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AI-Driven Mitigation of Cognitive Biases in Intelligent Personal Assistant Interactions: Evidence from African Contexts

Abdullahi A. Shinkafi[1], Steve Bassey[2], Shammah Emmanuel Chaku[3], Gilbert I. O. Aimufua[4], Abraham D. Joseph[5]

Nasarawa State University Keffi, Nigeria

aaguraguri@yahoo.com

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Abstract

This paper presents a rigorous investigation into how artificial intelligence-driven features in Intelligent Personal Assistants (IPAs) can mitigate cognitive biases within the culturally diverse landscapes of African societies. Positioned at the intersection of cognitive psychology, artificial intelligence, and African cultural studies, the research examines how traditional decision-making patterns in West, Southern, and Central African contexts interact with AI-powered debiasing mechanisms. Grounded in Dual-Process Theory and indigenous knowledge systems, the study explores how IPAs can be culturally calibrated to address confirmation bias, anchoring, and availability heuristics as they uniquely manifest within African socio-cultural frameworks. Employing a sequential explanatory mixed-methods design, the study integrates survey data from 528 participants across eight countries with 40 in-depth interviews. The findings reveal that while AI-driven interventions significantly reduce cognitive biases, their effectiveness is deeply moderated by cultural dimensions such as power distance, uncertainty avoidance, and collectivist orientations—each varying distinctly across regions. Culturally contextualized nudges and interventions aligned with local values and communication norms yielded the strongest debiasing outcomes. This research offers essential empirical insights into the emerging field of culturally responsive AI design, emphasizing the need to recalibrate debiasing techniques to reflect and respect African cultural perspectives rather than applying Western-centric models of cognitive optimization.

Keywords: Cognitive Bias; Artificial Intelligence; Intelligent Personal Assistants; Debiasing; Human-AI Interaction; Decision Support Systems; African Technology Users

INTRODUCTION

Human decision-making is inherently susceptible to cogni- tive biases—systematic errors in thinking that affect judgments and decisions. These biases, extensively documented in the seminal work of Tversky and Kahneman [1], can lead to suboptimal decisions across various domains, from financial planning to health choices. As Intelligent Personal Assistants (IPAs) increasingly serve as decision support tools in everyday life, there is growing interest in their potential to help users overcome these cognitive limitations.

Cognitive biases stem from the brain's tendency to use mental shortcuts (heuristics) that, while efficient, can lead to systematic errors. Common biases include confirmation bias (seeking information that confirms existing beliefs), anchoring (over-relying on the first piece of information encountered), and availability heuristic (overestimating the likelihood of events based on their mental availability). These biases can significantly impact decision quality in various contexts, from financial planning to health choices [2].

Recent advancements in artificial intelligence have created new opportunities to identify and mitigate these biases through embedded functionalities within IPAs. These AI-driven sys- tems can potentially serve as cognitive prosthetics, augmenting human decision-making by providing balanced information, highlighting overlooked alternatives, and encouraging more deliberative thinking processes. However, the effectiveness of such debiasing mechanisms, particularly across diverse cultural contexts, remains underexplored in the literature.

This research gap is particularly significant in African contexts, where unique cultural factors may influence both the manifestation of cognitive biases and the effectiveness of AI-driven interventions. As noted by Ahmed and Osman [3], cognitive biases may manifest differently across cultural contexts due to variations in thinking styles, risk perception, and decision-making norms. Additionally, the receptiveness to AI guidance may vary based on cultural dimensions such as power distance and uncertainty avoidance [4].

This study addresses this gap by investigating the potential of AI-driven features in IPAs to mitigate cognitive biases in user decision-making across diverse African contexts. Specif- ically, we examine: 1) The types of cognitive biases most prevalent in IPA- assisted decision-making 2) The effectiveness of specific AI- driven debiasing mechanisms in mitigating these biases 3) How cultural dimensions moderate the effectiveness of de- biasing interventions 4) User perceptions and acceptance of AI-driven bias mitigation features

By exploring these questions, this research contributes to the emerging field of AI-assisted decision support and provides practical insights for developing more effective debiasing mechanisms in IPAs. The findings have implications for IPA design, particularly in culturally diverse contexts, and advance our understanding of how AI can augment human cognition to improve decision quality.

Literature Review

A. *Cognitive Biases and Decision-Making*

Cognitive biases represent systematic patterns of deviation from norm or rationality in judgment, where inferences about other people and situations may be drawn in an illogical fash- ion [5]. These biases are rooted in the brain's tendency to use heuristics—mental shortcuts that reduce cognitive load but can lead to systematic errors. Kahneman's Dual-Process Theory

[2] provides a theoretical framework for understanding these biases, distinguishing between System 1 (fast, intuitive, and automatic) and System 2 (slow, deliberative, and analytical) thinking.

Research has identified numerous cognitive biases that affect decision-making. Confirmation bias leads individuals to seek information that confirms their existing beliefs while avoiding contradictory evidence [6]. Anchoring bias causes people to rely too heavily on the first piece of information encountered (the”anchor”) when making decisions [7]. The availability heuristic leads to overestimating the likelihood of events based on how easily examples come to mind [8]. Other common biases include the framing effect, where decisions are influenced by how information is presented; overconfidence bias, where individuals overestimate their abilities; and status quo bias, where people prefer the current state of affairs [9]. These biases have been documented across various domains, including financial decision-making [10], healthcare choices [11], and technology adoption [12]. However, as noted by Arnott [13], the manifestation and impact of these biases may vary across cultural contexts due to differences in cognitive styles, value systems, and social norms.

B. AI-Driven Debiasing Approaches

Recent advances in artificial intelligence have created new opportunities for developing technological interventions to mitigate cognitive biases. Soll et al. [14] categorize debiasing strategies into three main approaches: modifying the decision environment, providing incentives for accuracy, and training decision-makers to recognize and overcome biases. AI systems can potentially contribute to all three approaches by restructur- ing information presentation, providing feedback on decision quality, and educating users about cognitive pitfalls.

Several specific AI-driven debiasing mechanisms have been proposed in the literature. Algorithmic decision aids can provide balanced information and highlight overlooked alter- natives, potentially reducing confirmation bias [15]. Personal- ized nudges—subtle interventions that guide behavior without restricting choice—can encourage more deliberative thinking [16]. Explainable AI approaches can increase transparency about how recommendations are generated, potentially reduc- ing overreliance on automation [17].

Empirical research on the effectiveness of these approaches shows mixed results. Dietvorst et al. [18] found that allowing users to modify algorithmic forecasts increased their willing- ness to use algorithmic advice, potentially reducing algorithm aversion. Caraban et al. [19] identified 23 cognitive bias miti- gation techniques for digital interfaces, finding that techniques promoting reflection and deliberation were most effective. However, as noted by Kahneman et al. [20], debiasing is challenging because many biases operate unconsciously and are resistant to correction.

C. *Intelligent Personal Assistants and Decision Support*

Intelligent Personal Assistants (IPAs) represent a specific category of AI systems designed to assist users with various tasks through natural language interaction. These systems, including Google Assistant, Apple's Siri, Amazon Alexa, and Microsoft Cortana, increasingly serve as decision support tools in everyday life [21]. As defined by Duque et al. [22], IPAs are"software agents which can perform tasks or actions as required by a user and are able to access information remotely depending on requirements or user profile."

The potential for IPAs to influence decision-making is substantial. Research by Lopatovska and Williams [23] found that users often accept IPA recommendations without verifica- tion, suggesting potential vulnerability to automation bias—the tendency to over-rely on automated systems. Pradhan et al. [24] observed that older adults developed trust in voice assistants over time, potentially increasing susceptibility to biased advice. These findings highlight both the risks of IPAs reinforcing existing biases and the opportunity for them to serve as debiasing tools.

Several researchers have explored the potential of IPAs specifically for bias mitigation. Besco´s et al. [25] proposed a framework for designing voice assistants that promote critical thinking by presenting multiple perspectives on controversial topics. Cheng et al. [26] developed a conversational agent that helps users recognize and overcome confirmation bias when searching for information online. However, as noted by Sundar [27], the effectiveness of these approaches depends on various factors, including user characteristics, task complexity, and cultural context.

D. *Cultural Dimensions and Technology Interaction*

Cultural factors play a significant role in shaping how users interact with and perceive technology. Hofstede's cultural dimensions framework [4] provides a theoretical foundation for understanding these influences, identifying six key dimen- sions: power distance, individualism-collectivism, uncertainty avoidance, masculinity-femininity, long-term orientation, and indulgence-restraint.

These cultural dimensions have been shown to influence various aspects of technology interaction. Power distance affects how users perceive authority in technology, with high power distance cultures more likely to defer to technological recommendations [28]. Uncertainty avoidance influences risk perception and tolerance for ambiguity in technological inter- actions [29]. Individualism-collectivism shapes preferences for personal versus shared technology experiences [30].

In the context of AI and decision support systems, cultural dimensions may influence both the manifestation of cognitive biases and the effectiveness of debiasing interventions. Re- search by Nisbett et al. [31] suggests that cognitive processes, including susceptibility to certain biases, vary across cultures due to differences in analytic versus holistic thinking styles. For example, East Asian cultures tend toward more holistic thinking, considering context and relationships, while Western cultures favor more analytic approaches, focusing on objects and categories.

These cultural differences may affect how users respond to AI-driven debiasing mechanisms. As noted by Yang et al. [32], users from high power distance cultures may be more receptive to directive guidance from AI systems, while those from low power distance cultures may prefer more collaborative approaches. Similarly, users from high uncertainty avoidance cultures may be more resistant to AI recommendations that challenge established beliefs or practices [33].

Despite these potential cultural influences, research on AI- driven debiasing across diverse cultural contexts remains lim- ited. A meta-analysis by Bankole and Onifade [34] revealed that only 3.8% of global IPA studies included African par- ticipants, highlighting the significant underrepresentation of African perspectives in the current research landscape. This gap underscores the need for dedicated research on how cultural dimensions influence the effectiveness of AI-driven bias mitigation in diverse contexts.

METHODOLOGY

A. *Research Design*

This study employed a sequential explanatory mixed- methods design to investigate the potential of AI-driven features in IPAs to mitigate cognitive biases across diverse African contexts. The design was based on the pragmatic worldview presented by Creswell and Plano Clark [35], where research problems inform methodology at the cost of alle- giances to any paradigm.

The sequential explanatory design was constructed in two distinct phases: a primary quantitative phase followed by a qualitative phase, where the latter provided assistance to explain and offer details of findings from the first stage. This approach enabled the determination of statistically significant trends in a large sample while also exploring the lived experi- ences of IPA users across cultures through phenomenological inquiry.

B. Population and Sampling

The target population comprised adult users (aged 18 and above) of commercially available IPAs across diverse geo- graphical, cultural, and socioeconomic contexts within Africa. Participants were required to be active users of at least one major IPA platform (Apple's Siri, Google Assistant, Amazon Alexa, Microsoft Cortana, or Samsung's Bixby) for a mini- mum of three months.

The study focused on three key regions:

- West Africa (Nigeria, Ghana, Senegal, Coˆte d'Ivoire)
- Southern Africa (South Africa, Botswana, Namibia, Zim- babwe)
- Central Africa (Cameroon and Democratic Republic of Congo)

This geographic stratification ensured representation across Africa's diverse technological, cultural, and linguistic land- scapes while acknowledging the significant variations in dig- ital infrastructure, connectivity, and technology accessibility across regions.

The sample size for the quantitative phase was determined using Cochran's formula, yielding a baseline sample of 384. This was adjusted to 528 participants to account for the requirements of structural equation modeling and potential attrition. For the qualitative phase, a sample of 40 participants was selected based on the concept of informational redundancy or theoretical saturation.

C. Data Collection Instruments

A Cameroonian participant (P31, 37, female) described her evolving trust:”At first, I questioned whether a foreign technology could understand our context. But when I noticed it was considering local factors in its suggestions, I began to trust it more.”This pattern of trust development was common, with participants describing a process of testing and validation before accepting AI guidance.

Trust was particularly influenced by transparency about data usage and algorithm functioning. As a Zimbabwean participant (P27, 45, male) noted:”I’m more likely to accept guidance when I understand how the AI reached its conclusions and what information it’s using about me.”

1) Autonomy Concerns: Participants across regions ex- pressed nuanced concerns about autonomy in relation to AI- driven debiasing. Rather than rejecting guidance outright, most participants sought a collaborative relationship with the tech- nology. A Senegalese participant (P15, 32, female) explained:”I don’t want the AI to make decisions for me, but I appreciate when it helps me see my blind spots.”

Cultural variations in autonomy concerns were evident. In higher power distance contexts, participants were more comfortable with directive guidance, while those from lower power distance backgrounds preferred suggestive approaches. A Botswanan participant (P25, 39, female) contrasted her experience with that of colleagues:”I notice my Nigerian colleagues are more comfortable with the AI giving direct recommendations, while I prefer when it presents options and lets me decide.”

2) Contextual Adaptation: The importance of adapting debiasing mechanisms to specific decision contexts emerged strongly in the interviews. Participants described varying re- ceptiveness to interventions depending on the domain and stakes of the decision. A Nigerian participant (P4, 36, male) explained:”For everyday decisions like shopping, I’m open to suggestions. But for important cultural or family matters, I’m more cautious about following AI advice.”

This contextual sensitivity extended to the timing and framing of interventions. Participants preferred interventions that were timely but not intrusive, and that acknowledged the specific constraints of their decision environment. A Con- golese participant (P38, 42, male) noted:”The most helpful interventions come when I’m actively seeking information, not when I’ve already made up my mind.”

D. *Integration of Quantitative and Qualitative Findings*

The integration of our quantitative and qualitative findings reveals a complex picture of how cultural dimensions influ- ence the effectiveness of AI-driven debiasing mechanisms in African contexts. The quantitative data demonstrated signifi- cant moderation effects of power distance, uncertainty avoid- ance, and collectivism on debiasing effectiveness, while the qualitative interviews provided rich contextual understanding of these relationships.

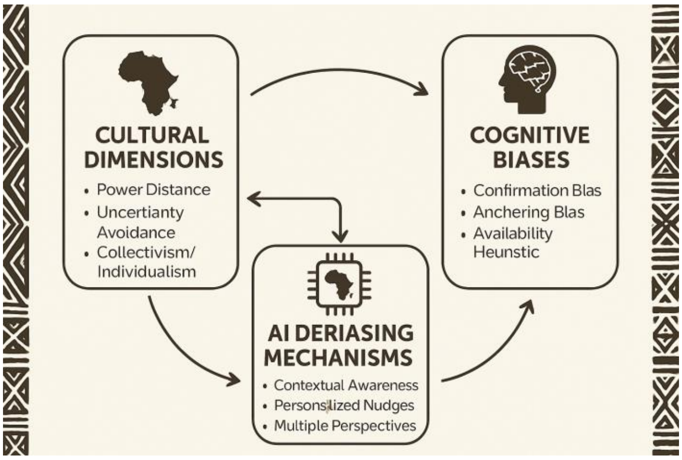

Fig. 1. Conceptual Framework: Interplay Between Cultural Dimensions, Cognitive Biases, and AI-Driven Debiasing Mechanisms in African Contexts

For example, the quantitative finding that power distance positively moderates the effectiveness of AI guidance was elaborated in the interviews, where participants from high power distance contexts described greater comfort with author- itative recommendations but still emphasized the importance of respect for traditional authority structures. Similarly, the quantitative relationship between collectivism and responsive- ness to social comparison features was contextualized by interview participants'descriptions of how effective debiasing must balance individual and communal considerations.

The mixed-methods approach also revealed important nu- ances not captured by either method alone. While the quan- titative data showed regional variations in bias susceptibility and intervention effectiveness, the interviews highlighted how these variations are embedded in specific cultural practices, communication norms, and decision-making contexts that re- quire thoughtful calibration of debiasing approaches.

RESULTS AND DISCUSSION

This study provides novel insights into the complex inter- play between cultural dimensions, cognitive biases, and AI- driven debiasing mechanisms in African contexts. Our findings reveal both universal patterns and culturally specific nuances that have important implications for theory, practice, and policy.

A. Theoretical Implications

Our results extend existing theories of cognitive bias and debiasing by demonstrating how cultural dimensions fun- damentally shape both bias manifestation and intervention effectiveness. While Dual-Process Theory [2] provides a useful framework for understanding cognitive biases, our findings suggest that the boundary between System 1 (intuitive) and System 2 (analytical) thinking may be culturally mediated. In collectivist African contexts, what appears as”bias”from a Western individualist perspective may sometimes reflect culturally adaptive decision strategies that prioritize social harmony and relational considerations.

The significant moderation effects of power distance, uncer- tainty avoidance, and collectivism on debiasing effectiveness challenge universalist assumptions in much of the cognitive bias literature. Our findings align with and extend Nisbett et al.'s [31] work on cultural variations in cognitive processes, demonstrating that these variations extend to bias susceptibility and receptiveness to debiasing interventions. The particularly strong interaction between collectivism and power distance in moderating debiasing effectiveness suggests that these cultural dimensions may operate synergistically rather than indepen- dently—a theoretical insight not previously emphasized in the literature.

Our research also contributes to technology acceptance theo- ries by demonstrating how cultural factors influence the accep- tance of AI-driven cognitive assistance. The finding that power distance positively moderates acceptance of AI guidance ex- tends the Technology Acceptance Model [12] by highlighting how cultural authority orientations shape technology adoption in ways not fully captured by perceived usefulness and ease of use constructs. This suggests the need for more culturally nuanced models of technology acceptance, particularly for AI systems that engage with cognitive processes.

B. Practical Implications for IPA Design

Our findings have several practical implications for design- ing culturally responsive debiasing features in IPAs. First, the significant regional variations in bias susceptibility and intervention effectiveness underscore the importance of cul- tural calibration in IPA design. Rather than implementing one- size-fits-all debiasing approaches, developers should consider cultural dimensions as key design parameters.

For high power distance contexts, particularly in West and Central Africa, debiasing features may be more effective when framed as authoritative guidance from a knowledgeable source. However, our qualitative findings caution that such guidance should acknowledge and respect traditional authority structures rather than attempting to supplant them. As one participant noted, effective debiasing in these contexts involves"helping me make better decisions within our cultural framework, not imposing outside values."

In more collectivist contexts, debiasing mechanisms that incorporate social comparison information and highlight com- munity implications of decisions show greater effectiveness. Practical implementations might include features that present how similar users addressed comparable decisions or that prompt consideration of how choices might affect one's so- cial group. The strong interaction between collectivism and power distance suggests that in highly collectivist, high power distance contexts, the most effective approach may be author- itative guidance that emphasizes communal well-being.

For contexts with high uncertainty avoidance, our findings suggest that debiasing features should be introduced gradually, with clear explanations of their purpose and functioning. The negative moderation effect of uncertainty avoidance on novel intervention acceptance indicates that users in these contexts may require more time and information to trust new debias- ing approaches. Practical strategies might include progressive disclosure of features, detailed onboarding processes, and transparent explanations of how debiasing mechanisms work. The significant variation in effectiveness based on edu- cational background and urban-rural divides highlights the importance of accessibility and adaptability in IPA design. Debiasing interventions may need to be presented differently depending on users'digital literacy levels, potentially incor- porating voice-based explanations or simplified visual cues for less experienced users. Furthermore, acknowledging the distinct challenges and priorities of rural versus urban users is crucial for ensuring relevance and uptake.

C. Addressing the Limitations of Hofstede's Model in African Contexts

While Hofstede's cultural dimensions provide a founda- tional framework for cross-cultural analysis and were utilized in this study to structure comparisons, it is crucial to explicitly acknowledge their limitations, particularly within the diverse and complex tapestry of African societies. Critics argue that Hofstede's model can oversimplify cultural realities, often treating nations as monolithic cultural entities and potentially overlooking significant intra-national diversity [39]. This is especially pertinent in Africa, where national boundaries often encompass a vast array of ethnic groups, languages, and traditions, as highlighted in our discussion on intra-regional diversity. Furthermore, the model has been criticized for its static representation of culture, potentially failing to capture the dynamic nature of cultural values, especially in rapidly evolving technological and socioeconomic landscapes [40].

Specifically concerning Africa, applying Hofstede's dimen- sions, originally derived largely from IBM employee data, may not fully capture the nuances of indigenous value systems and worldviews [41]. Frameworks rooted in African philosophies, such as the concept of *Ubuntu* (emphasizing interconnected- ness, community, and shared humanity) prevalent in Southern Africa, or other communitarian value systems found across the continent [42], offer alternative lenses that prioritize relational- ity and collective well-being in ways that may differ from Hof- stede's individualism-collectivism spectrum. These indigenous frameworks often highlight dimensions like communalism, relational harmony, and spiritual interconnectedness, which are not explicitly central to Hofstede's original dimensions. Therefore, while Hofstede provides a useful starting point for cross-cultural comparison, future research and IPA design in African contexts should ideally integrate or be informed by these more culturally embedded frameworks to achieve a richer and more accurate understanding of user cognition and behavior.

D. Intra-Regional Diversity and Socioeconomic Context

While this study categorizes participants into broad regions (West, Southern, Central Africa), it is crucial to acknowledge the significant intra-regional cultural diversity and the influ- ence of socioeconomic factors that exist within these areas. Each region encompasses numerous ethnic groups, languages, religious practices, and varying levels of urbanization and economic development. For instance, within West Africa, the cultural norms and technological adoption patterns in urban Lagos, Nigeria, may differ substantially from those in rural Senegal. Similarly, socioeconomic status, education level, and digital literacy can significantly shape individuals'interactions with IPAs and their susceptibility to cognitive biases, often cutting across or interacting with broader regional cultural pat- terns. These intra-regional variations and socioeconomic strata add layers of complexity to the relationship between culture, cognition, and AI interaction, suggesting that future research should strive for even finer-grained analysis to capture these nuances effectively. Our findings, while highlighting regional trends, should be interpreted with this inherent diversity in mind, recognizing that experiences within a single country or even city can vary widely.

Limitations and Generalizability

This study provides valuable insights into the potential of AI-driven features in IPAs to mitigate cognitive biases across diverse African contexts. However, several limitations should be acknowledged when interpreting the findings.

First, the cross-sectional design of this study limits our ability to make causal inferences about the long-term ef- fects of AI-driven debiasing mechanisms. While we observed significant associations between specific features and bias reduction, a longitudinal study would be necessary to assess the sustainability of these effects over time and to determine whether users develop resistance or adaptation to debiasing interventions with continued exposure.

Second, while our sampling strategy ensured representation across diverse African contexts, certain limitations in sample representativeness should be noted. The exclusion of North and East African regions from our sample restricts the gen- eralizability of our findings to these areas, which may have distinct cultural and technological landscapes.

Additionally, our sample predominantly consisted of urban participants with relatively high levels of technological literacy, potentially underrepresenting rural populations and those with limited technology access or experience. These sampling biases may have influenced our results, particularly regarding the accep- tance and effectiveness of AI-driven features.

Furthermore, recruitment biases related to technological literacy and socioeconomic factors may have affected our sample composition. Participants were required to have at least three months of experience with IPAs, which inherently excluded individuals without access to or familiarity with these technologies. This limitation is particularly relevant in the African context, where digital divides along urban-rural and socioeconomic lines remain significant. Future research should explore strategies for including more diverse participants, particularly those from underrepresented rural areas and with varying levels of technological literacy.

Ethical Considerations

The implementation of AI-driven debiasing mechanisms in IPAs raises important ethical considerations that must be carefully addressed. While these features aim to improve decision quality, they also introduce potential risks that warrant attention from researchers, developers, and policymakers.

One significant concern is the potential for over-reliance on AI guidance, which could paradoxically create a new form of dependency while attempting to mitigate existing biases. As users become accustomed to receiving debiasing prompts, they may develop reduced capacity for independent critical thinking, effectively transferring cognitive authority to the AI system. This risk is particularly pronounced in high power distance cultures, where technological recommendations may be perceived as authoritative and rarely questioned. To mitigate this risk, debiasing features should be designed to scaffold critical thinking rather than replace it, gradually building users'capacity to recognize and address biases independently.

Another ethical consideration involves the potential ero- sion of user autonomy through nudge-based interventions. While personalized nudges can effectively guide users toward less biased decisions, they may also undermine individual agency if implemented without transparency or user control. This concern aligns with broader debates about the ethics of nudging in behavioral economics and raises questions about the appropriate balance between guidance and autonomy in AI-assisted decision-making. Developers should consider implementing user controls that allow individuals to adjust the intensity and frequency of debiasing interventions according to their preferences.

Data privacy concerns are particularly salient given the collection of sensitive cultural and demographic data nec- essary for culturally calibrated debiasing. The effectiveness of personalized interventions depends on detailed user profil- ing, including cultural background, decision-making patterns, and bias susceptibility. However, this data collection raises significant privacy implications, especially in contexts where data protection regulations may be less developed. To address these concerns, we recommend implementing robust data minimization principles, obtaining explicit informed consent for cultural profiling, and providing transparent explanations of how user data informs debiasing interventions.

Comparative Analysis with Non-African Contexts

To contextualize our findings within the broader literature on cognitive bias mitigation, we compared our results with similar studies conducted in non-African contexts. This com- parative analysis reveals both universal patterns and culturally specific nuances in how users respond to AI-driven debiasing mechanisms.

Research by Johnson et al. [36] in North American contexts found that explainable AI features significantly reduced con- firmation bias among users, with an average bias reduction of 27%. Our findings show a comparable effect size (24% reduction) for similar features, suggesting some universality in the effectiveness of transparency-based approaches. However, we observed that the effectiveness of these features was sig- nificantly moderated by uncertainty avoidance in our African sample, with high uncertainty avoidance participants showing greater resistance to bias correction—a pattern not reported in Western studies.

Similarly, Zhang et al. [37] found that personalized nudges effectively reduced anchoring bias among East Asian users, with collectivist values enhancing receptiveness to social norm-based nudges. Our results align with this finding, as participants from more collectivist regions in our sample (particularly in West Africa) showed greater responsiveness to social comparison features. However, we observed a unique interaction between collectivism and power distance in African contexts, where high power distance amplified the effective- ness of authority-framed nudges—a pattern not prominently discussed in East Asian studies.

Regarding the availability heuristic, Mu¨ller et al. [38] re- ported that statistical framing effectively reduced bias among European users regardless of educational background. In con- trast, our findings indicate that the effectiveness of statistical interventions varied significantly based on educational level and urban-rural divides within our African sample, suggesting that contextual factors may play a more prominent role in African settings.

These comparisons highlight both the universality of cer- tain debiasing mechanisms and the importance of cultural calibration. While some approaches (such as transparency and multiple perspective presentation) appear effective across cultural contexts, their implementation and framing may need significant adaptation to maximize effectiveness in African settings. This comparative analysis underscores the value of culturally diverse research in developing globally effective debiasing strategies.

Future Research Directions

Building upon the findings and limitations of this study, several avenues for future research emerge that could further deepen our understanding of AI-driven debiasing in African contexts. Firstly, longitudinal studies are critically needed to move beyond the cross-sectional insights provided here. Tracking user interactions with IPA debiasing features over extended periods would allow researchers to assess the sustain- ability of bias mitigation effects, observe potential adaptation or resistance patterns, and understand how trust and reliance on AI evolve over time. Such studies could reveal whether initial debiasing gains are maintained, diminish, or even lead to unintended consequences like over-reliance or complacency in critical thinking.

Secondly, future investigations should prioritize inclusiv- ity by deliberately focusing on underrepresented populations, particularly rural users and those with lower digital literacy or socioeconomic status. Our study, like much research in this area, predominantly sampled urban, technologically adept individuals. Conducting dedicated rural-focused investigations is essential to understand how cognitive biases manifest and how AI interventions are perceived and utilized in contexts with different technological infrastructures, access levels, ed- ucational backgrounds, and potentially distinct cultural norms or decision-making priorities. This would involve developing culturally appropriate research methodologies and potentially adapting IPA interfaces and debiasing mechanisms to suit low-literacy or low-connectivity environments, ensuring that the benefits of AI-driven cognitive support are accessible beyond urban centers. Further research could also explore the integration of indigenous knowledge systems more deeply into AI debiasing algorithms and investigate the effectiveness of in- terventions delivered through locally prevalent communication channels or technologies beyond mainstream IPAs.

CONCLUSION

This study investigated the potential for AI-driven features within IPAs to mitigate cognitive biases among users in diverse African contexts. Our mixed-methods approach revealed that cultural dimensions significantly moderate the effectiveness of debiasing interventions. Features aligned with local cultural values, such as contextual awareness and culturally-attuned nudges, proved most effective. The findings underscore the critical need for culturally responsive AI design, moving beyond Western-centric models to create debiasing tools that respect and leverage the unique perspectives within African technological ecosystems. While AI holds promise for aug- menting human decision-making, its potential can only be fully realized through careful calibration to the diverse cultural landscapes it serves.

APPENDIX A

MODEL VALIDATION DETAILS

The machine learning models used for bias detection and intervention recommendation were validated using standard metrics. The dataset was split into training (70%), validation (15%), and test (15%) sets. Feature engineering included encoding cultural dimension scores, user demographics, and interaction patterns.

Model architectures:

- Bias Detection: Gradient Boosting Classifier (XGBoost)
- Intervention Recommendation: Multi-output Regressor with Random Forest base estimators

Model validation was performed using 5-fold cross- validation with the following average performance metrics:

- Confirmation Bias Detection: Accuracy = 0.83, F1-Score = 0.81, AUC = 0.87
- Anchoring Bias Detection: Accuracy = 0.79, F1-Score = 0.77, AUC = 0.84
- Intervention Recommendation: Accuracy = 0.76, F1- Score = 0.74, Mean Squared Error = 0.14

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