

Table 1. Key Findings from 5 AI Platforms

Feature / Platform	Chat	DeepSeek	Gemini	Copilot	Perplexity
Core Stance on Cultural Bias	AI can be culturally biased because it learns patterns from human-created data, which contains biases. It does not have opinions or ideology.	AI is demonstrably culturally biased. It's a well-documented, systemic issue rooted in how models are built and the data they are trained on.	AI models are not culturally neutral; they reflect the values and biases of their training data and developers. They carry a Western-centric worldview.	AI isn't culturally neutral. Systems mirror the cultural patterns, values, and biases embedded in their training data, unintentionally amplifying dominant norms.	Yes. Most modern AI systems show cultural bias, where outputs systematically reflect some cultures' values over others.
Key Causes of Bias	<ul style="list-style-type: none"> <li>- Training Data: Dominated by Western (US/Western Europe) content; English-language perspectives dominate.</li> <li>- Language Bias: Language itself carries cultural assumptions (gender roles, power dynamics).</li> <li>- Design &amp; Evaluation: Teams from similar backgrounds shape what is considered "neutral" or "professional."</li> </ul>	<ul style="list-style-type: none"> <li>- Data Dominance: Training data is dominated by English and Western perspectives; minority group data is often underrepresented or filtered out.</li> <li>- Algorithmic Monoculture: Models gravitate toward a narrow set of values.</li> <li>- Lack of Diversity: Homogeneous development teams fail to notice potential biases.</li> </ul>	<ul style="list-style-type: none"> <li>- Data Imbalance: Trained on massive scrapes of the English-speaking internet.</li> <li>- "Garbage In, Garbage Out": Bias stems from data collection, model architecture, and human reinforcement feedback.</li> </ul>	<ul style="list-style-type: none"> <li>- Training Data: Over-represents Western, English content.</li> <li>- Models Encode Cultural Values: AI aligns more closely with certain cultural norms.</li> <li>- Language Changes "Personality": The same prompt in different languages yields culturally distinct answers.</li> <li>- Global Asymmetries: Western-led development reflects Western socio-political assumptions.</li> </ul>	<ul style="list-style-type: none"> <li>- Data Imbalance: Training data over-represents English and Western (especially US/European) sources.</li> <li>- Homogeneous Development: Teams concentrated in a few countries encode their own assumptions into design and safety policies.</li> <li>- English-Language Prompts: Prompts without cultural context pull models toward default Western settings.</li> </ul>
Manifestations & Examples of Bias	<ul style="list-style-type: none"> <li>- Representation Bias: Some cultures appear less often.</li> <li>- Stereotyping Bias: Reinforcement of harmful generalizations.</li> <li>- Normative Bias: Treating one standard as universal (e.g., communication style).</li> <li>- Translation Bias: Loss of meaning in non-dominant languages.</li> </ul>	<ul style="list-style-type: none"> <li>- Marginalization of Non-Western Perspectives: Erasure of minority groups from "high-quality" data filtering.</li> <li>- Lack of Global Preferences: Models fail to represent the world's diversity.</li> <li>- Specific Stereotypes: Can reinforce caste stereotypes, which new tools like DECASTE aim to detect.</li> </ul>	<ul style="list-style-type: none"> <li>- The "American Smile": Image generators impose Western smiling norms on all cultures.</li> <li>- Individualism vs. Collectivism: Model advice shifts based on language prompt (English vs. Chinese).</li> <li>- Stereotyping "The Other": Depicts non-Western cultures in "exotic" or "folkloric" ways.</li> <li>- Linguistic Erasure: Misinterprets dialects like African American English (AAE) as "less professional."</li> </ul>	<ul style="list-style-type: none"> <li>- AI Reproduces Societal Stereotypes: e.g., gendered stereotypes in image search (UNESCO).</li> <li>- Language-Dependent Answers: MIT research shows models shift between independent vs. interdependent thinking based on language.</li> <li>- XAI Overlooks Culture: Explainable AI studies rarely consider how cultural background affects expectations of explanations.</li> <li>- Reinforces Dominant Narratives: Subtly reproduces discourse that appears neutral but reflects specific cultural assumptions.</li> <li>- Western Bias is Pervasive: Georgia Tech study found Western bias even in models prompted in Arabic or trained on Arabic data.</li> </ul>	<ul style="list-style-type: none"> <li>- Moral &amp; Social Framing: Default values cluster around English-speaking and European countries (self-expression, environmentalism).</li> <li>- Unequal Cultural Alignment: Models align better with Western values than non-Western ones.</li> <li>- Translation Issues: Over-use of formal registers and selection of more negative interpretations for certain groups, reinforcing stereotypes.</li> </ul>
Real-World Impacts	Not explicitly detailed, but implies impacts on fairness and representation.	<ul style="list-style-type: none"> <li>- AI-driven Hiring/Moderation: Misinterpretation of dialects can lead to unfair outcomes.</li> <li>- Healthcare Disparities: Diagnostic AI can be less accurate for patients from different backgrounds.</li> </ul>	<ul style="list-style-type: none"> <li>- Linguistic Erasure: AI tools misinterpret non-standard dialects.</li> <li>- Algorithmic Colonization: Exporting AI forces Western norms onto global users.</li> <li>- Healthcare Disparities: Diagnostic AI trained on Western data is less accurate for other groups.</li> </ul>	<ul style="list-style-type: none"> <li>- Shapes Representation: Affects how people are represented online and whose values get amplified.</li> <li>- Impairs Trust: Affects how global users interpret AI-generated information.</li> <li>- Affects High-Stakes Tools: Bias influences hiring, education, healthcare and political discourse.</li> <li>- Distorts Cultural Heritage: Can flatten culturally specific knowledge in heritage contexts.</li> </ul>	<ul style="list-style-type: none"> <li>- Unequal Cultural Alignment: Models align better with Western values than with those of non-Western countries.</li> </ul>
Mitigation Strategies	<ul style="list-style-type: none"> <li>- More diverse training datasets.</li> <li>- Bias audits.</li> <li>- Human feedback from multiple regions.</li> <li>- Cultural adaptation layers.</li> </ul> <p>Acknowledges bias can be reduced, not eliminated.</p>	<ul style="list-style-type: none"> <li>- Bias Detection Tools: Development of tools like IndiCASA and DECASTE to measure specific biases.</li> <li>- Improved Training Methods: Techniques like negatively-correlated sampling.</li> <li>- Better Data &amp; Governance: Push for more representative datasets and continuous evaluation.</li> </ul>	<ul style="list-style-type: none"> <li>- Cultural Prompting: Instructing the AI to "act as a local resident" to improve cultural alignment.</li> <li>- Diverse Benchmarking: Testing models against multilingual datasets.</li> <li>- Inclusive Teams: Ensuring development teams represent the global population.</li> </ul>	<ul style="list-style-type: none"> <li>- More diverse and representative training datasets.</li> <li>- Cultural alignment benchmarks.</li> <li>- Region-specific model tuning.</li> <li>- Transparency around model behavior.</li> <li>- Involving global communities in AI governance.</li> </ul>	<ul style="list-style-type: none"> <li>- Explicit Cultural Prompting: Specifying a cultural perspective in the prompt can significantly improve alignment.</li> <li>- Better Data Curation, Diverse Teams, Region-Specific Fine-Tuning, and Ongoing Audits.</li> </ul>
Key Nuances & Distinctions	<ul style="list-style-type: none"> <li>- No Intent: AI does not have ideology or intention. Bias arises from statistical pattern learning.</li> <li>- Reflects, Doesn't Create: AI reflects culture more than it creates it.</li> </ul>	<ul style="list-style-type: none"> <li>- "Algorithmic Monoculture": The concept that different models converge on a narrow set of values.</li> </ul>	<ul style="list-style-type: none"> <li>- Language-Dependent Behavior: The same model can exhibit different cultural values depending on the language of the prompt.</li> </ul>	<ul style="list-style-type: none"> <li>- Bias in AI Research: Points out that even the field of "explainable AI" (XAI) can be culturally biased in how it communicates.</li> <li>- Cites Specific Studies: References 2024 PNAS Nexus, Georgia Tech, and MIT Sloan studies for evidence.</li> </ul>	<ul style="list-style-type: none"> <li>- Default Values: The concept of a model's "default" cultural setting being tied to English-speaking and Protestant European values.</li> </ul>

Source: Eulalia Codipietro, Consultant | Coach | Creative - MoveToJoy