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SYNTHETIC FAST FOOD? AUDITING GENERATIVE AI'S REPRESENTATIONS OF EUROPEAN STATES

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ABSTRACT

This article explores how Generative AI visually and textually represents national identities and cultures, focusing on depictions of selected Western and Eastern/Central European states. Patterns of bias embedded in AI-generated depictions of everyday life, work, family, national character etc. are identified. The article reveals a fragmented vision of "synthetic Europe": Eastern/Central European countries are predominantly portrayed through rural, traditional, and often backward-looking imagery while Western Europe is depicted as urban, albeit in a romanticised and historicised ways. These patterns reflect and reinforce existing stereotypes, historical hierarchies, and power disparities. The findings highlight the potential role of the "coded gaze" in perceptions of the continent and likely trajectories for producing and perpetuating bias through an increasingly shared human-AI agency. The article serves as an illustration case of the potential of AI auditing that moves beyond technical compliance to address the normative and cultural dimensions of bias.

KEYWORDS

AI bias, auditing, algorithmic gaze, Generative AI, stereotypes.

INTRODUCTION

Generative Artificial Intelligence (GenAI) has become indispensable in shaping how individuals, communities, and societies are represented, understood, and interpreted. These systems are also entwined with the values, assumptions, and cultural logics embedded in their design, training data, and deployment. Hence, AI bias is not simply a technical flaw or oversight but a reflection of broader societal power dynamics and inequalities. Hence, the rapid adoption of GenAI has introduced both unprecedented opportunities and significant challenges, particularly in the realm of sociotechnical fairness, necessitating an examination of GenAI's potential to perpetuate and amplify societal biases. Questions must thus be raised with regards to the substance of GenAI outputs that contribute to the formation of worldviews, shaping not only how we see others, but also how we see ourselves. The latter becomes particularly important as we assume a "coded gaze", which actively partakes in the construction of identities and the shaping of societal norms, intertwining human and AI agency.

This article interrogates GenAI bias by examining how such models visually and textually represent selected European countries, particularly focusing on national stereotyping. Through qualitative analysis of AI-generated outputs, recurring tropes, omissions, and distortions in AI-generated depictions of everyday life, work, family, and other aspects are identified. Thereby, the ways in which AI models construct a "synthetic Europe" as a continent stuck in a time warp are exposed. Crucially, GenAI's amplification of bias poses not just a representational problem, but also a governance challenge that necessitates regular auditing. Algorithm and AI auditing provides crucial tools for scrutinising, understanding, and mitigating the harms caused by biased outputs. Hence, in addition to its role in identifying ethical issues with GenAI models, auditing is also seen here as a contributor to the broader frameworks of AI governance. As AI-generated content increasingly informs public discourse, the need for transparent, accountable, and culturally sensitive AI systems has never been greater. While existing research tends to focus on the individual (gender, racial, bodily etc. features) or group (e.g. specific professions) level, this project deals with macro (state) level representations. This is of particular importance in times when a shared European identity and solidarity have become not just an abstract aspiration but also a geopolitical necessity in face of external threats (and, likewise, the erosion of such solidarity has become one of the aims of information warfare), making the matter of representation paramount. Indeed, it is important to keep in mind that not only GenAI transpires to possess an epistemological politics of its own[1] but also becomes a lens through which events and shared stories are remembered (and misremembered),[2] which, unsurprisingly, turns it into a useful tool in influence operations.[3] Of course, the very concept of "European identity" employed above could be seen as inherently problematic and hard to define. However, the way it is used here is completely minimal – understood as a general sense of overarching commonality, shared belonging, and common interest and to some extent encompassing both cultural and political variables. It is here that studies of AI become meaningful – one needs to inquire what tropes reproduced by AI could count as overarching similarities and whether some common ground can be determined.

BIAS AND THE AUDITING OF ALGORITHMS AND AI

In this article, we adopt a definition from Nah et al., whereby "bias refers to the inclination that AI generated responses or recommendations could be unfairly favoring or against one person or group".[4] Similarly, for Ferrara, bias can be broadly understood as 'a systematic error in decision-making processes that results in unfair outcomes'.[5] Crucially, bias in AI is hardly avoidable because "[a]ll digital technologies are guided by specific ideologies, preferences, and other logics that infuse their design and tasks with meaning, giving rise to particular outputs and specific implications".[6] The question of who is privileged and who is marginalised thus becomes of paramount.[7] This combination of privilege and marginalisation is further entrenched though algorithmic governance and the normative status of AI's outputs. The latter manifests itself as AI subjects individuals and communities to data-based representations through so-called "coded gaze", i.e. the normative classifying gaze inherent in digital technologies and derived from existing dominant representations.[8] The role, value, status, and other attributes of individuals, groups, and communities are determined by this gaze, with the ones misrecognised, misclassified, and/or misrepresented bearing the cost. Hence, the coded gaze is never passive or one-sided because it affects identities, (self-)representations, and the functioning of societal structures: "[t]he digital is always inextricably linked to the social".[9] Biased manifestations of AI's outputs, then, may result in discrimination, oppression, and symbolic violence exerted through the coded gaze.

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1 Louise Amoore, "A World Model: On the Political Logics of Generative AI," *Political Geography* 113 (2024) // https://doi.org/10.1016/j.polgeo.2024.103134

2 Mykola Makhortykh et al., "Shall Androids Dream of Genocides? How Generative AI Can Change the Future of Memorialization of Mass Atrocities," *Discover Artificial Intelligence* 3, 28 (2023) // https://doi.org/10.1007/s44163-023-00072-6

3 Lance Y. Hunter et al., "Artificial Intelligence and Information Warfare in Major Power States: How the US, China, and Russia Are Using Artificial Intelligence in Their Information Warfare and Influence Operations," *Defense & Security Analysis* 40(2) (2024) // https://doi.org/10.1080/14751798.2024.2321736

4 Fiona Fui-Hoon Nah et al., "Generative AI and ChatGPT: Applications, Challenges, and AI-Human Collaboration," *Journal of Information Technology Case and Application Research* 25(3) (2023): 285 // https://doi.org/10.1080/15228053.2023.2233814

5 Emilio Ferrara, "Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies," *Sci* 6(1) (2024): 2 // https://doi.org/10.3390/sci6010003

6 Pamela Ugwudike, "AI Audits for Assessing Design Logics and Building Ethical Systems: The Case of Predictive Policing Algorithms," *AI and Ethics* 2 (2022): 200 // https://doi.org/10.1007/s43681-021-00117-5

7 Roberto Santiago de Rook, "To Become an Object Among Objects: Generative Artificial 'Intelligence', Writing, and Linguistic White Supremacy," *Reading Research Quarterly* 59(4) (2024): 603 // https://doi.org/10.1002/rrq.569

8 Petra Jääskeläinen et al., "Intersectional Analysis of Visual Generative AI: The Case of Stable Diffusion," *AI & Society* 40 (2025): 4343 // https://doi.org/10.1007/s00146-025-02207-y; see also Joy Buolamwini, *Unmasking AI: My Mission to Protect What Is Human in a World of Machines* (New York: Random House, 2023).

9 Pamela Ugwudike, *supra* note 6, 200.

Notably, AI now plays a constitutive role in the development of worldviews. Not only human identity is heavily affected by the individual's perception of their cultural context but also "AI systems can mismatch the cultural norms and expectations of target cultural groups and produce cultural barriers" in a multitude of ways, including "imposing hegemonic classifications, offensive or toxic settings, violating cultural values that are important for a group, and by omitting, trivialising, or simplifying certain identities and histories"[10]. Such tendencies are further strengthened by cognitive offloading to AI. It is often the case that "[o]ver-reliance on generative AI technology can impede skills such as creativity, critical thinking, and problem-solving as well as create human automation bias due to habitual acceptance of generative AI recommendations".[11] If that is the case, then biases in the coded gaze can be accepted uncritically, leading to further harm to those misrepresented. Indeed, as the content generated by AI becomes a fact of life, it becomes hardly questioned at all, with audiences simply accepting the biases and alternative realities pushed by AI[12] – this further underscores the need for auditing. Crucially, biased AI outputs, e.g. racialised language, gendered imagery, politicised disinformation, or national/cultural stereotypes can, disproportionately influence users' beliefs, identities, and social attitudes.[13] Such representations can subtly influence young users' perceptions of societal roles and self-identity as well as their understanding or their own and other societies and cultures.[14] When individuals are exposed to biased AI-generated content, it can negatively shape their understanding of the world, reinforce stereotypes, and contribute to discriminatory attitudes.[15] This is especially the case as generative AI becomes one of the main sources of information, particularly among younger users.[16]

It must be recognised that GenAI systems are trained on extensive data corpora that frequently mirror existing social inequalities. As a result, their outputs may encode, reproduce, circulate, and intensify harmful biases linked to gender, race, socioeconomic position, and other attributes.[17] In doing so, these systems often reflect hegemonic

[10] Ingrid Campo-Ruiz, "Artificial Intelligence May Affect Diversity: Architecture and Cultural Context Reflected Through ChatGPT, Midjourney, and Google Maps," *Humanities & Social Sciences Communications* 12 (2025): 3 // https://doi.org/10.1057/s41599-024-03968-5

[11] Fiona Fui-Hoon Nah et al., *supra* note 4, 285–286.

[12] Yue Zhang, Jiao Tian and Fengyi Deng, "In Generative AI We Trust: An Exploratory Study on Dimensionality and Structure of User Trust in ChatGPT," *Interacting With Computers* 38(1) (2026): 58–76 // https://doi.org/10.1093/iwc/iwaf029

[13] Veronica Barassi, "Amplified Visibility: Critical Reflections on Children's Social Media Presence, Sharenting and Tech-Abuse in the Age of Generative AI"; in: Taylor Annabel et al. (eds.), *The Hashtag Hustle: Law and Policy Perspectives on Working in the Influencer Economy*. Cheltenham, and Northampton (MA): Edward Elgar, 2025; Yucong Lao, Noora Hirvonen and Stefan Larsson, "AI and Authenticity: Young People's Practices of Information Credibility Assessment of AI-Generated Video," *Journal of Information Science* // https://doi.org/10.1177/01655515251330605; Yucong Lao, Noora Hirvonen and Stefan Larsson, "Everyday Encounters with Deepfakes: Young People's Media and Information Literacy Practices with AI-Generated Media," *Journal of Documentation* 81(7) (2025): 216–235 // https://doi.org/10.1108/JD-01-2025-0007

[14] Roberto Santiago de Rook, *supra* note 7; Martin Miragoli, "Conformism, Ignorance & Injustice: AI as a Tool of Epistemic Oppression," *Episteme* 22(2) (2025) // https://doi.org/10.1017/epi.2024.11; Luke Munn and Leah Henrickson, "Tell Me a Story: A Framework for Critically Investigating AI Language Models," *Learning, Media and Technology* 50(4) (2025) // https://doi.org/10.1080/17439884.2024.2327024

[15] Luciano Floridi et al., "An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations," *AI and Society 36*(4) (2021): 689–707 // https://doi.org/10.1007/s11023-018-9482-5; Leslie Ramos Salazar, Shanna F. Peeples and Mary E. Brooks, "Generative AI Ethical Considerations and Discriminatory Biases on Diverse Students Within the Classroom"; in: Sanae Elmoudden and Jason S. Wrench (eds.), *The Role of Generative AI in the Communication Classroom*. Hershey: IGI Global, 2024.

[16] Ryen W. White and Chirag Shah, *Information Access in the Era of Generative AI* (Cham: Springer, 2025).

[17] Luhang Sun et al., "Smiling Women Pitching Down: Auditing Representational and Presentational Gender Biases in Image-Generative AI," *Journal of Computer-Mediated Communication* 29(1) (2024) // https://doi.org/10.1093/jcmc/zmad045; Petra Jääskeläinen et al., *supra* note 8; Elisabetta Risi, Marco Briziarelli and Yousuf Muhammad, "Unpacking the Outputs of Generative AI Platforms and Revealing Gender and

worldviews while marginalising alternative perspectives,[18] thus contributing to varied forms of epistemic injustice.[19] Biases in this context are, therefore, not isolated statistical artefacts but, instead, structurally embedded; consequently, they give rise to recurring patterns of misrepresentation that reinforce stereotypes or exclude entire groups from visibility.[20] The problem becomes especially acute when such biases remain unexamined, since GenAI outputs can then shape perceptions in ways that are subtle yet powerful. Cultural bias in generative AI can produce wide-ranging consequences, including the reinforcement of cultural misunderstandings and inequalities,[21] the constraining of artistic expression, and the entrenchment of cultural hegemony.[22] Such biases may also generate dissatisfaction, mistrust, and even feelings of alienation among individuals from negatively or otherwise inaccurately stereotyped backgrounds.[23] Representations of specific places and regions can similarly influence self-perception – particularly when individuals encounter negative stereotypes about their own communities or are exposed to depictions framed as normative or aspirational – shape attitudes towards peers from stereotyped groups while increasing vulnerability to disinformation about those communities.

The above effects are further reinforced by the fact that AI is becoming increasingly constitutive of cultural production practices,[24] meaning that its effects are not just individual – they are also collective, shaping self-perception of cultural groups and their perception by others. In this sense, one could say that GenAI becomes a cultural authority on its own.[25] Its growing use, however, results in homogenisation[26] as AI

Social Re-Presentations"; in: Erkan Saka, ed. *Understanding Generative AI in a Cultural Context: Artificial Myths and Human Realities*. Hershey: IGI Global, 2025; Yiran Yang, "Racial Bias in AIGenerated Images," *AI & Society* 40 (2025) // https://doi.org/10.1007/s00146-025-02282-1

18 Kate Crawford, *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence* (New Haven: Yale University Press, 2021); Tarleton Gillespie, "Generative AI and the Politics of Visibility," *Big Data & Society* 11(2) (2024) // https://doi.org/10.1177/20539517241252131; Christopher J. Jenks, "Communicating the Cultural Other: Trust and Bias in Generative AI and Large Language Models," *Applied Linguistics Review* 16(2) (2025) // https://doi.org/10.1515/applirev-2024-0196

19 Isobel Barry and Elise Stephenson, "The Gendered, Epistemic Injustices of Generative AI," *Australian Feminist Studies* 40 (2025) // https://doi.org/10.1080/08164649.2025.2480927; Apoorv Pragya, "Generative AI and Epistemic Diversity of Inputs and Outputs: Call for Further Scrutiny," *AI & Society* 40 (2025) // https://doi.org/10.1007/s00146-024-02097-6

20 Michael Dugeri, "The Cannibalization of Culture: Generative AI and the Appropriation of Indigenous African Musical Works," *Journal of Intellectual Property and Information Technology Law* 4 (2024) // https://doi.org/10.52907/jipit.v4i1.502; Elin Kanhov, Anna-Kaisa Kaila and Bob L. T. Sturm, "Innovation, Data Colonialism and Ethics: Critical Reflections on the Impacts of AI on Irish Traditional Music," *Journal of New Music Research* 53(1–2) (2024) // https://doi.org/10.1080/09298215.2024.2442359; Lucinda McKnight and Cara Shipp, "'Just a Tool'? Troubling Language and Power in Generative AI Writing," *English Teaching: Practice & Critique* 23(1) (2024) /// https://doi.org/10.1108/ETPC-08-2023-0092; Alice Xiang, "Fairness and Privacy in an Age of Generative AI," *The Columbia Science & Technology Law Review* 25 (2024) // https://doi.org/10.52214/stlr.v25i2.12765

21 John Danaher, "Generative AI and the Future of Equality Norms," *Cognition* 251 (2024) // https://doi.org/10.1016/j.cognition.2024.105906; Tiina Räisä and Matteo Stocchetti, "Epistemic Injustice and Education in the Digital Age," *Journal of Digital Social Research* 6(3) (2024) /// https://doi.org/10.33621/jdsr.v6i3.33235

22 Payal Arora, "Creative Data Justice: A Decolonial and Indigenous Framework to Assess Creativity and Artificial Intelligence," *Information, Communication & Society* 28(3) (2025) // https://doi.org/10.1080/1369118X.2024.2420041; Michael Dugeri, *supra* note 20; Elin Kanhov, Anna-Kaisa Kaila and Bob L. T. Sturm, *supra* note 17.

23 Roberto Santiago de Rook, *supra* note 7; Judith Simon, "Generative AI, Quadruple Deception & Trust," *Social Epistemology* 40(1) (2025) // https://doi.org/10.1080/02691728.2025.2491087

24 Arisa Yasuda and Yoshihiro Maruyama, "Creativity in the Age of Generative AI," *AI and Ethics* 6 (2026) // https://doi.org/10.1007/s43681-025-00848-9

25 Doudou Mou, "After Authorship: Generative AI and the Reorganization of Cultural Authority in Mass Communication," *Visual Communication and Media Arts* 2(1) (2026).

26 Valerie Visanich and J. Michael Ryan, "The AI-ization of Society and Cultural Management Through a McDonaldization Lens," *Journal of Cultural Management and Cultural Policy* 11(2) (2025) // https://doi.org/10.1177/27018466251374265

reproduces epistemological hierarchies, particularly vis-à-vis non-dominant cultures.[27] Hence, it ends up reinforcing hegemonic memory, derived from datafied assumptions, instead of disrupting it; AI cannot provide equitable representations if it has not been trained accordingly.[28] This is also not a problem that would be easy to solve: on the contrary, bias can be (and is) introduced in every step of the AI pipeline, including but not limited to data selection and annotation, model design, and user interaction, thereby strengthening the sterotypicality of both cultural production and cultural representation.[29] Likewise, GenAI can be seen as prone to stereotypisation and oversimplification simply because of the way the models themselves work, regardless of other factors, such as the richness and diversity of training data.[30] If anything, AI's operational logic means that dominant representations of cultures and cultural identities can be pushed to (almost) caricatured extremes,[31] thereby precluding real intercultural communication and understanding.[32] To that effect, the (inter)cultural role of GenAI can be seen as inherently problematic.

In everyday situations, AI "interfaces with humans", particularly in the case of generative models that are directly prompted by human users, "creating multimodal spaces of interaction and communication that are consequential to how societies make sense of, and carry out actions", including those that pertain to (inter)cultural interactions and learning about cultures and societies.[33] AI models "serve as central figures in shaping discourse, molding the narratives that shape perceptions, preservation and sharing of cultures".[34] Increasingly, GenAI intermediates the transmission and interpretation of even one's own culture, becoming an actor in socialisation and the passing on of tradition through digital representations.[35] As Jenks notes, "algorithmic biases are cultural biases"[36]: not only they are inherent in data and the programmers' points of view, subsequently imprinted in AI models, but also they directly impact how we view our surroundings and the multiple others therein.[37] Human-AI interaction should then be understood not as a back-and-forth between two distinct entities, but as entanglements[38] through which they become inseparable, coexisting and co-constituting each other on a horizontal plane, meaning that agency in communication is *shared* between humans and digital artifacts, including AI.[39]

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27 Matthew Nyaaba, Alyson Leigh Wright and Gyu Lim Choi, "Generative AI and Digital Neocolonialism in Global Education: Towards an Equitable Framework," *Journal of Digital Educational Technology* 6(1) (2026) // https://doi.org/10.30935/jdet/17862

28 Olli Hellmann, "Colonial Bias in AI Training Data: Prompting Sora to Generate Images of Aotearoa New Zealand's Historical Past," *Kōtuitui: New Zealand Journal of Social Sciences Online* 21(1) (2026) // https://doi.org/10.1002/kot2.70016

29 Anna Foka et al., "Tracing the Bias Loop: AI, Cultural Heritage and Bias-Mitigating in Practice," *AI & Society* 40 (2025) // https://doi.org/10.1007/s00146-025-02349-z

30 Rodney, S. Jones, "Culture Machines," *Applied Linguistics Review* 16(2) (2024) // https://doi.org/10.1515/applirev-2024-0188

31 Jakub Wdowicz, "Not a Mirror, a Caricature: How LLMs Reproduce Cultural Identity?" *AI and Ethics* 6 (2026) // https://doi.org/10.1007/s43681-025-00898-z

32 David Wei Dai and Zhu Hua, "When AI Meets Intercultural Communication: New Frontiers, New Agendas," *Applied Linguistics Review* 16(2) (2025) // https://doi.org/10.1515/applirev-2024-0185

33 Christopher J. Jenks, *supra* note 18, 788.

34 Zhaoming Liu, "Cultural Bias in Large Language Models: A Comprehensive Analysis and Mitigation Strategies," *Journal of Transcultural Communication* 3(2) (2024): 230–231 // https://doi.org/10.1515/jtc-2023-0019

35 Yan Tao et al., "Cultural Bias and Cultural Alignment of Large Language Models," *PNAS Nexus* 3(9) (2024) // https://doi.org/10.1093/pnasnexus/pgae346

36 Christopher J. Jenks, *supra* note 18, 792.

37 Yan Tao et al., *supra* note 35.

38 Christopher J. Jenks, *supra* note 18, 788.

39 Ignas Kalpokas, *Malleable, Digital, and Posthuman: A Permanently Beta Life* (Bingley: Emerald, 2021).

The human-AI entanglement is further underscored by the fact that not only humans depend on AI-produced outputs, but also AI depends on human-generated data. In the latter case, bias once again creeps in: if AI models have been trained on incomplete or biased data, their outputs will merely reproduce such patterns.[40] If the training data contains discriminatory attitudes, stereotypes, implicit cultural assumptions, or simply one-sided representations, the output generated by AI would further perpetuate existing harms.[41] Hence, disparities of influence between cultures, points of view, regional perspectives etc. become major obstacles to AI's intercultural and international fluency.[42] As the "real" world is ripe with biases and the models need extremely large amounts of data from a rich variety of sources to be trained effectively, it is reasonable to assume that all AI models would be biased in some way, just like humans are; the difference is that while the biases of almost every human (except for those in positions of unchecked power) are unlikely to have impact beyond their immediate social circles, those built into AI acquire global significance. Even in cases where utmost care is taken to avoid biases, they may well arise or become more prominent *after* the model has been released, such as through feedback loops as "[u]sers contribute […] by reinforcing biases through interactions or providing positive feedback to outputs reflecting their own cultural biases" while AI, in turn, "interprets this feedback as a preference for biased content".[43] Thus, a further way in which human-AI entanglement can become a source of bias emerges. In turn, the biases inherent in AI models pose significant challenges because they affect not only the direct users of the models in question but also have trickle-down effects through downstream applications:[44] AI models are integrated into other tools and services, meaning that biases and other shortcomings are going to manifest themselves across the board. Therefore, the growing use and impact of AI models across a wide range of domains creates an urgent need to better understand their impact, including potential harms and shortcomings.[45] One way to gain such understanding is auditing.

It is typically – rightfully – asserted that the training data underpinning GenAI models largely reflect cultural norms, values, and viewpoints dominant in Western, English-language contexts.[46] Accordingly, AI models internalise and reproduce these particularities, generating outputs that may be skewed, culturally insensitive, or overtly discriminatory towards people and communities from other cultural backgrounds. This process reinforces dominant cultural narratives[47] and perpetuates stereotypical or inaccurate portrayals of non-Western people, objects, and environments. However, less

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[40] Katharina Simbeck, "They Shall Be Fair, Transparent, and Robust: Auditing Learning Analytics Systems," *AI and Ethics* 4 (2024): 557 // https://doi.org/10.1007/s43681-023-00292-7; see also Roberto Santiago de Rook, *supra* note 7; Yan Tao et al., *supra* note 35.

[41] Zhaoming Liu, *supra* note 34, 228.

[42] Kostas Karpouzis, "Shadows in the Digital Cave: Controlling Cultural Bias in Generative AI," *Electronics* 13(8) (2024) // https://doi.org/10.3390/electronics13081457

[43] Zhaoming Liu, *supra* note 34, 229–230.

[44] Jakob Mökander et al., "Auditing Large Language Models: A Three-Layered Approach," *AI and Ethics* 4 (2024): 1103 // https://doi.org/10.1007/s43681-023-00289-2

[45] Christopher J. Jenks, *supra* note 18, 788.

[46] Emily M. Bender et al., "On the dangers of stochastic parrots: Can language models be too big?" *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (2021) // https://doi.org/10.1145/3442188.3445922; Kate M. Miltner, "'AI Is Holding a Mirror to our Society': Lensa and the Discourse of Visual Generative AI," *Journal of Digital Social Research* 6(4) (2024) // https://doi.org/10.33621/jdsr.v6i440456

[47] Gregory Gondwe, "CHATGPT and the Global South: How are Journalists in Sub-Saharan Africa Engaging with Generative AI?" *Online Media and Global Communication* 2(2) (2023) // https://doi.org/10.1515/omgc-2023-0023; Elise Berlinski, Jérémy Morales and Samuel Sponem, "Artificial Imaginaries: Generative AIs as an Advanced Form of Capitalism," *Critical Perspectives on Accounting* 99 (2024) // https://doi.org/10.1016/j.cpa.2024.102723

attention is generally paid to potential stereotypes and biases pertaining to Wester societies themselves or national and regional differences within the West. This is precisely the gap that this article aims to address.

LAYING GROUND: AUDITING GENERATIVE AI OUTPUTS

AI auditing has roots in earlier practices of software auditing as well as in broader business practices.[48] Following Brown, Davidovic and Hasan, "audits involve collecting data about the behavior of an algorithm as it is used in a particular context, and then using that data to assess whether the behavior is negatively impacting some interests (or rights) of people affected by that algorithm".[49] Auditing can be seen as a governance mechanism that enables the identification and mitigation of risks pertaining to, in this case, GenAI systems.[50] In particular, if auditing practices and criteria are standardised, the latter can help make AI governance more practical and enforceable.[51] Thus, auditing helps go beyond the bare minimum of compliance with codified norms and critically engage with the values, assumptions, and practices, embedded in AI models.[52] Hence, AI auditing is crucial in maintaining fairness and transparency, reducing bias, and ensuring fairness.[53]

Koshiyama et al. identify three layers of algorithm auditing: data (the input), model (its parameters and other features), and development (design, documentation etc.).[54] However, there is a need to add a fourth layer – output – because, first, two of the aforementioned layers (data and model) often lack transparency in the case of GenAI, hence, they can only be inferred from the output and, second, the complexity and scale of such models means that biases may not be picked up in the preceding layers but become apparent in the output. Consequently, this research focuses on extraction of salient features and potential biases from AI-generated images and text containing national representations.

According to Goodman and Trehu, three questions must be explicitly answered when conducting AI auditing: *what* (the subject), *why* (objectives), and *how* (methods).[55] In terms of *what*, this research focuses on the visual and textual outputs of GenAI models purporting to represent the daily lives and inhabitants of selected Western and Eastern/Central European countries. As for *why*, the aim is to identify biases (if any)

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[48] Jakob Mökander and Luciano Floridi, "Operationalising AI Governance Through Ethics-Based Auditing: An Industry Case Study," *AI and Ethics* 2 (2023): 451–468 // https://doi.org/10.1007/s43681-022-00171-7

[49] Shea Brown, Jovana Davidovic and Ali Hasan, "The Algorithm Audit: Scoring the Algorithms that Score Us," *Big Data & Society* 8(1) (2021): 2 // https://doi.org/10.1177/2053951720983865

[50] Jakob Mökander et al., *supra* note 44, 1085.

[51] Alexander Blanchard, Christopher Thomas and Mariarosaria Taddeo, "Ethical Governance of Artificial Intelligence for Defence: Normative Tradeoffs for Principle to Practice Guidance," *AI & Society* 40 (2025) // https://doi.org/10.1007/s00146-024-01866-7; see also Matti Minkkinen, Joakim Laine and Matti Mäntymäki, "Continuous Auditing of Artificial Intelligence: A Conceptualization and Assessment of Tools and Frameworks," *Digital Society* 1 (2022) // https://doi.org/10.1007/s44206-022-00022-2; David Manheim et al., "The Necessity of AI Audit Standards Boards," *AI & Society* 40 (2025) // https://doi.org/10.1007/s00146-025-02320-y

[52] Jakob Mökander and Luciano Floridi, "Ethics-Based Auditing to Develop Trustworthy AI," *Minds and Machines* 31 (2021) // https://doi.org/10.1007/s11023-021-09557-8

[53] Daniel S. Schiff, Stephanie Kelley and Javier Camacho Ibáñez, "The Emergence of Artificial Intelligence Ethics Auditing," *Big Data & Society* 11(4) (2024) // https://doi.org/10.1177/20539517241299732; Luhang Sun et al., "Smiling Women Pitching Down: Auditing Representational and Presentational Gender Biases in Image-Generative AI," *Journal of Computer-Mediated Communication* 29(1) (2024) // https://doi.org/10.1093/jcmc/zmad045

[54] Adriano Koshiyama et al., "Towards Algorithm Auditing: Managing Legal, Ethical and Technological Risks of AI, ML and Associated Technologies," *Royal Society Open Science* 11 (2024) // https://doi.org/10.1098/rsos.230859

[55] Ellen P. Goodman and Julia Trehu, "Algorithmic Auditing: Chasing AI Accountability," *Santa Clara High Technology Law Journal* 39(3) (2023).

and broader representational patterns pertaining to these countries. And with regards to *how*, textual (inquiry-based reading) and image content analysis is performed on a selection of outputs.

Content analysis can be defined as a research methodology that strives to make inferences from a given medium within the use context of the material in question.[56] In its qualitative form (embraced in this article), content analysis works through interpretation of patterns and themes.[57] Through it, "[c]onclusions can be drawn about the communicator, the message or text, the situation surrounding its creation – including the sociocultural background of the communication – and/or the effect of the message", aiming for the "big picture" of the subject represented by the research sample.[58] Content analysis is an interpretivist methodology that is multifaceted and flexible, suitable "for analyzing linguistic and visual content across many social science research frameworks".[59] In particular, attention must be given to the multimodal nature of content analysis and the ways in which "multiple modes – for example, illustrations, photography, written language, and design elements – add to or expand the meaning potential of texts beyond the meaning potentials of individual modes": the sum total of different elements and their interrelationship is seen as a means to access meaning.[60]

For text analysis, inquiry-based reading (IBR) is adopted as a method to identify and dissect country representations generated by the AI model. As a research method, IBR is "persistently oriented by a topic of inquiry that both precedes and surpasses reading a given text"; consequently, IBR can be understood as a necessarily critical and a "means of producing knowledge about an object external to the text itself".[61] When using IBR, then, "the various texts become stepping stones in a continuous journey towards more complex understandings of the object of inquiry".[62] Here, the aim is to identify the encoded stereotypes, ideological assumptions, historical and political cliches, and other biased representations of the selected countries and potential regional tendencies. IBR as a method presupposes indictive identification of biases, i.e. starting without a prior list or preconceptions and building a picture within the process of reading itself.

Three sets of images and texts pertaining to selected European countries were generated in different waves: late December 2024, late February 2025, and late April 2025 to account for possible changes in the models. In total, eight countries were selected: four from Eastern/Central Europe (Lithuania, Poland, Ukraine, Romania) and four from Western Europe (Germany, France, the Netherlands, Belgium). For image generation, Microsoft Designer, Canva, DeepAI, and Adobe Express were used. All platforms were prompted using the same textual cues during all three waves of generation:

- 'A scene from everyday life in [country]';
- 'A [nationals of the country] family having fun';

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56 Marilyn Domas White and Emily E. Marsh, "Content Analysis: A Flexible Methodology," *Library Trends* 55(1) (2006) // https://doi.org/10.1353/lib.2006.0053

57 Frank Serafini and Stephanie F. Reid, "Multimodal Content Analysis: Expanding Analytical Approaches to Content Analysis," *Visual Communication* 22(4) (2023): 626 // https://doi.org/10.1177/1470357219864133

58 Marilyn Domas White and Emily E. Marsh, *supra* note 52, 27, 39.

59 Frank Serafini and Stephanie F. Reid, *supra* note 56, 625.

60 Ibid., 629.

61 Lina Katan and Charlotte Andreas Baarts, "Inquiry-Based Reading: Towards a Conception of Reading as a Research Method," *Arts and Humanities in Higher Education* 19(1) (2020): 60, 70 // https://doi.org/10.1177/1474022218760261; see also Ignas Kalpokas and Julija Kalpokienė, "I VR Therefore I Am: Toxic Binary Thinking in Visions of the Metaverse," *Information, Communication & Society* 28(5) (2025) // https://doi.org/10.1080/1369118X.2024.2427119

62 Lina Katan and Charlotte Andreas Baarts, *supra* note 60, 71; see also Ignas Kalpokas and Julija Kalpokienė, *supra* note 61.

- ‘A picture of [nationals of the country] having a good time’;
- ‘A picture of [nationals of the country] at work’;
- ‘A typical afternoon scene in [country]’.

For text generation, the prompt was: ‘Outline for a Novel Set in Contemporary [country]’, using ChatGPT, Gemini, and Claude. The decision to form the prompt for textual output indirectly, in this case – as an outline for a novel, was made because while it can be expected that, when asked for a straightforward description of contemporary life in a particular country, the model would regurgitate a mix derived from the current affairs stories in its training data, an indirect prompt helps assess how particular tropes and salient features are embedded as *quintessential* to life in that country (see e.g. Munn and Henrickson 2024).

VISUAL REPRESENTATIONS: MUSEUM EUROPE?

Beginning with visual representations, in the case of Lithuania, there was some propensity to associate life and activities with rural, even historicised, settings, including villages and farmhouses reminiscent of the nineteenth or early twentieth century (although there were several images of afternoons and scenes of everyday life set in old towns as well). When combining with instances of traditional clothing, half of the Lithuanian sample in April contained at least one historicised element, thereby constructing a very specific image of typical Lithuanianness. While there were some instances of alcohol consumption in the December batch, it was in February and April that this trend became particularly visible, with having a good time mostly involving alcohol consumption.

As for Romania, the propensity of displaying rural villagescapes (with or without people) was extremely evident, particularly in images representing everyday life and typical afternoons. Traditional clothing was also quite visible, mostly in conjunction with village settings: most images in every batch included at least one rural/historicised element. A notable feature in December and February was the prevalence of older people, mostly but not exclusively coinciding with village scenes. The general impression given by the AI-generated images was that of a sleepy backwater of Europe. To a slightly lesser extent, the rural trend was also visible in Ukraine, again in typical life and afternoon scenes, strengthened by the presence of traditional attire. While less prevalent than in Romania, village/rural scenes still comprised a significant proportion. In general, there was at least one rural element in approximately half of the images. Alcohol in Ukraine images was more prevalent than in Romania or Poland, associated with having fun more than with other prompts.

Poland, meanwhile, was arguably the least pronounced out of all countries in the sample, with some propensity towards alcohol and rural settings, but also providing some old town views and city settings (although they were few and far between), making it difficult to establish clear national patterns. It seems that Poland was a land in-between and, therefore, left largely feature-less.

Illus. 1. Left to right: a typical afternoon in Lithuania (Adobe Express), a scene from everyday life in Lithuania (Microsoft Designer), typical afternoon in Poland (Canva), Polish people having a good time (Deep AI)

Illus. 2. Left to right: Polish people at work (Microsoft Designer), Romanians at work (Adobe Express), a typical Romanian afternoon (Adobe Express), everyday life in Romania (Microsoft Designer)

Illus. 3. Left to right: Ukrainians at work (Adobe Express), Ukrainians at work (Canva), Ukrainian everyday life (Deep AI), Lithuanian everyday life (Canva)

Illus. 4. Left to right: Lithuanian everyday life (Microsoft Designer), Polish everyday life (Adobe Express), Polish family (Deep AI), Romanians at work (Deep AI)

Illus. 5. Left to right: Romanians having a good time (Microsoft Designer), Ukrainians at work (Deep AI), Lithuanians at work (Adobe Express), Lithuanian family (Deep AI)

Illus. 6. Left to right: Belgian everyday life (Microsoft Designer), French family (Deep AI), German family (Canva), everyday life in the Netherlands (Canva)

By contrast, Belgium, more than any other, was presented as a country of city-scapes: all scenes of everyday lives and afternoons featured a city or old town view, with people spending time in street cafes in at least half of those cases. Any instances of rural settings were exclusively of family scenes. Also, alcohol was quite prevalent, typically associated with having a good time. Contrary to the Eastern/Central European sample, only one example of traditional clothing was identified. Meanwhile, in France, images of cities and old towns were also prevalent, comprising most depictions of everyday life and afternoon scenes, typically in conjunction with street cafes. In the remaining instances, afternoon scenes were represented by images of tranquil countryside. Also, alcohol was quite prevalent while multiple images contained the Eiffel Tower, which served as an indication of Frenchness. While there were some instances of traditional attires, in several cases they referenced migrant communities living in France. Of course, one might ask whether the relative preponderance of traditional costume in Eastern/Central vs Western Europe could be seen as a form of bias or merely just another cultural marker. However, it is necessary to take one step further and as why, out of all potential markers of identity, particularly this one turned out to be prevalent and to what extent that corresponds to the actual lived practices of individuals.

Illus. 7. Left to right: afternoon in France (Adobe Express), the Dutch at work (Canva), the Dutch having a good time (Canva), Belgian afternoon (Microsoft Designer)

Illus. 8. Left to right: afternoon in France (Canva), Germans having a good time (Adobe Express), German afternoon (Canva), Dutch at work (Microsoft Designer)

Likewise, in Germany, representations of cities and old towns were prevalent in depiction of everyday life and afternoons, although sometimes replaced by villages and countryside. Street cafes were significantly less prevalent than in depictions of Belgium and France. Alcohol, as usual, was quite common, associated mostly with having fun and with daily life. Traditional attire was also more frequent than elsewhere in the Western European sample. Finally, the Netherlands were less associated with cities and cafes than other Western European countries in the sample while representations of countryside were more frequent that in other cases in the same group. Most images also featured windmills and/or canals, making this the only case where landmarks were dominant.

Crucially, regional differences were evident. Among the Eastern/Central European group, there were only limited signs of urbanisation, with scenes often depicting generic outdoors settings or small town and village surroundings. Only in Poland and Lithuania there were several instances of old town settings while in the case of Ukraine several images included what looked like war-damaged Soviet-era apartment blocks. The situation was markedly different in the Western European group where, despite internal variations, life was generally seen to be taking place in cities, particularly in or around old town districts. The latter point is notable, though: only France and the Netherlands had one image each with skyscraper-like shapes in the far background. Overall, then, synthetic Europe seems to be stuck in a time warp and somewhat museum-like: a largely rural and even ethnographic Eastern/Central Europe and Western Europeans spending time in old-town cafes, sometimes escaping into tranquil rural or small-town settings. In the same vein, one could observe a broad trend towards shabbiness and backwardness in Eastern Europe and idyllic contentness and romanticisation in Western Europe. In their own ways, though, both parts of the continent can be characterised by their anti-modernity.

Another largely anti-modern attribute was the prevalence traditional-like costumes, but that was almost exclusive to Eastern/Central Europe (Germany somewhat constituting an exception in the Western European sample). However, 'traditional' clothes displayed were mostly generic, with designs and patterns broadly reminiscent of traditional folk dress, but largely devoid of specificities. One notable exception was the Ukrainian vyshyvanka, the prevalence of which can be easily explained by its popularity as a symbol of identity, resilience, and international support during Russia's war against the country. Meanwhile, in the case of Germany, traditional attires were reminiscent of Bavarian costumes. Nevertheless, the regional split clearly contributed to the apparent division between the more urban West and a rural East.

Anti-modernity can be seen also in depictions of work: while in most cases and all countries involved, images of generic office work were generated, it was in the more specific images that an interesting trend could be observed: they portrayed people engaged in manual labour (from non-mechanised agriculture to manual assembly), traditional crafts, or selling fruit and vegetables at market stalls, thus further contributing to the sense of synthetic Europe being a large open-air museum. In Eastern/Central Europe, some construction jobs were also identifiable. In either case, no high-tech jobs were portrayed. In fact, the only instances of technology displayed were laptops in generic office settings and (rarely) cars.

In most cases, however, images were largely devoid of context, with individuals displayed without clear surroundings. Again, some differences could be observed, with Poland in particular (and, to a lesser extent, Lithuania) being more generic and decontextualised and existing in a somewhat non-descript space (Romania and Ukraine had more instances of place and contexts – largely rural and village backdrops). Moreover, only depictions of Western European countries (particularly the Netherlands, followed by France) had identifiable country-specific landmarks (windmills and canals for the Netherlands, the Eiffel Tower for France; also, several waffle kiosks for Belgium). Germany, just like its more eastern counterparts, had none. Overall, the scenes of people having fun tended to be the most generic, typically displaying young individuals partying or otherwise enjoying themselves, typically in seemingly outdoor settings. Likewise, families were also mostly devoid of specificities, with prevalent depictions of nuclear families, again, mostly outdoors, although in settings that were typically too ill-defined to be ascribed to, for example, the countryside. While such images could be largely interchangeable, they were sometimes superficially localised: for example, a generic picnic could feature an Eiffel Tower for France, a bouquet of tulips or a windmill for the Netherlands or some national flags for Germany (again, no specific indications in Eastern/Central Europe, further pushing it into a generic limbo).

Another notable feature was that in Eastern/Central Europe only heterosexual families were depicted, whereby in France four images in the sample had same-sex individuals with children; there was also one such image each in Germany, Belgium, and the Netherlands; also, there were only two images of a single parent (in the Netherlands and France). There were no individuals with visibly identifiable disabilities across the sample, other than the bodily distortions characteristic of AI-generated content. There was also considerable racial diversity in representations of France and, to a slightly lesser extent, Belgium; while Germany and the Netherlands were shown as considerably more "white", diversity was encountered nevertheless. By contrast, there was no diversity in Eastern/Central Europe. Finally, while young adults were more shown more often than any other age group, in the Eastern/Central European sample there was some tendency to populate images with mostly or solely older individuals, typically in rural settings, thus further contributing to the split between the younger urban Westerners enjoying city life and the more rural and traditional demographically challenged Easterners.

AI-GENERATED PLOT SUGGESTIONS: PRISONERS OF HISTORY?

The prompts requesting depiction of life in the sample countries almost invariably returned results focusing on political and societal challenges. There were only several plot suggestions that did not involve political themes: for example, some ChatGPT's plot suggestions for Belgium and France dealt with art theft. In a few cases, though, the political aspect seems to be stretched to fit national specificities, as in a plot for Belgium, suggested by Claude in April, which revolved around a conspiracy to mistranslate EU documents. Elsewhere, one storyline for Germany (by Gemini) dealt with surveillance and digital control rather than historically rooted tensions or corruption. Nevertheless, it is worth stressing that in most cases generative AI output did not display significant variation within the same month, with very similar plots being recycled, only adding national specificities.

The December batch of generated texts was more overtly political, particularly in the case of Western Europe, focusing on immigration, colonial legacies etc.; in later months, more abstract depictions of corruption and entanglement between politicians and organised crime as well as other societal ills became prevalent, although usually still with echoes of historical challenges and injustices or structural inequalities. Heritage and history thereby functioned as a weight that had to be dealt with either at a societal level (ongoing oppression) or at a personal/family level (dark ancestral secrets), or both. However, with every subsequent batch, the plots seemed to take a darker turn, particularly inasmuch as the representations of Western European states were concerned: if in December, societal tensions and inequalities were played out in the open, with the state and civil society ultimately able to sort things out (happily ever after endings), in subsequent batches, the state, or high-ranking officials, themselves became part or even the source of the problem, entangled in a web of crime, conspiracy, and potentially attempts to subvert democracy itself. Likewise, while particularly in the December batch, generative AI models (and ChatGPT more than others) represented an optimistic outlook, portraying grassroots emancipation and victory over discrimination and corruption (except for Lithuania and Poland, where corrupt officials were portrayed to have largely won), in the subsequent batches, the outcomes were significantly more ambiguous, often leaving an open question as to whether the pursuit of truth or societal change was even worth it.

While all countries seemed to be burdened by history, the Eastern/Central European group was significantly more so, with almost all plot suggestions including some aspect of dealing with the communist past. These included a wide range of occurrences, from flashbacks and parallels between anti-communist resistance and present struggles to a more general background of post-communist wastelands and problematic socio-economic transition to shady former communist and security service characters clandestinely running the government and organised crime networks. In fact, in Lithuania, Poland, and Romania, the very transition to independence/democracy was presented as corrupt and/or corruption-enabling. Perhaps unsurprisingly, Germany occupied a middle ground, with communist legacies in the eastern part of the country still providing an important backdrop in AI suggestions. Also, tradition and European integration were presented as polar opposites that Eastern/Central European societies (and, to some extent, again Germany) had to deal with. In general, it transpires that the pattern used by generative AI models was identification of a historical collective trauma (colonialism, communism, or, in several German plots, Nazism) and then using it as a central organising feature.

Within the Eastern/Central European group, plot suggestions portrayed these states as permeated by systemic and endemic corruption, with entanglements between state officials and organised crime gangs often forming the crux of the conflict (particularly in Lithuania and Romania). Another major theme involved cultural transformations, with tensions between "traditional" worldviews and social attitudes on the one hand and modern European values on the other, showing these societies as still not "really" European; while such tensions were identified in most Eastern/Central European plots, they were particularly explicit in the depictions of Poland. Emigration and return migration, including the effects on rural-urban divides, were clearly visible as were patterns of economic exploitation. Post-communist economic transformation, typically presented as continuing economic decline, was presented across Lithuania, Poland, and Romania as a major source of brain drain and inequality, thereby contributing to societal tensions. In Lithuania, geopolitical tensions and threats posed by Russia and Belarus were frequently mentioned, although that was not the case in Poland, which does face a similar threat environment. Rising nationalism and xenophobia were also identified as salient features in the Lithuanian plots, even though the "other" was mostly left undefined (except for several cases portraying anti-Belorussian hatred). However, corruption and the intertwining between government and organised crime, often with Soviet-era roots, was the most frequent theme. Meanwhile, in the Polish case, tensions between conservative and liberal progressive values as well as the influence of the Catholic Church were heavily referenced, often connecting those with tensions between rural and urban communities. Likewise, the growth of right-wing populism and deterioration of democracy, with or without an additional element of corruption, was commonly suggested as part of the plot. In fact, Poland was the only country in the sample, in which presumable authoritarian tendencies (e.g. political persecution) were described. At the same time, Romania in particular was described as "a nation grappling with corruption, environmental degradation, and the outmigration of its youth" (ChatGPT, December). More than elsewhere, post-communist economic collapse was consistently portrayed as a notable feature, allegedly turning most of the country into a wasteland. Local and national government was shown as closely intertwined with organised crime and operatives of the communist regime. Finally, Ukraine was a rather special case, with AI-suggested plots revolving around Russia's war against the country, exploring matters of trauma, loss, resilience, and national identity. While references to the soviet past were also present, they were less salient as society-defining features – because the war was. There were also fewer references to corruption, although some plots did revolve around aid misappropriation.

In the Western European group, matters of national identity, challenges posed by immigration, the tension between multiculturalism and integration, disillusionment with mainstream politics, rise of far-right extremism and political polarisation more broadly, and environmental issues were particularly strongly pronounced, often also in conjunction with corruption. Other major themes included socio-economic disparities and urban-rural divides. Urban redevelopment and gentrification, typically at the expense of migrant communities (thus adding to structural discrimination and marginalisation) and driven by unscrupulous businesspeople and politicians, was a frequent theme as well. In February and especially April, terrorist plots or other forms of violence that involved an insider job within the government to stoke tensions became more prevalent. Likewise, the colonial past of Belgium, France, and the Netherlands was portrayed as not having been properly dealt with in both the public and private domains, thus producing new conflicts. The plots proposed by GenAI also tended to involve far-right politicians and community/grassroots activists (the latter usually from a migrant background) engaged in a direct confrontation, thereby framing a societal conflict within which the protagonist becomes entangled.

Each country within the group also had its specific concerns, for example, plot suggestions concerning Belgium would often reference the Flemish-Walloon divide or, in the case of France, the fate of secularism and other republican ideals; although never central, they functioned more like signposts that help separate one country from the other. In the Netherlands, meanwhile, the specific matter of flood defences was more pronounced, usually intertwined with corruption and broader instances of discrimination. In Germany, traumas of communism and the ensuing historical and post-unification divides were recurrent themes proposed by AI. Several Germany-specific plots involved infiltration of government by ex-Stasi agents, bringing it closer to some of the themes observed in Eastern/Central Europe. Nevertheless, it is notable that the plots for the Western European group involved less inter-country variation and were more interchangeable.

CONCLUSIONS

This article underscores the role of AI as an active agent in shaping worldviews, identities, and intercultural understandings. The entanglement of human and AI agency means that biases are not static; they are co-produced, iteratively reinforced, and widely disseminated through interactions between users and models. These processes contribute to the normalisation of misrepresentations, potentially deepening societal divides and exacerbating inequalities. This article has highlighted GenAI's biases, particularly in representations of selected European states. The findings demonstrate that AI-generated outputs tend to reproduce and amplify existing stereotypes and assumptions through generalised representations. Eastern/Central European countries were largely portrayed through rural, traditional, and somewhat backward-looking lenses and as permanently scarred by communism while Western Europe was often depicted in terms of historical urban chic, albeit not without societal ills or unsolved historical legacies, such as colonialism. Such representations not only reflect but also reinforce perceptions of a culturally and developmentally fragmented Europe – a synthetic construction shaped as much by historical biases as by contemporary data imbalances, suggesting the need for regular auditing of GenAI models as a way towards fostering fairer, more inclusive AI systems through vigilance and accountability in AI development and deployment.

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