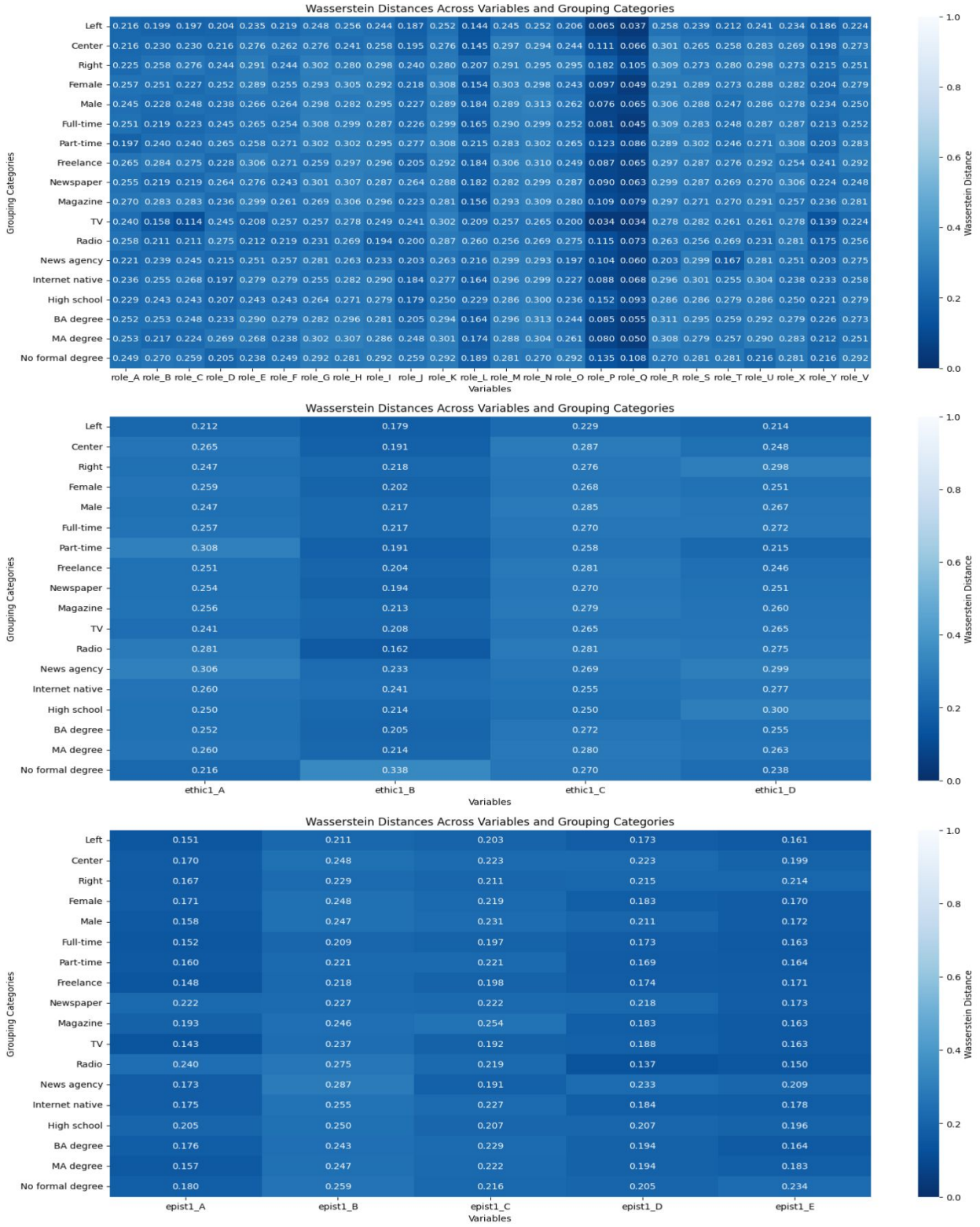
S4. Wasserstein Distances by Subgroups across the US, UK, and Germany datasets

(1) US: Role Perception – Ethical Orientation – Epistemological Belief



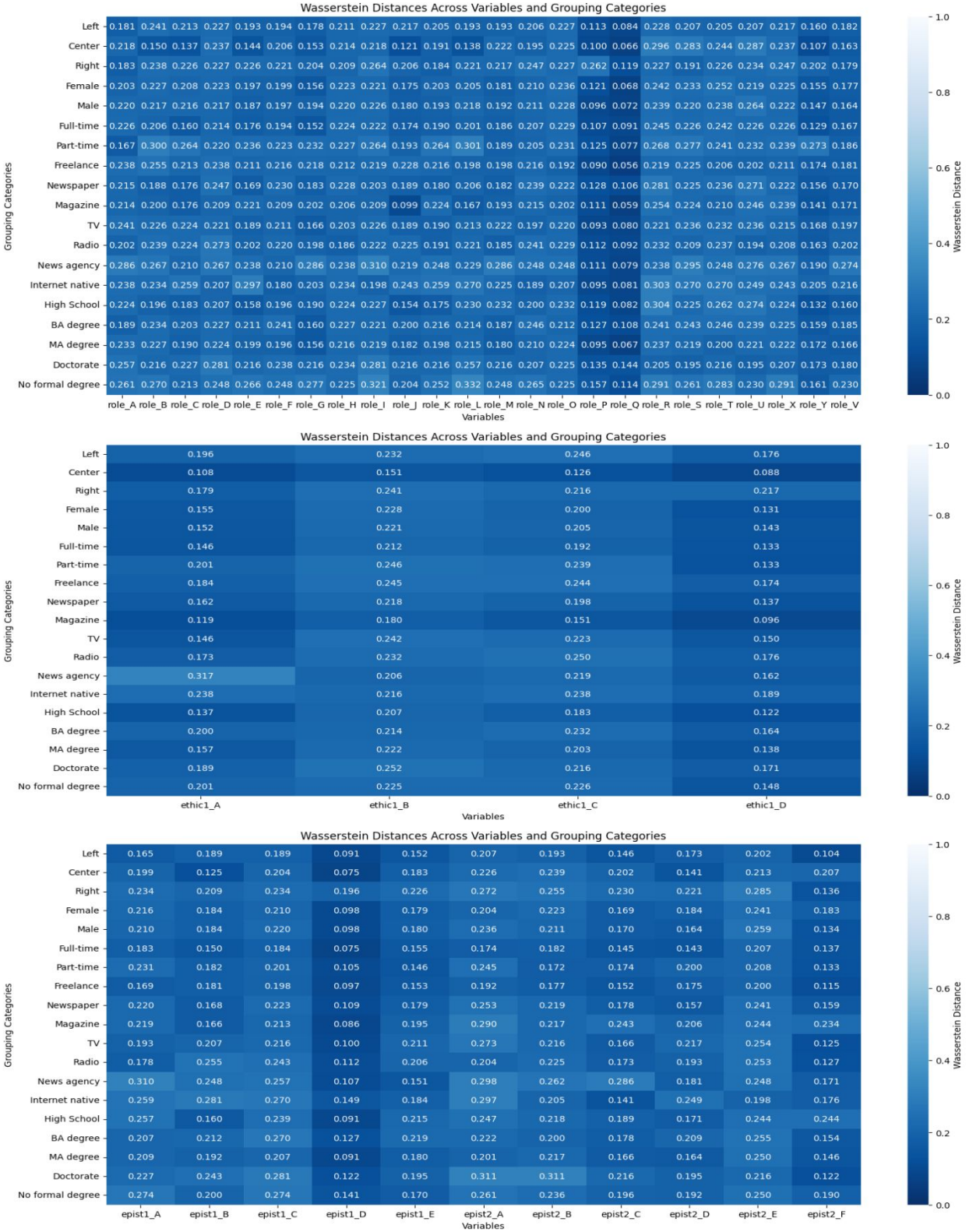
Note. The subgroups of "Telecommunications" or "Other" outlet, "Not completed high school," "Complete high school," and "Doctorate" were excluded from the analysis due to small sample sizes.

(2) UK: Role Perception – Ethical Orientation – Epistemological Belief



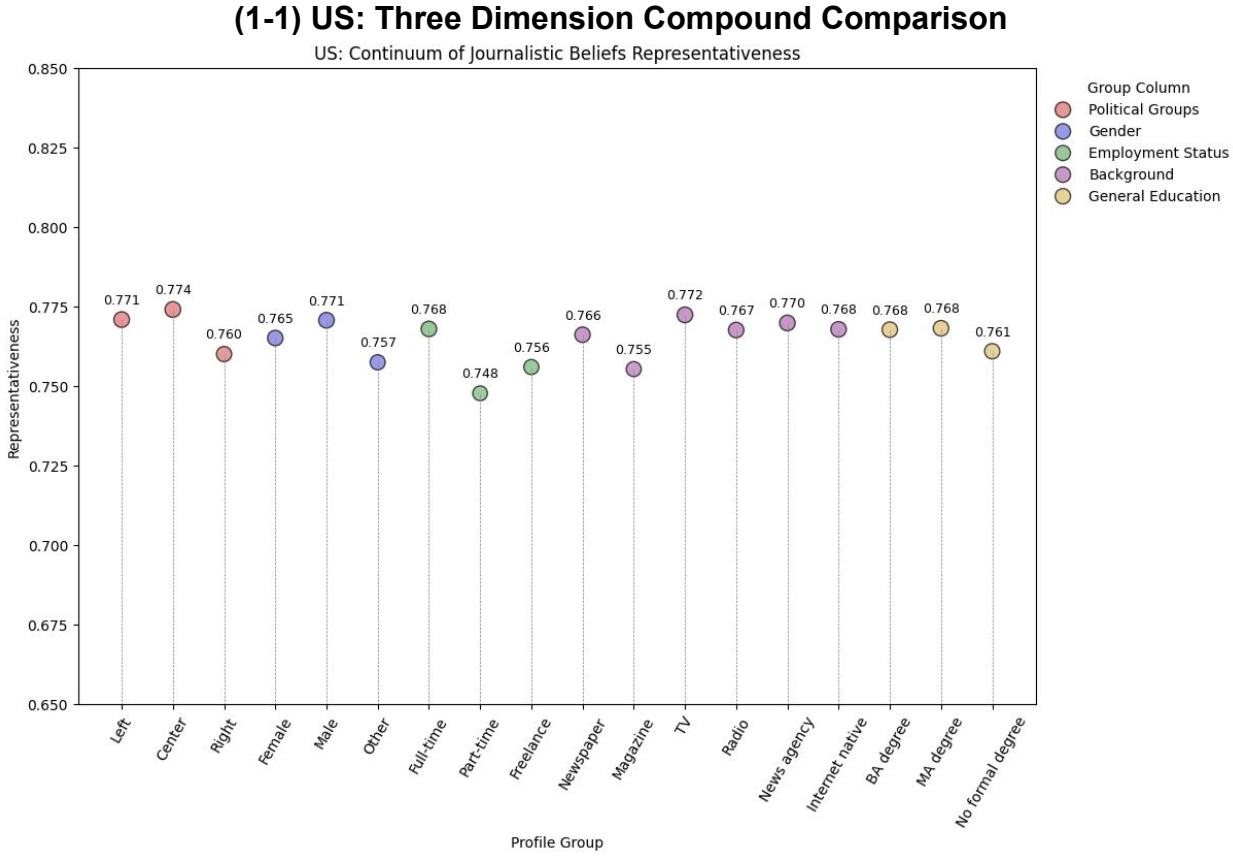
Note. The subgroups of "Other gender," "Telecommunications" or "Other" outlet, "Not completed high school" and "Doctorate" were excluded from the analysis due to small sample sizes.

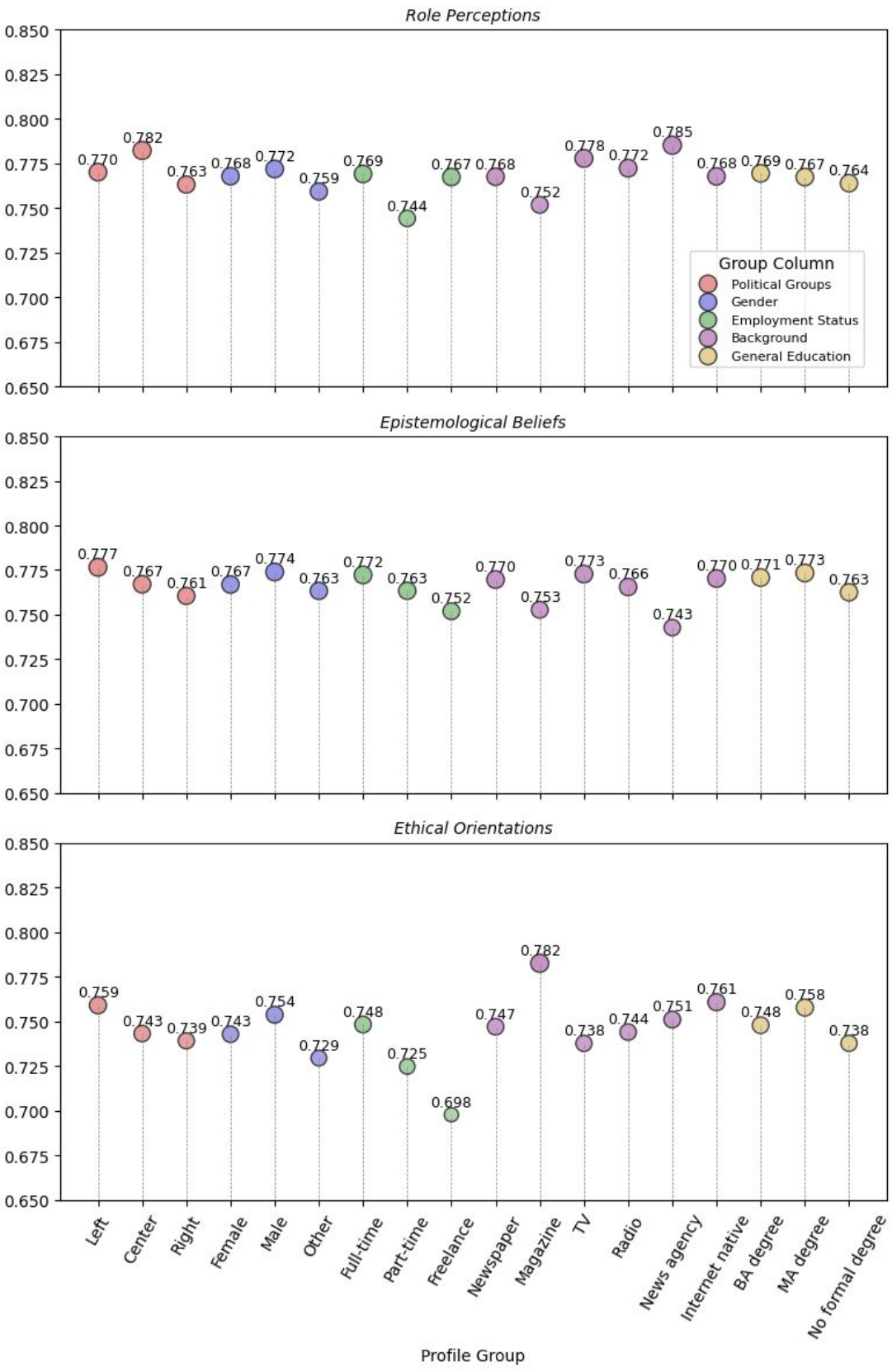
(3) Germany: Role Perception – Ethical Orientation – Epistemological Belief

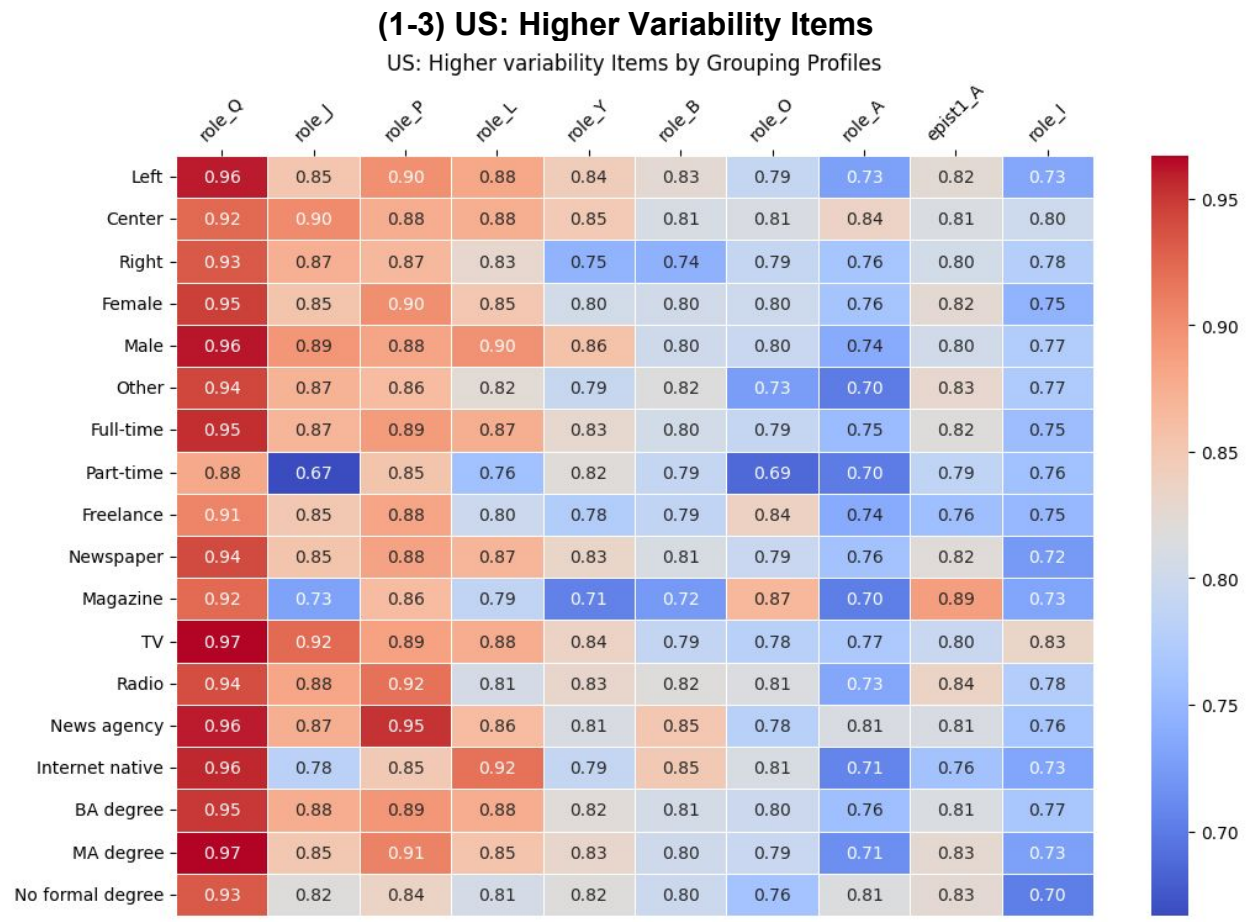


Note. The subgroups of "Other gender," "Telecommunications" or "Other" outlet, "Not completed high school" were excluded from the analysis due to small sample sizes.

S5. GPT-4o Representativeness for Belief Dimensions across the US, UK, and Germany



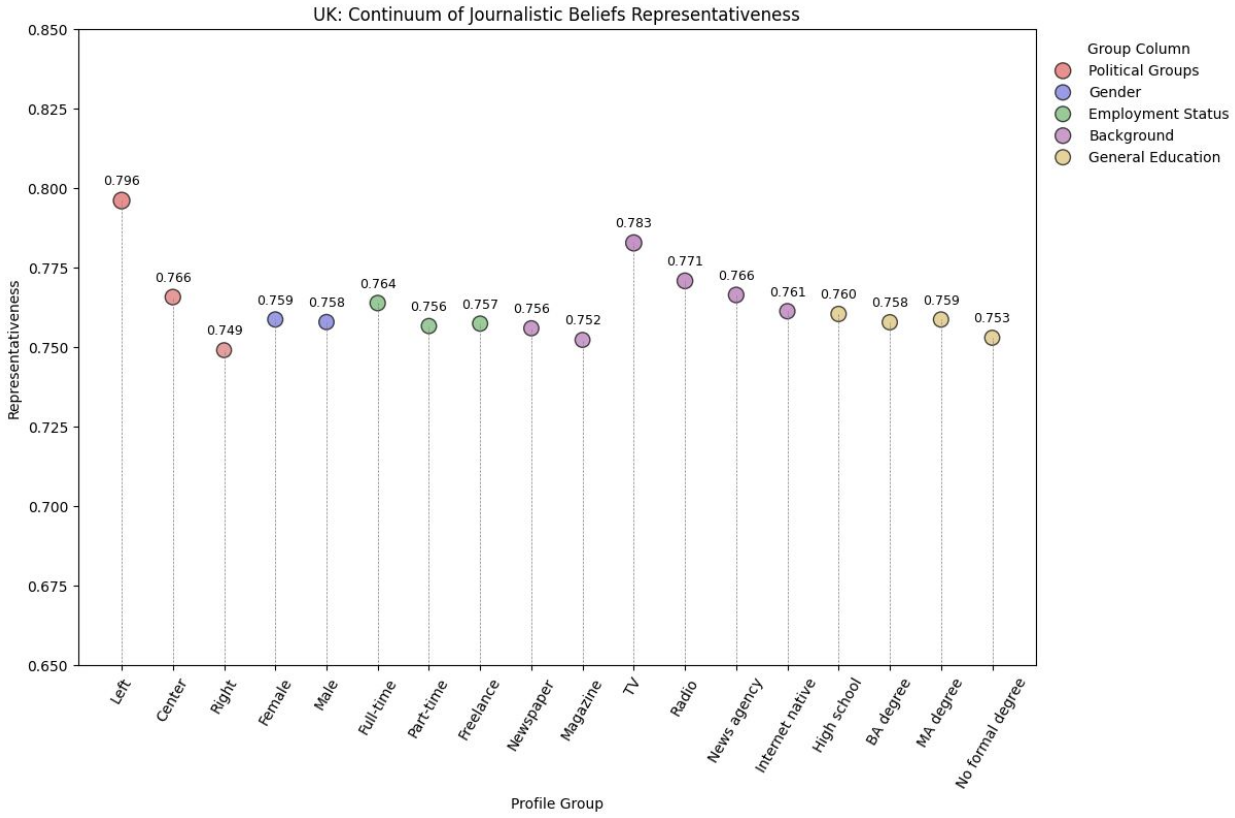

(1-2) US: Across Dimensions
Role Perceptions
Epistemological Beliefs
Ethical Orientations
Group Column
Political Groups
Gender
Employment Status
Background
General Education
Left
Center
Right
Female
Male
Other
Full-time
Part-time
Freelance
Newspaper
Magazine
TV
Radio
News agency
Internet native
BA degree
MA degree
No formal degree
Profile Group



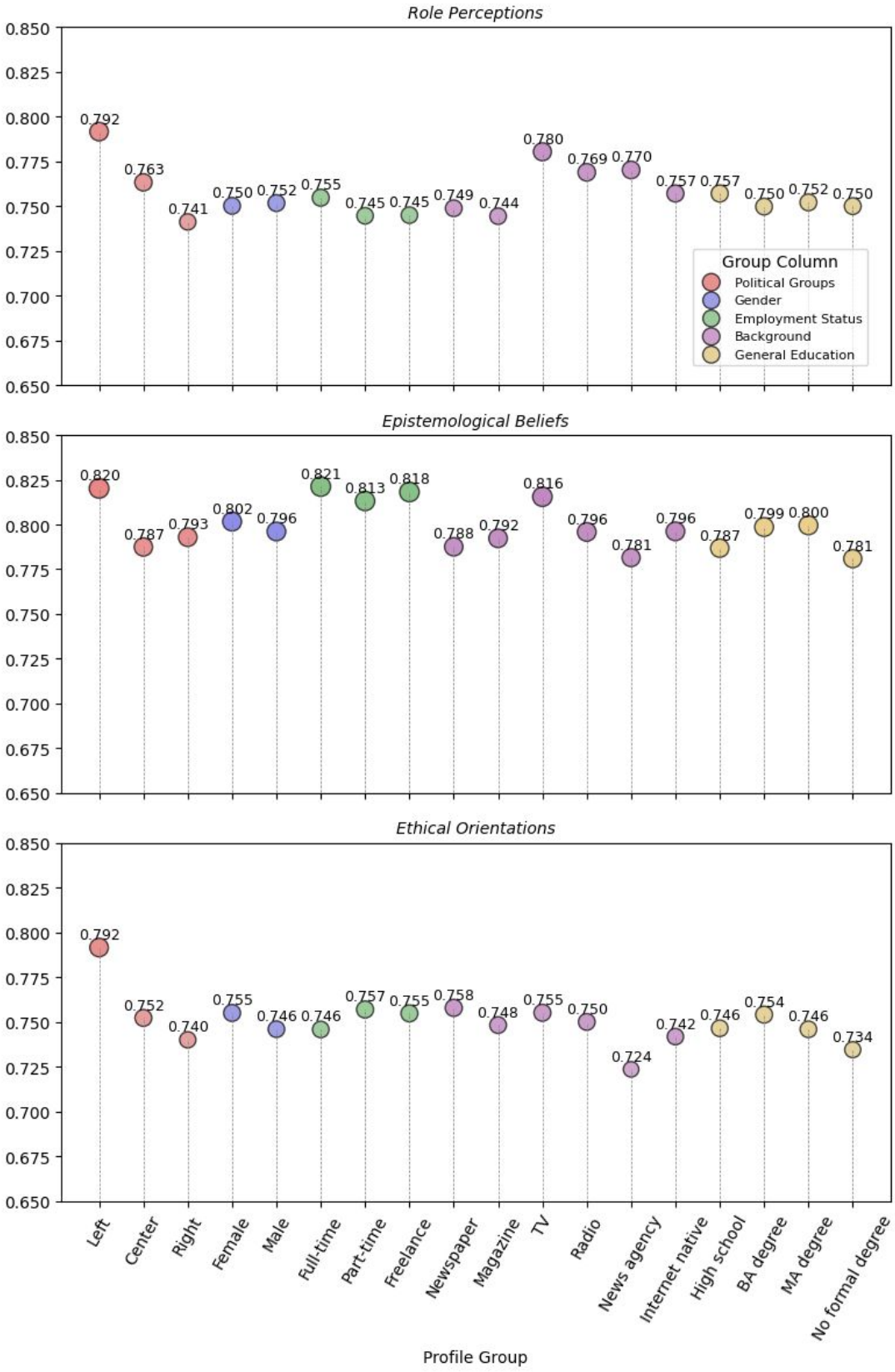
#.	1	2	3	4	5	6	7	8	9	10
	role_Q	role_J	role_P	role_L	role_Y	role_B	role_O	role_A	epist1_A	role_I
CV	0.375	0.251	0.232	0.215	0.212	0.150	0.146	0.144	0.127	0.110

Note. CV = coefficient of variation.

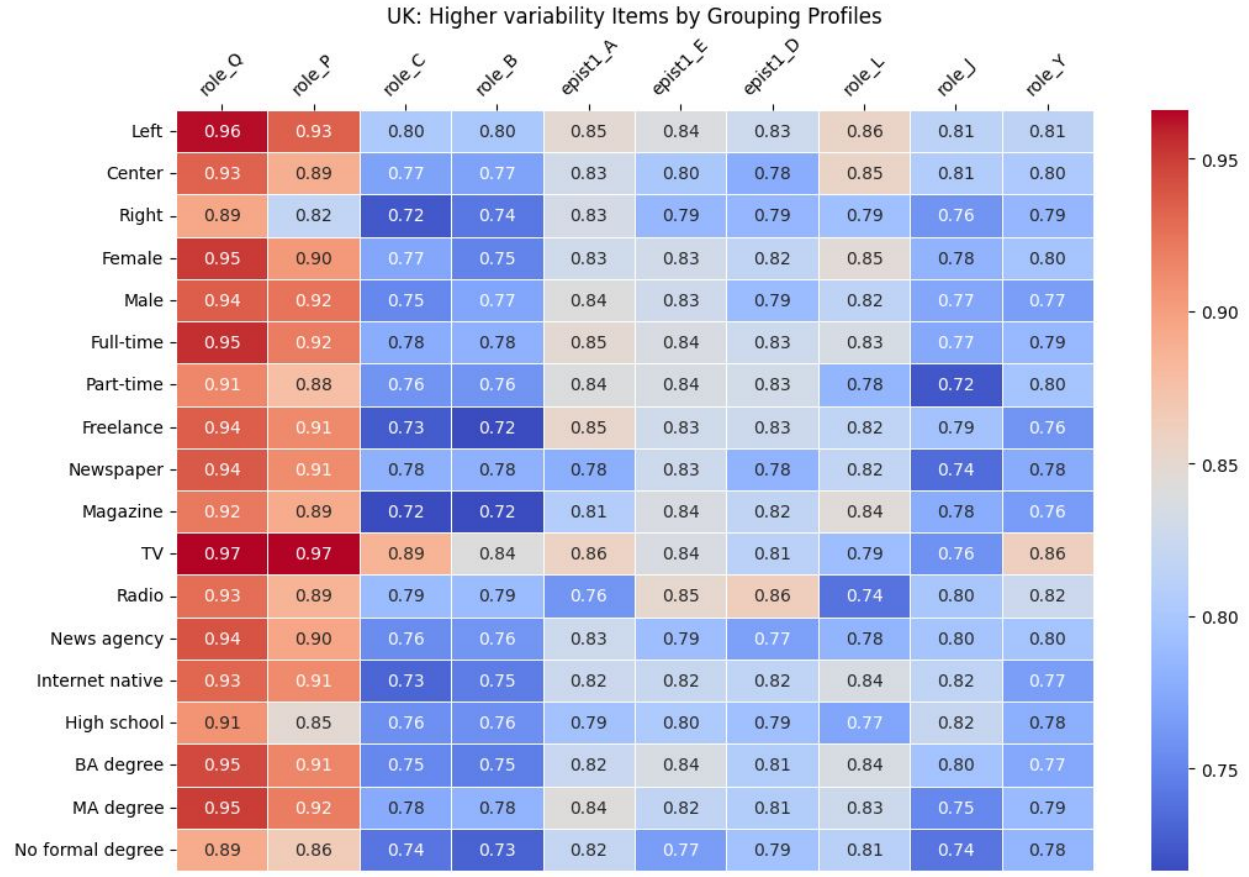
(2-1) UK: Three Dimension Compound Comparison



(2-2) UK: Across Dimensions



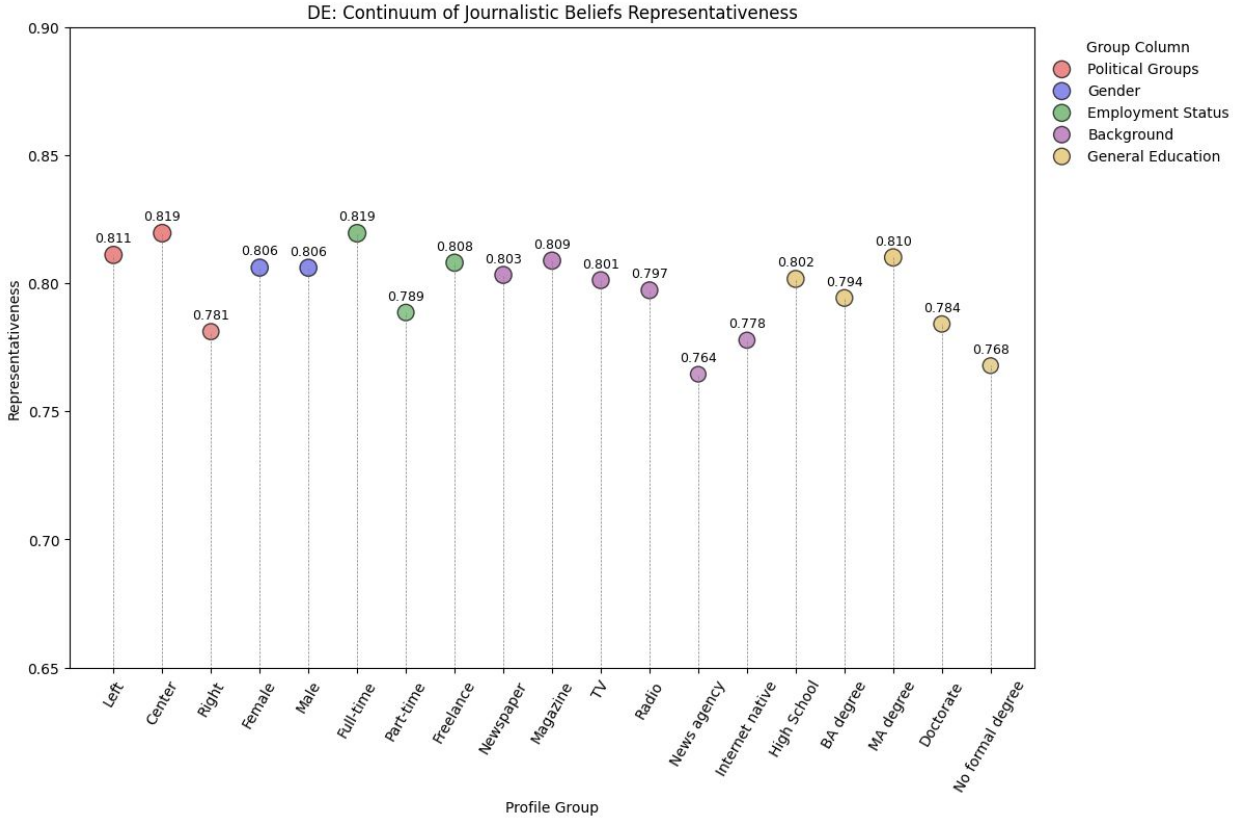
(2-3) UK: Higher Variability Items



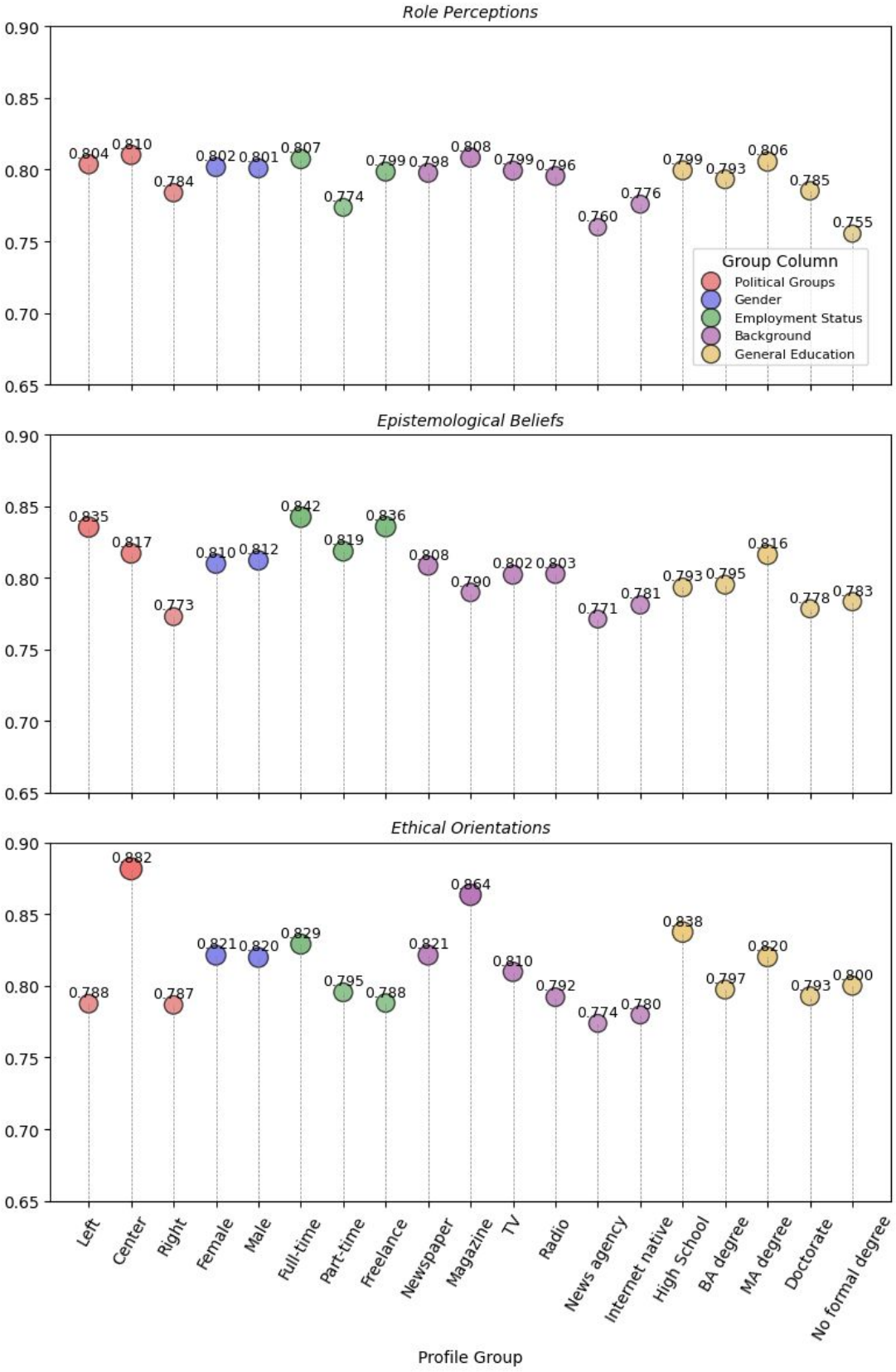
#.	1	2	3	4	5	6	7	8	9	10
	role_Q	role_P	role_C	role_B	epist1_A	epist1_E	epist1_D	role_L	role_J	role_Y
CV	0.342	0.260	0.157	0.146	0.141	0.140	0.131	0.125	0.113	0.106

Note. CV = coefficient of variation.

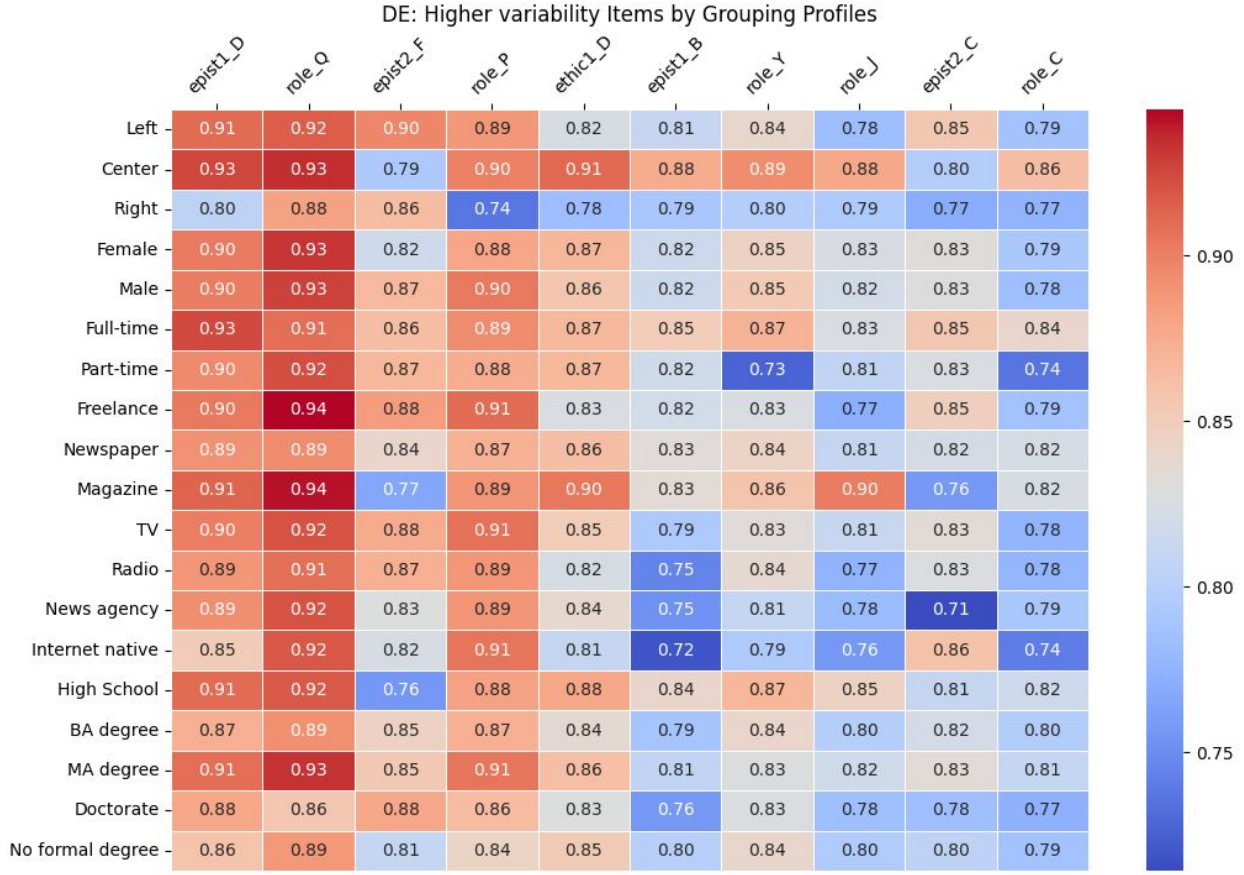
(3-1) Germany: Three Dimension Compound Comparison



(3-2) Germany: Across Dimensions



(3-3) Germany: Higher Variability Items

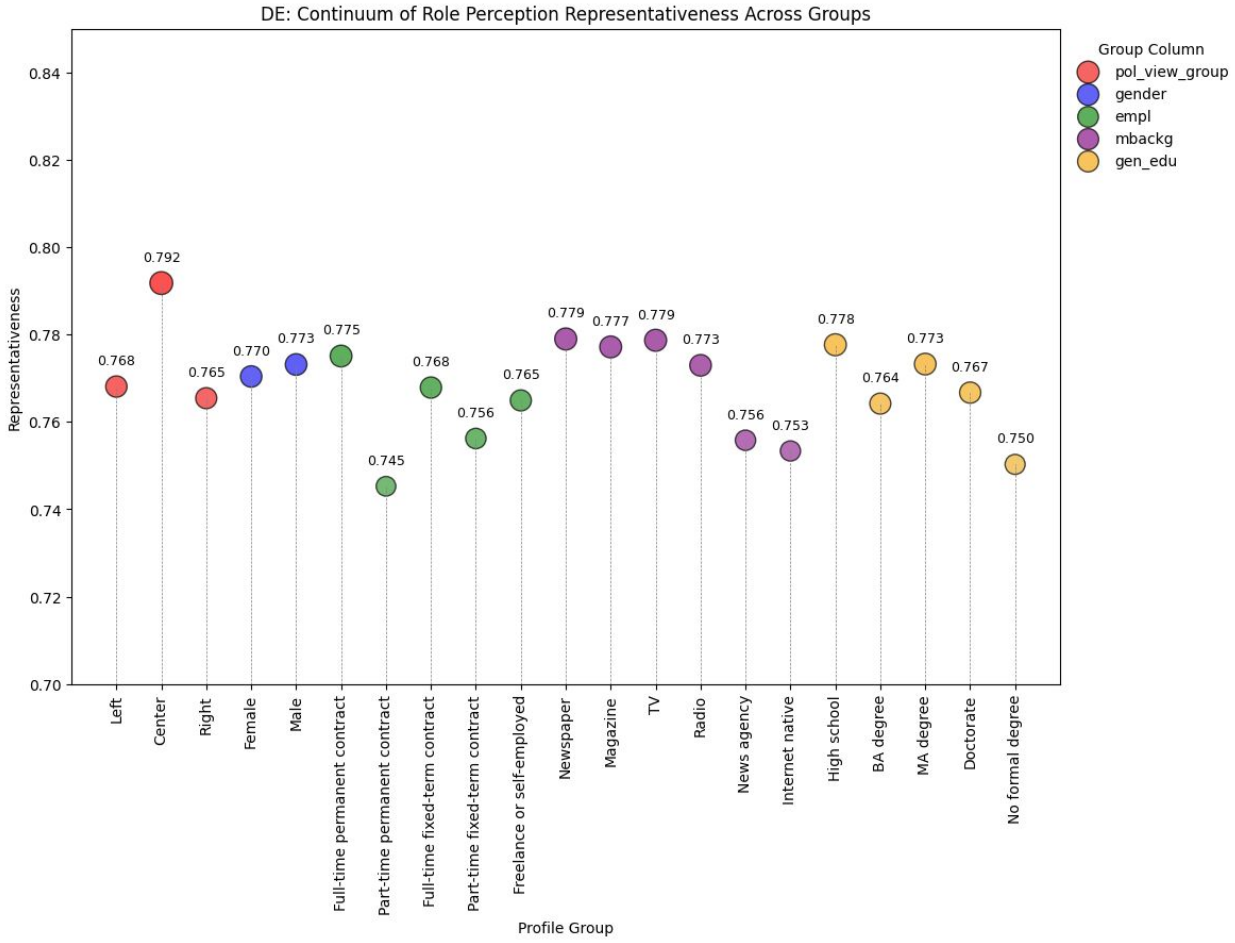


#.	1	2	3	4	5	6	7	8	9	10
	epist1_D	role_Q	epist2_F	role_P	ethic1_D	epist1_B	role_Y	role_J	epist2_C	role_C
CV	0.327	0.295	0.243	0.239	0.217	0.213	0.207	0.183	0.179	0.156

Note. CV = coefficient of variation.

S6. GPT-4o Representativeness prompted by German Survey Template

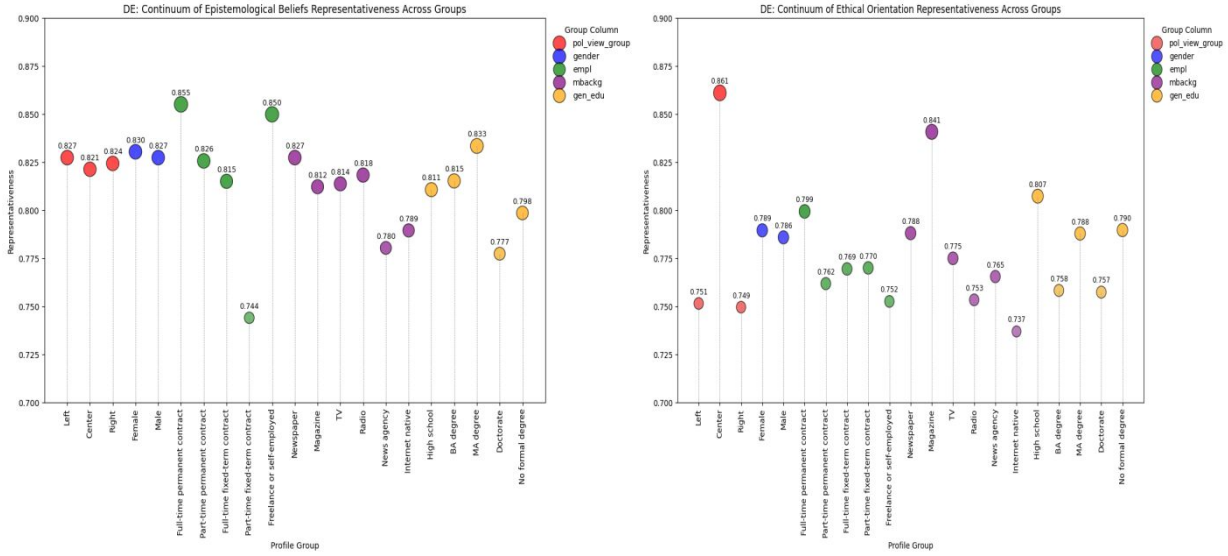
Besides the main cross-national comparisons, we designed a GPT simulation using the German-language version of the Worlds of Journalism Study (WJS) questionnaire to construct a QA prompt template. This additional prompting was intended to more closely mirror the actual survey context of German journalists. Using this template, GPT-4o was prompted in the same way to generate responses to the WJS journalistic culture batteries. These responses were then compared with the actual distribution of responses from German journalists, following the same procedure as in the main analysis.



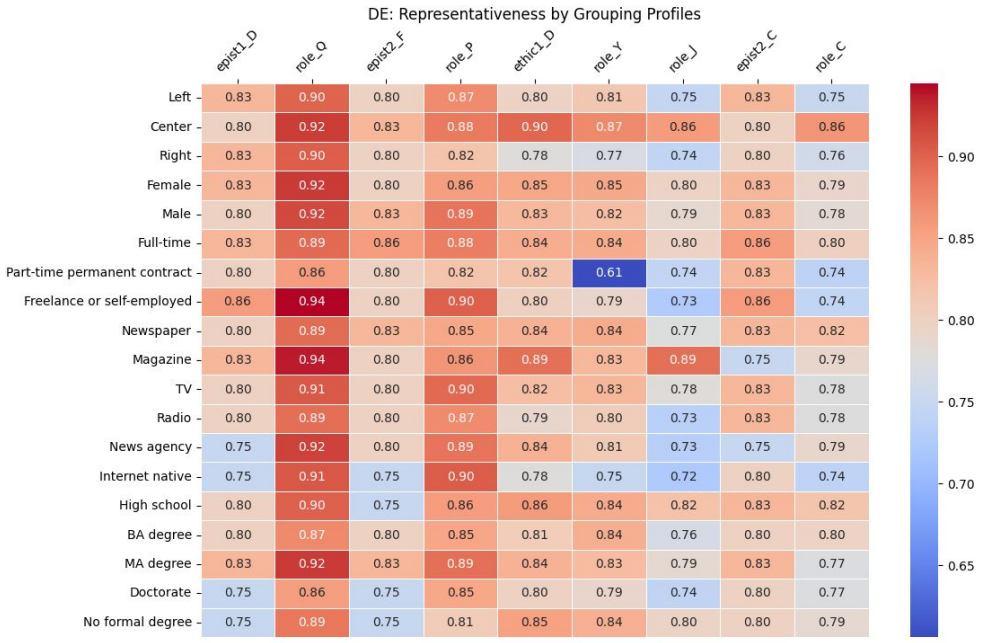
Repeated promptings yielded a Krippendorff's alpha of 0.86, indicating highly consistent outputs—particularly given that the response options were ordinal on a five-point Likert scale. While the German-language prompts showed slight numerical differences from the English prompts, the overall patterns were highly similar. Specifically, the Krippendorff's alpha between the two prompting conditions was 0.85, further confirming a high level of similarity. Since the main analysis showed the strongest alignment between GPT responses and the German dataset, these findings are consistent with expectations of similarity across the two model predictions.

Overall, a pronounced centrist bias appeared in both English and German prompting when compared with the responses of German journalists, but notable differences emerged in the

dimension of epistemological beliefs. In the main analysis, left-leaning orientations were followed by centrist and then right-leaning orientations. By contrast, the German-language prompts still reflected a left bias, but centrist orientations were less strongly represented than right-leaning ones. Although this difference is not large, it suggests that epistemic orientation may become more ideologically driven when using German-language prompts. This pattern points to the need for further investigation in future research.



Lastly, although there were also numerical differences in item response variability across groups, the overall pattern remained consistent with the main analysis.



S7. Krippendorff's Alpha Between Outputs From the Main Simulation and Additional Simulations

	Full Context	Generic	US	UK	Germany
Full Context	1				
Generic	0.753	1			
US	0.722	0.875	1		
UK	0.809	0.818	0.902	1	
Germany	0.854	0.746	0.763	0.870	1
No Context	0.551	0.498	0.365	0.430	0.551

Note. Full Context denotes GPT outputs generated with system prompts specifying the journalist identity and survey timing used in the main analysis. Generic denotes outputs generated with prompts instructing responses as a general journalist. US and UK denote outputs generated with prompts assuming a journalist working in the US or the UK, respectively. Germany uses identical prompts administered in a German-language questionnaire. No Context denotes outputs generated without journalist role-taking system prompts.

Additional simulations were conducted using a total of five system prompt variations. The objective of these simulations was to estimate the extent to which the contextual system prompt used in the Main Simulation—"Assume you are a journalist, and the survey was conducted in 2023."—influenced the results generated by the GPT-4o model.

1. GPT WJS Survey Simulations

(1) Generic Simulation

The Generic Simulation was performed by engineering the contextual system prompt to simply state **"Respond as a journalist."** The primary difference between the Main and Generic simulations is that the latter does not include the survey year, 2023, in the system prompt.

Of course, the keyword "journalist" may already function as a cue causing the model's operation to deviate from the baseline. However, this minimal instruction is a prerequisite for conducting this simulation, as the question batteries of the WJS survey are designed exclusively to ask journalists. If this keyword were removed from the system prompt, the responses simulated by GPT-4o would address entirely different questions.

For example, consider a role_A stating, "How important is it in your daily work to... 'Be a detached observer'?" If respondents are not explicitly assumed to be journalists, the question would not measure journalistic culture; that is, without the system prompt instructing GPT-4o to assume the role of a journalist, the model would answer regarding the importance of being an observer in a general workplace rather than in journalistic work. Nevertheless, the fifth simulation may provide a reference point.

(2) US Simulation

The US Simulation was conducted with the input of **"Respond as a journalist working in the US"** as the contextual system prompt. This case aims to have the GPT-4o model output responses reflecting regional/national characteristics rather than those of a general journalist.

(3) UK Simulation

The UK Simulation was conducted with the input of **"Respond as a journalist working in the UK"** as the contextual system prompt. This aims to have the GPT-4o model output responses reflecting the specific media cultural characteristics of the UK rather than those of a general journalist.

(4) Germany Simulation

The Germany Simulation followed the same approach as the US and UK simulations, but the survey template provided to GPT-4o was the German version (see S6).

(5) No Context Simulation

The No Context Simulation was performed by inputting **"Answer the questions"** instead of a system prompt assigning the journalist role. However, the context of journalism culture was maintained within the phrasing of the questions themselves.

For example, for role_A stating "How important is it in your daily work to...", the question wording was revised to include **"[...] in a journalist's daily work."** The best estimate for the variation caused by this modification is that GPT-4o's baseline model inferred the journalist culture.

This approach presents a *trade-off*. It may capture the patterns of journalism culture representation held by the model's default settings closely. However, it requires modifying the original WJS questions, and more importantly, since there is no human data where non-journalists answered the WJS survey, there is *no* ground truth standard to evaluate this simulation. Ultimately, the characteristics of its representation pattern can only be indirectly estimated through comparison with other simulations.

2. Results

(1) Main vs. Generic Simulations

GPT-4o showed acceptable inter-coder reliability (ICR) between the Main Simulation and Generic Simulation (Krippendorff's Alpha = .753). This result indicates a 75.3% agreement between the two system promptings.

Notably, for items measured on a 5-point scale, there were no instances where the directionality of responses between the two simulations flipped (from positive to negative or vice versa) based on the median value of 3. Across 39 items, only ethic_A shifted from a positive value (4) to a neutral value (3), and epist1_C shifted from a neutral value (3) to a negative value (2); these were the only cases affecting response directionality. Furthermore, a Pearson

correlation of $r = .86$ suggests that the GPT simulation is not highly sensitive to the differences between the two system prompts.

(2) Generic vs. Country Specific Simulations

The outputs of the Generic Simulation and the simulations specific to the US, UK, and Germany revealed interesting differences compared to the Main Simulation. Although the Main and Generic simulations produced patterned consistent outputs, the pattern of agreement between the Generic and Country Specific Simulations differed from that of the Main Simulation.

Specifically, the output of the Main Simulation was most consistent with that of the Germany Simulation (0.854), whereas the output of the Generic Simulation showed a pattern most similar to the US Simulation (0.875).

This implies that the difference between the Main Simulation, which included the actual survey timing (2023) in the system prompt, and the Generic Simulation, which was not guided by such information, can interact with national characteristics. In other words, the simulation assuming the year 2023 aligns more closely with the Germany Simulation, whereas in the absence of such an assumption, the alignment with the US Simulation was higher at the time of simulation execution (December 2025).

It should be noted that since this is a comparison between GPT simulations rather than between human output and GPT output, it does not affect the finding of the main analysis that the results are most similar to the responses of human German journalists. However, if using multi-models, the fact that this national/regional prompting alters the model's operation suggests that the influence of these geographical and temporal context needs to be integrated into benchmarks evaluating LLM simulation approaches.

(3) Comparisons between Country Specific Simulations

The highest agreement was observed between the US and UK simulations (Krippendorff's Alpha = .902). Agreement between the UK and Germany simulations was also high (Krippendorff's Alpha = .870), whereas agreement between the US and Germany simulations was relatively lower (Krippendorff's Alpha = .763). Nonetheless, all three scores remain within the acceptable range for inter-coder reliability (ICR). This overall consistency suggests that variations resulting from country-specific prompting manifest in micro-patterns rather than in general trends.

(4) No Context Simulation

The output of the simulation using a system prompt that did not assume a journalist role showed low agreement with all other simulations. The ICR scores ranged from Krippendorff's Alpha 0.430 to 0.551, failing to cross the acceptable threshold. This suggests that the algorithmic inference patterns evaluating journalistic culture differ significantly when the GPT-4o model is assigned to the role of a journalist compared to when it is not.

Furthermore, these results support the implications of prior studies (e.g., Kang et al., 2025; Shani et al., 2025) that emphasize the necessity of closely reflecting the characteristics of social groups when leveraging LLMs to simulate social phenomena. One point to note is that the output of the No Context Simulation shows the highest similarity with the Germany Simulation (.551). This provides additional support for the "German-prone pattern" observed in the main results, as both the Full Context Simulation (Main Simulation) and the No Context Simulation are most similar to the Germany Simulation compared to other country-specific simulations.

Taken together, these additional simulations provide consistent evidence that GPT's representational tendencies regarding journalism culture are stable, while simultaneously distinct from the representativeness of general (non-contextual) LLMs. Crucially, this supports the present study's main argument that knowledge regarding AI bias generated outside the journalistic context cannot be directly applied to the domain of journalism. The discrepancy between No Context Prompting and Full Context or Generic Prompting suggests that GPT's responses simulating baseline values and those simulating journalists are not interchangeable.

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Kang, T., Thorson, K., Peng, T. Q., Hiaeshutter-Rice, D., Lee, S., & Soroka, S. (2025). Embracing Dialectic Intersubjectivity: Coordination of Differential Perspectives in Content Analysis With LLM Persona Simulation. *Social Science Computer Review*, 08944393251410155. https://doi.org/10.1177/08944393251410155

Shani, C., Soffer, L., Jurafsky, D., LeCun, Y., & Shwartz-Ziv, R. (2025). From tokens to thoughts: How LLMs and humans trade compression for meaning. *arXiv preprint arXiv:2505.17117*. https://doi.org/10.48550/arXiv.2505.17117

S8. The Survey Responses From the Main Simulation and Additional Simulations

	Full Context	Generic	US	UK	Germany	No Context
role_A	4	4	5	5	5	3
role_B	5	5	5	5	5	5
role_C	5	5	5	5	5	4
role_D	4	5	5	4	4	4
role_E	5	5	5	5	5	3
role_F	5	5	5	5	5	4
role_G	5	5	5	5	5	4
role_H	4	5	5	4	4	3
role_I	3	4	3	3	4	4
role_J	3	4	5	5	4	1
role_K	5	5	5	5	5	5
role_L	5	5	5	5	5	4
role_M	4	5	5	5	4	4
role_N	5	5	5	5	5	5
role_O	4	5	4	4	4	4
role_P	1	1	3	2	1	4
role_Q	1	1	1	1	1	3
role_R	3	3	4	3	3	4
role_S	3	4	4	4	4	4
role_T	4	4	4	4	5	5
role_U	4	5	5	5	5	4
role_X	5	4	5	5	5	4
role_Y	5	5	5	5	5	5
role_V	5	5	5	5	5	5
ethic1_A	4	3	3	4	4	3
ethic1_B	4	4	4	4	4	4
ethic1_C	4	4	4	4	4	4
ethic1_D	2	2	2	2	2	2
epist1_A	4	5	5	4	4	4
epist1_B	4	4	4	4	4	4
epist1_C	3	2	2	2	4	4
epist1_D	2	2	2	2	1	2
epist1_E	4	3	4	3	3	3
epist2_A	4	3	3	3	2	3
epist2_B	2	2	2	2	2	2
epist2_C	4	4	4	4	4	4
epist2_D	4	4	4	4	4	4
epist2_E	5	4	4	4	5	4
epist2_F	5	5	5	5	5	5