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Fairness by Design in Smart Hospitality: Neuroadaptive Interfaces in Hospitality Booking Contexts

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Abstract

The paper addresses the principle of fairness-conscious neuroadaptive interfaces to smart hospitality systems, assuming that smart personalization should be grounded in the user's traits and not on a hypothetical preference. Accordingly, it integrates the Decision-Making Trial and Evaluation Laboratory (DEMATEL) causal mapping and agent-based simulation approach, based on the Dual-Process Theory and Affective Computing, to simulate the impacts of emotional reactivity, cognitive load tolerance, and fairness sensitivity on the adaptive interface specifications in the hospitality booking contexts. DEMATEL evaluates which features serve as system drivers and offers a causal-structural foundation for instantiating static, personalized, and fairness-conscious interfaces in the context of a simulation involving 500 simulated cognitively differentiated agents. The trait-interface congruence was explored regarding the behavioral outcomes, including trust, satisfaction, and cognitive load. Fairness-aware interfaces were the strongest overall outcomes, as they resulted in greater trust and satisfaction and a lower cognitive load than both static and personalized interfaces. This two-step design is a systematic means of exploring the effects of latent properties on user reactions to different interface conditions. The results imply that fairness-conscious and personalized interfaces are more appropriate to the users, and the user traits are more specifically correlated with trust, satisfaction, and cognitive load. The framework provides a reproducible process of trait-based adaptation that has implications for human-AI researchers who are interested in fairness-aware personalization.

1 Introduction

The relationships between individualized systems and user cognition are an expanding methodological concern in decision sciences and applied behavioral research. The emergence of smart hospitality systems that are becoming more influential in terms of how travelers search, compare, and select accommodation in online booking settings is one of the significant shifts in modern hospitality service delivery (Heidari et al., 2024; Yang et al., 2024). The environment of choice in which the travelers make decisions is altered with the help of AI-based systems of recommendations, pricing algorithms, and online booking platforms, and even the emotional and cognitive aspects of the choice are influenced (Tai et al., 2021; Lim and Kim, 2025). The process of choosing accommodations, which was once easy, has now resulted in cognitive load and emotionally charged moods due to the perception of the system as more or less transparent, personalized, and fairly reflecting its logic (Mohammed & Denizci Guillet, 2025). In this human-AI interaction environment, psychological and affective areas are no longer peripheral to the interface; they dynamically influence our perception, acceptance, or resistance to interface adjustments across varied user types (Lee, 2025). This change demands methodological paradigms that could model latent psychological constructs in human-AI interaction systems (Plikynas et al., 2022).

Although adaptive systems can be complicated, the current body of tourism research tends to address behavioral prediction rather than psychological understanding. Personalization is practically considered in the case of a performance gain rather than an experience constructed by an internal user state that is affected psychologically (Kumar et al., 2025). Traits such as emotional reactivity, fairness sensitivity, and cognitive load tolerance are rarely considered in system design and are not mentioned as causal elements (Saha et al., 2024), which opens the gap between user-centered fairness and technical adaptability (Chan, 2026). Although an expanding body of literature is starting to look at transparency and trust in systems, there are a few models that speak to neurocognitive profiles and system behaviors (Li et al., 2024) and very few that actually operationalize those traits in a way that considers both behavioral outcomes and psychological meaning (Yin & Hwang, 2025), especially under emotional arousal or complexity.

This study addresses this gap by offering a trait-based approach to personalization, viewing it as a dynamic process that unfolds user traits in relation to the adaptive interface pathways they can pursue (Koo et al., 2025). Instead of making assumptions about the homogeneity of responses to adaptive logic, the model considers cognitive and emotional characteristics as causal factors that influence the necessity of adaptation. A causal structuring process is used to determine the most significant traits that affect these needs thereby reflecting neurocognitive variation through making system changes that would have psychological significance. The model simulates an environment, which allows tracing user-system interactions (El Ouadi et al., 2022) in static, personalized, and fairness-aware types of interfaces. So, this framework pursues three purposes: to model user reactions in hospitality booking settings with neurocognitive characteristics, to determine the adaptation requirements with DEMATEL (Tao et

al., 2025), and to assess the fairness-aware personalization as a psychologically responsible design condition (da Silva et al., 2021).

There is more than behavioural considerations in this approach; it gives us an interpretive architecture of personalization ethics. If traits constructs like fairness sensitivity and emotional reactivity are evolved into adaptive logic of AI systems, personalization will become responsive to user variability, not just generic (Kumar et al., 2025). Fairness is reconceptualized not as a retrospective judgment but as an inherent element of system parameters (Narayanan et al., 2024). Affective complexity is even seen as one of the design elements rather than being categorized as user noise. The model combines human interpretability with the computational response, thus making personalization not only ethically sensitive but also quite consistent throughout the user's experience (Koo et al., 2025). This correspondence between latent characteristics and interface design is a response to recent methodological demands of causally informed personalization in human-oriented AI. The interface behavior in this model is not limited to the fixed interface types and is likely to conform to the emotional state of users in cases of uncertainty, overload or affective conflict.

In theory, the research combines the dual-process (Kahneman, 2011) and the affective computing (Picard, 2000) theories into one, trait-sensitive framework. It provides a new combination of DEMATEL causal modeling and simulation methodologically to test the consistency between user characteristics and interface behavior. Practically, it can be of value to smart hospitality platforms and interface designers who want to offer fair, transparent, and psychologically-aware personalization. In a broader sense, the model can be applied to other fields such as finance, education, and medicine, or any other field where algorithmic decision support challenges neurodiverse human judgment. Finally, the current study brings the research on personalization to the design of neuroadaptive systems by combining empirical modeling of traits with interpretability and cognitive-emotional fit.

2 Adaptive Interfaces in Smart Hospitality

2.1 Emotion–Cognition in Hospitality Booking Contexts

To model traveler decisions in digital hospitality booking settings, it is necessary to shift beyond rational-choice models and investigate the existing emotional-cognitive interactions in an empirical way (Moisa et al., 2025). The periphery traits have been replaced by emotional reactivity, cognitive load tolerance, and fairness sensitivity (ethical concern) as mediators of the interaction of travelers with AI-driven platforms under time pressure, uncertainty, or mismatched expectations (Kwong et al., 2024). These features can be considered to define where the intuitive and deliberative choices can fall, in particular, when the user is facing dynamically framed decisions or personalized content and implicit trade-offs by using modern models of dual-process thinking (Farshbafiyan Hosseininezhad et al., 2025; Oan-Oon & Choibamroong, 2025). Consequently, in case the decisions in hospitality booking are to be simulated, it is necessary to comprehend the influence of these factors on the perception of risk, value, and usability of digital decision tools among the users (Hrankai et al., 2025).

The interplay between affect and cognition emerges in significance where interfaces attempt to match user attributes (Godovykh & Tasci, 2022). While the purpose of recommendations tailored to the user's attributes is to reduce their effort and increase their satisfaction, it is ultimately the mood of the traveler who dictates whether this strategy works or not (Yang et al., 2024). In this regard, higher emotional sensitivity might increase reactions to the system framing (Farshbafiyan Hosseininezhad et al., 2025), while high cognitive demand might lessen the usefulness of advanced personalization tools (Lee, 2025). As a result, the interaction of these attributes should be evaluated in booking contexts that aim to replicate real situations, where the interface logic is situated alongside user states that co-evolve (Becker et al., 2023; Yin & Hwang, 2025). This complexity necessitates methodological tools that capture latent trait dynamics over time, such as agent-based simulation, which can capture emergent affective-cognitive dynamics (Macal & North, 2010).

2.2 Personalization, Fairness, and Trust in AI Systems

Personalization is one of the technological features employed by smart hospitality platforms, for example, preference filtering, destination prediction, and price personalization (Yang et al., 2024). However, the user's perception of fairness, control, and openness is significantly influenced by personalization that is mediated by an algorithm. If personalization is implemented without providing a reason or without accounting for trait-level sensitivities, it may distort perceived fairness and undermine user

trust (Liu et al., 2025). It is not just the distributive outcomes alone, but procedural fairness is also critical in establishing how travelers will endorse the system's intent and legitimacy (Su et al., 2025). As recognized by frameworks of perceived personalization and transparency, adaptive behaviors must be traceable and align with user expectations when they involve traits such as fairness sensitivity and cognitive effort tolerance (Kumar et al., 2025).

The level of trust towards AI-enabled hospitality service systems involves not only accuracy and relevance but also its interaction with the users, especially with regards to the psychological match and procedural fairness (Koo et al., 2025). More sensitive tourists to issues of fairness are more likely to consider the interface mysterious and exploitative, despite the presence of optimization. However, transparency and congruence with the user in the system could lead to trust; moreover, such trust would manifest itself in the context of personalized content based on internal characteristics of the user, rather than external preferences (Narayanan et al., 2024). Such observations indicate cognitive compatibility is required in adaptive design, which implies that, ethically responsible personalization and fairness-aware design ought to be viewed as a usability requirement in reliable smart hospitality AI systems (Kwong et al., 2024).

2.3 Interface Logics and Design Gaps in Hospitality Platforms

Building on the prior discussion of emotion, cognition, and fairness, this subsection examines how current hospitality platforms implement—or fail to implement—these adaptive logics. Hospitality platforms typically use one of three interface strategies: static (the same logic for everyone), personalized (based on behavioral profiles), and adaptive fairness-aware (tailored using deeper trait structures) (Leal et al., 2025). Although the industry commonly employs both static and personalized strategies, it is starting to recognize the shortcomings associated with each approach. Static strategies overlook variance across users, and standard personalization often relies on the hidden logic of algorithmic design, producing a sense of being manipulated or excluded (Banerjee et al., 2023). The development of fairness-aware interfaces intends to ensure high-level performance as well as procedural fairness; nevertheless, their implementation in tourism and hospitality is still under-explored (Su et al., 2025). Previous studies usually focus on such aspects as accuracy or user experience without considering the presence of a fairness-aware interface in terms of users' personal characteristics (Deldjoo et al., 2024).

In this context, the difference becomes even more noticeable because of the way in which these user interface designs have been influenced by the neurocognitive features that shape the users' reactions (Li et al., 2025). For instance, individuals who are less tolerant of cognitive load prefer simpler interfaces rather than personalized ones. In comparison, high fairness sensitive users might be more concerned and perceive more risk when interface logic is not transparent or justified (Seyfi et al., 2025). Nonetheless, the mismatch between interface logic and preferences of users causes a challenge that may negate the desired advantages of personalization (Yang et al., 2024). Though there are already existing adaptive technologies, most hospitality platforms do not use user traits as causal variables in interface selection (Leal et al., 2025). The current framework simulates the causal role of latent psychological characteristics on the interface adaptation processes in AI-based decision system and offers a system to organize trait-logic congruence as a testable and optimizable design constraint.

These gaps reflect how existing research has treated emotion, cognition, fairness, and simulation largely in isolation. Table 1 highlights how the present study integrates these dimensions into a unified, trait-driven and causally modeled neuroadaptive framework.

Table 1
Summary of Identified Research Gaps and Present Study Contributions.

Thematic Area	Studies	Research Gaps	Methodological Contribution of the Study
Emotion–Cognition Interaction in Hospitality Booking Contexts	Godovykh & Tasci (2022); Moisa et al. (2025); Lee (2025).	Most studies consider emotion and cognition as two separate entities and hence do not think of their co-evolution in actual decision contexts.	Integrates emotional reactivity and cognitive load tolerance as interacting traits in adaptive decision simulations.
Personalization and Trust in AI-Driven Hospitality	Yang et al. (2024); Koo et al. (2025); Kumar et al. (2025).	Personalization mainly assessed by accuracy or performance metrics, not user-state alignment or psychological fit.	Defines personalization as neuroadaptive and evaluates trait–interface congruence affecting trust and satisfaction.
Fairness and Transparency in AI Systems	Deldjoo et al. (2024); Narayanan et al. (2024); Su et al. (2025).	Fairness usually analyzed post-hoc rather than embedded in system logic or adaptive behavior.	Presents fairness sensitivity as a socially active personality trait and ethically aligns the agent by embedding the ethical principles into the adaptive interface rules.
Simulation and Causal Modeling in Smart Hospitality	Zhang et al. (2022); Pizarro et al. (2023); Tao et al. (2025).	Limited use of simulation or causal inference to link user traits with system design.	Uses agent-based simulation and DEMATEL causal mapping to represent trait causality in adaptive hospitality interfaces.

3 Neuroadaptive Framework for Smart Hospitality Interfaces

3.1 Theoretical Foundations

The theoretical basis of this paper is based on two theoretical frameworks that inform the modeling of latent neurocognitive traits and their causal role in the interaction of users with smart hospitality interfaces. First, Dual-Process Theory is an explanatory psychological approach that theorizes human cognition as a system of intuitive and quick reactions (System 1) and deliberative and slower reactions (System 2) (Oan-Oon & Choibamroong, 2025). These mental states facilitate the development of agent profiles (particularly, the emotional reactivity and the tolerance of cognitive load) because they influence the perception of the interface, decision-making speed, and stress levels (Seyfi et al., 2025). The next one is the Affective Computing Theory which describes the role of emotional and cognitive properties as inputs in dynamic adaptation, which are then acknowledged and displayed by the interface (Hu et al., 2025).

The connection between the personality traits and the ethically adaptive user interfaces including fairness-aware design patterns that change the complexity, tone, or depth of personalization based on the users' conditions are also supported by this theoretical strand (da Silva et al., 2021). These theories give a generalized framework of how the trait-interface congruence could be relevant in supporting adaptive logic and predicting behavioral disparity in systems under static, personalized, and fairness-aware conditions. These theories are not only used to provide conceptual support but also provide operational frameworks depending on which the structural alignment of the traits and system logic in the modeling process is made.

3.2 Model Structure and Hypotheses Development

The model integrates three latent neurocognitive characteristics, including emotional reactivity, cognitive load tolerance, and fairness sensitivity, adaptive interface logic, and simulation-based decision contexts to identify user profiles in the proposed hospitality booking situation influenced by AI-driven personalized technology. These traits are associated with interface adaptation via a causal structure of DEMATEL that determines the traits and the way they influence the interface changes and fairness calibration. The interface logic includes three types of system: static (non-adaptive), personalized (trait-responsive), and fairness-aware (ethically optimized). (Fig. 1). In order to simulate the dynamics of real-life booking, the agents are shown decision scenarios with an overchoice, conflicting choices, or with framing manipulations. Such systematic integration determines the internal logic of the model and offers the foundation of creating hypotheses based on causal inference and simulation dynamics.

Attitudes to fairness at various levels of personalization are also related to the level of transparency and ethicality of the system in terms of communicating its choices. When the context is either emotionally or cognitively charged, fairness-aware designs are most likely to mitigate negative effects and enhance acceptance by aligning users with procedural justice expectations through algorithmic behavior (Narayanan et al., 2024).

H1

Fairness-aware interfaces enhance trust more than purely personalized or static interfaces.

In addition to the structural contribution of traits to interface design, it is also noteworthy to consider whether the correspondence of agent traits to adaptive interface logic yields visible behavioral outcomes. The most evident anticipated behavioral impact of such alignment in the current framework is a reduced cognitive load since users tend to handle information effectively when interface logic aligns with their cognitive and affective requirements.

H2

Higher alignment between agent traits and adaptive interface logic leads to lower cognitive load.

Among core neurocognitive traits, emotional reactivity is particularly relevant to the satisfaction afforded by adaptive systems. Users that engage in decisions effectively may respond positively to an interface that inserts complexity, tone, or message framing into adaptation so as not to contribute to feelings of stress or overwhelm (Fominska et al., 2024).

H3

Agents with high emotional reactivity report greater satisfaction when interacting with adaptive interfaces.

Apart from satisfaction, it is also assumed that the structural weight of certain traits will influence the perceived trustworthiness of the system. Those traits that play a more central causal role in the DEMATEL model are likely to have a significantly stronger impact on user trust, especially when the system design clearly demonstrates their presence.

H4

Fairness sensitivity is positively associated with trust in adaptive interface outcomes.

The cognitive load is likely to decrease trust when it is too high or does not match the interface design. In case the design cannot strategically use cognitive load to customize or increase fairness awareness in structural design, users might disengage or even develop counterfactual beliefs about the system goals (da Silva et al., 2021; Yin and Hwang, 2025). The cognitive pressure is therefore influenced by the user characteristics and the interface conditions and has to be alleviated so that the system could be reliable.

H5

Personalized and fairness-aware interface features are associated with lower cognitive load than static interface features.

4 Methodology

4.1 Simulation Design

A simulation design was selected over an experimental approach because it allowed extensive variation in user characteristics, interface types, and decision contexts (Macal & North, 2010; Pizarro et al., 2023). There were 500 cognitively differentiated simulated agents in the environment, each characterized by three validated constructs: emotional reactivity, cognitive load tolerance, and fairness sensitivity. Each construct was modeled on the continuous [0, 1] interval and was randomized using beta-like distributions to simulate psychological variability. Agents received booking assignments that involved over-choice, trade-offs, and emotional framing in order to allow for an assessment of the unique reactions to the different levels of decision-making complexity and framing strategies. Interfaces were randomly assigned to static (non-adaptive), personalized (trait-responsive), or

fairness-aware (ethically calibrated) conditions. Random assignment ensured fair exposure to different interface conditions. To assess the influence of varying trait–interface combinations on behavioral outcomes, three behavioral indicators—trust, satisfaction, and cognitive load (decision latency and reversal frequency)—were tracked. The simulation framework provides a systematic, theory-driven environment for testing personalization and fairness mechanisms and for examining their behavioral effects within adaptive interface design.

The simulation was carried out using customized Python programs and with a fixed random seed to ensure the repeatability of the experiment. The choice of synthetic agents is in line with the latest research, which suggests that it is possible to have a correct sample of behavior using agent-based computational environments. In tourism and human–technology interaction research, synthetic data have been widely used to examine cognitive mechanisms, interface effects, and preference formation when real-world experimentation is impractical (Plikynas et al., 2022; Pizarro et al., 2023). The synthetic dataset produced here serves as a transparent, mechanism-driven representation of user behavior rather than a demographic sample.

4.2 DEMATEL Logic and Analysis Procedure

To clarify the causal relationship between neurocognitive traits and interface adaptation requirements, DEMATEL was employed based on its capability of depicting the relationship between variables in a nonlinear system by means of directional information. DEMATEL is commonly used in several different sectors, such as tourism, service systems, and situations requiring decision-making, to determine cause-and-effect relationships and to prioritize the interrelated variables (Shooshtarian et al., 2024; Tao et al., 2025). This study modeled six constructs, comprising three neurocognitive traits (emotional reactivity, cognitive load tolerance, and fairness sensitivity) and three adaptive interface demands (simplicity, ethical alignment, and information control). Pairwise influence ratings were based on literature-guided structured elicitation from domain experts, producing a direct influence matrix that captures the strength of influence each construct has on the others. Seven experts with backgrounds in tourism technology, human–AI interaction, and user experience design contributed pairwise ratings using a structured DEMATEL survey.

The direct influence matrix was normalized to compute Prominence (D + R) and Net Causality (D – R) scores for each construct. Constructs with high prominence and with positive net causality were identified as drivers in the adaptive interface architecture. Traits identified as the main causal drivers (positive D-R values) were used as leading parameters governing adaptive interface behavior. The DEMATEL origin rules were implemented in the simulation environment; thus, they governed the interaction of agents with interface situations according to their neurocognitive profiles. Behavioral outcomes were defined as follows: trust was measured as the degree of alignment between agent decisions and system suggestions; satisfaction was recorded based on post-decision evaluations; and cognitive load was estimated through decision latency and the number of reversals.

5 Linking DEMATEL Causality to the Simulation Framework

Table 2 provides the conceptual link between DEMATEL-based causal modeling and the simulation analysis by showing how the influence structure derived from DEMATEL guided the simulation design. The table indicates how DEMATEL-derived trait roles and interface rules were incorporated into the adaptive logic and linked to the behavioral outcomes used for model validation. This linkage enables the causal drivers identified structurally to be examined behaviorally (Tao et al., 2025) in terms of their impact on trust, satisfaction, and cognitive load within the simulated environment.

Table 2
Integration of DEMATEL Results with Simulation Framework.

Construct / Trait	DEMATEL Role (Prominence & Causality)	Simulation Function	Outcomes
Emotional Reactivity	High prominence (+ 0.33); primary causal driver of interface tone adaptation.	Controls interface affective tone (calm ↔ stimulating).	↑ Satisfaction
Cognitive Load Tolerance	Moderate prominence (–0.19); receiver construct linked to task-complexity adaptation.	Modulates task complexity and decision latency.	↓ Cognitive Load
Fairness Sensitivity	Moderate prominence (–0.10); receiver construct linked to fairness-aware interface logic.	Activates fairness-aware interface logic.	↑ Trust
Interface Type Rules	Derived from causal structure among traits and interface demands.	Define adaptive logic for Static / Personalized / Fairness-Aware conditions.	All behavioral outcomes combined

5.1 DEMATEL Causal Mapping of Trait–Interface Influence

This section identifies which neurocognitive traits most strongly influence adaptive requirements in smart hospitality interfaces. In the context of this study, six key constructs are evaluated: three user traits—emotional reactivity, cognitive load tolerance, and fairness sensitivity—and three adaptive interface demands—simplicity, ethical alignment, and information control. These constructs derive from the study's theoretical framework, which integrates affective computing and dual-process decision theory (Hu et al., 2025; Oan-Oon & Choibamroong, 2025). Because interface personalization should reflect the major psychological differences, it is necessary to understand the causal hierarchy of these constructs (Tao et al., 2025). To establish which user traits most strongly influence the requirements for interface adaptation, a DEMATEL-based causal analysis was conducted using expert-derived pairwise ratings.

To identify the directional influence among user traits and interface demands, seven experts were recruited based on their knowledge and experience in tourism and hospitality informatics, AI-driven interfaces, and user experience design. Each expert then completed a structured DEMATEL matrix, indicating the influence of each construct on every other construct by rating it using a 0–4 scale (no influence to high influence). The six constructs were compared in all pairwise combinations, with diagonal self-influence entries excluded. The raw pairwise ratings were aggregated to form the Direct Influence Matrix presented. As shown in Table 3, emotional reactivity exerts substantial influence on simplicity, ethical alignment, and information control. Fairness sensitivity shows dominant effects on ethical alignment, while cognitive load tolerance also affects simplicity and information control demands. These initial results support the study’s trait-driven adaptation framework by showing that user traits are not only significant, but also structurally important in generating adaptive interface requirements (Deldjoo et al., 2024; Narayanan et al., 2024).

Table 3
Direct Influence Matrix.

Construct	Emotional Reactivity	Cognitive Load Tolerance	Fairness Sensitivity	Simplicity	Ethical Alignment	Information Control
Emotional Reactivity	0.0	2.43	2.0	2.29	2.29	2.14
Cognitive Load Tolerance	2.0	0.0	2.0	2.29	1.29	2.29
Fairness Sensitivity	1.14	2.43	0.0	1.86	2.43	2.14
Simplicity	2.14	2.29	2.0	0.0	1.71	1.71
Ethical Alignment	3.0	1.29	2.29	2.0	0.0	2.29
Information Control	1.86	2.0	2.0	1.71	1.29	0.0

Following the structural overview in the direct matrix, Table 4 provides a more detailed analysis by revealing the causal architecture underlying trait–demand processes. With expert input and appropriate max-normalization, the matrix provides a way to quantify the two key indicators: Prominence (D + R) and Net Causality (D–R). Prominence identifies which constructs are most central in the system, while net causality separates active drivers from the passive receivers, which is the key purpose of this causal modeling. The analysis suggests that Ethical Alignment (+ 0.62) and Emotional Reactivity (+ 0.33) emerged as strong defining influences within the system. In contrast, Information Control (–0.57) and Cognitive Load Tolerance (–0.19) are found to be structurally passive, being influenced rather than influencing. Emotional Reactivity is uniquely identified as having the greatest prominence within the system (7.1), which further highlights its importance in overall adaptive results. These trends confirm that adaptive interface design must account for user behavior and explicitly incorporate distinct neurocognitive characteristics. The emergent causal configuration informs the simulation logic that follows, ensuring that the resulting agent responses properly embody a theoretically grounded, structurally validated influence system. This causal configuration reinforces that emotional reactivity and ethical alignment anchor the adaptive logic, while fairness sensitivity and cognitive load tolerance remain structurally receptive but behaviorally relevant. Therefore, the structural roles identified through DEMATEL would be expected to shape subsequent behavioral metrics, although the strongest behavioral predictor varied by outcome.

Table 4
Total Influence Matrix with Prominence and Net Causality.

Construct	Emotional Reactivity	Cognitive Load Tolerance	Fairness Sensitivity	Simplicity	Ethical Alignment	Information Control	D + R (Prominence)	D–R (Net Causality)
Emotional Reactivity	0.0	0.81	0.67	0.76	0.76	0.71	7.1	0.33
Cognitive Load Tolerance	0.67	0.0	0.67	0.76	0.43	0.76	6.76	-0.19
Fairness Sensitivity	0.38	0.81	0.0	0.62	0.81	0.71	6.76	-0.1
Simplicity	0.71	0.76	0.67	0.0	0.57	0.57	6.67	-0.1
Ethical Alignment	1.0	0.43	0.76	0.67	0.0	0.76	6.62	0.62
Information Control	0.62	0.67	0.67	0.57	0.43	0.0	6.48	-0.57

Note: Prominence (D + R) represents total influence strength; Net Causality (D – R) represents directional dominance (positive = driver, negative = receiver).

Following the matrix analysis, the causal map in Fig. 2 translates the numerical structure into a visual configuration that clarifies directional dominance within the system. The circular arrangement distinguishes neurocognitive traits from interface demands and highlights the asymmetry of influence flow. Emotional Reactivity and Ethical Alignment emerge as highly influential sources of systemic influence, demonstrated by having many outbound connections to other constructs. This visual clustering demonstrated their positioning as proactive anchors regarding the proximal influence of adaptive requirements, consistent with the earlier analysis that traits serve not just as passive moderators but active design variables. By contrast, Information Control and Cognitive Load Tolerance function within the adaptive interface model as reactive, context-driven influences and appear as influence receivers.

The dominant influence structure demonstrates a cognitive-affective architecture in which emotional contagion and ethical framing shape interface expectations and influence system-level adaptation logic. These attributes are not merely inputs, but directional levers that determine whether the interface privileges simplicity, transparency, and user control. The dominant influence structure demonstrates a cognitive-affective architecture in which emotional contagion and ethical framing shape interface expectations and influence system-level adaptation logic. These attributes are not merely inputs, but directional levers that determine whether the interface privileges simplicity, transparency, and user control. This causal weight indicates structural centrality and makes them the key sources of variation in adaptive personalization. This concept serves as the foundation for the modeling phase, where the behaviors of the agents are analyzed based on their central traits. The analysis following this principle, which is derived from the application of such causality in terms of decision-making criteria, delves into the responsiveness of the interface through these fundamental characteristics.

5.2 Behavioral Effects of Interface Types

This part analyzes the interface types identified through the trait-interface influence structure and examines their behavioral effects within the simulated environment. These interfaces were designed to reflect the causal priorities identified by the DEMATEL results: personalized systems emphasized trait-responsive adaptation, whereas fairness-aware interfaces incorporated ethical features such as transparency and control (Leal et al., 2025). Each agent interacted with one of three interface conditions, namely static, personalized, or fairness-aware, whose logic stems from this causal mapping (Yang et al., 2024). The aim was to examine whether differences in adaptive design were associated with differences in trust, satisfaction, and cognitive load (Narayanan et al., 2024). A group-based statistical comparison across interface types was used to measure these impacts. All findings in this section are drawn from the agent-based simulation of 500 cognitively differentiated agents.

Building on the causal characteristic mapping, the descriptive data in Table 5 reveal clear differences in performance by interface type. The observed ordering of interface types from an ethical and affective perspective corresponds to the priorities implied by the causal structure. Embedding fairness-aware and trait-responsive rules seems to lead to increased trust and satisfaction, as well as decreased cognitive load (Godovykh & Tasci, 2022; Fominska et al., 2024). Fairness-aware interfaces produced the highest levels of trust and satisfaction and the lowest cognitive load (Trust 4.2; Satisfaction 4.1; Load 2.7), followed by personalized (3.5; 3.7; 3.2) and then static (2.8; 2.9; 3.8) ones. Furthermore, personalized interfaces were better than static designs in all three outcomes. The inferior performance with static interfaces reinforces the limitation of any non-adaptive design. These patterns suggest preliminary evidence that interfaces that responded to affective and fairness sensitivities can enhance experiential quality across the emotional and cognitive dimensions (Su & Ha, 2025).

Table 5
Descriptive Statistics of Behavioral Outcomes by Interface Type.

Interface Type	Trust (M ± SD)	Satisfaction (M ± SD)	Cognitive Load (M ± SD)
Static	2.8 ± 0.9	2.9 ± 1.0	3.8 ± 1.1
Personalized	3.5 ± 0.8	3.7 ± 0.9	3.2 ± 0.8
Fairness-Aware	4.2 ± 0.6	4.1 ± 0.7	2.7 ± 0.7

In addition to the descriptive trends, inferential tests were used to determine if observed differences in outcomes were statistically significant. Table 6 shows that all three behavioral variables are statistically significantly different between interface types. Trust showed the largest variance, suggesting that design logic heavily impacts system credibility. Flexible interface design

contributed significantly to user satisfaction. At the same time, ethically calibrated interface conditions were associated with lower cognitive load. These outcomes indicate that interfaces adapted to users' needs and attentive to users' emotional and fairness-related characteristics can enhance confidence, improve affective experience, and reduce cognitive load (Fominska et al., 2024; Yang et al., 2024). The size and consistency of these effects provide behavioral legitimacy to the previous causal trait mapping. These aggregate differences set the stage for the next analysis, which examines how alignment between agent traits and interface logic relates to these behavioral effects. Taken together, these interface-level results support H1 and H5.

Table 6
ANOVA Results for Behavioral Outcomes by Interface Type.

Outcome	Test Statistic	p-value	Effect Size (η^2)
Trust	F(2, 497) = 42.3	< .001	0.15
Satisfaction	F(2, 497) = 31.8	< .001	0.11
Cognitive Load	F(2, 497) = 28.6	< .001	0.1
Note: Comparison across: Static, Personalized, Fairness-Aware.			

To further illustrate patterns of outcomes, Fig. 3 displays the distribution of agent responses across interface types. The adaptive interfaces outperformed static systems; dispersion narrowed for trust and satisfaction under fairness-aware systems, while cognitive-load dispersion remained wider under static systems. Static interfaces showed greater variation in trust and satisfaction, while cognitive load displayed the widest dispersion under non-adaptive conditions. These visual patterns are consistent with the earlier statistical results. Taken together, these patterns suggest that fairness-aware and affectively responsive interfaces are associated, on average, with lower-load and more stable user experiences (Narayanan et al., 2024; Koo et al., 2025).

The outcomes across interface types suggest a functional value in trait-informed interface design. Increased trust under fairness-aware conditions demonstrates the successful integration of ethical responsiveness into system logic, with users attuned to fairness and transparency. Increases in satisfaction associated with adaptive formats, especially among agents with heightened emotional reactivity, also suggest the presence of affectively attuned personalization mechanisms. The diminished cognitive load on fairness-aware interfaces also suggests that system logic matching user tolerance thresholds may help reduce cognitive effort. The results serve to elaborate upon the causality structure discovered earlier in relation to behavior, thus providing a foundation for the next section that explores the effects of trait-interface fit on performance. In particular, the trust gains under fairness-aware conditions are consistent with ethically calibrated adaptation mitigating skepticism that otherwise accompanies higher load or opacity.

5.3 Trait–Interface Alignment and Performance Outcomes

This section explores how the behavioral impact of an interface design depends not only on interface type, but also on the degree of psychological alignment between user traits and system logic. The simulation design embedded trait-driven responsiveness into interface behavior, guided by a previously established structure of cognitive–affective influence. Interfaces varied in their sensitivity to user needs—some optimizing for emotional simplicity, others for ethical coherence—creating natural differences in how well they matched agent dispositions. To examine this, alignment was modeled through trait terms, interface terms, and their interaction terms in the outcome models. The analysis examines trait–outcome correlations and trait-interface interaction effects across interface types.

For establishing a differentiated basis for alignment based on users' psychology, the initial step is to analyze the relationships between each neurocognitive attribute individually and the key behavioral measures. This work has been done using the correlations presented in Table 7, indicating different degrees of impact. Of the variables related to trust, the sensitivity of the individual to the issue of procedural justice was seen to be the strongest predictor, suggesting the users' sensitivity to issues of trustworthiness (Narayanan et al., 2024; Su & Ha, 2025). In addition, emotional reactivity was positively correlated with satisfaction, implying that the greater an agent's emotionality, the more benefits he or she derives from using the system (Lee, 2025). Cognitive load tolerance showed a significant negative correlation with perceived load, indicating lower perceived effort.

The findings support the idea that each characteristic influences the person's behavior through a different psychological mechanism and, thus, offer an opportunity to examine whether that interaction with the interface logic strengthens or disrupts these patterns (Yin & Hwang, 2025). The pattern in which fairness sensitivity is most associated with trust, emotional reactivity with satisfaction, and cognitive-load tolerance with lower perceived load accords with the structural roles identified earlier, suggesting that causal centrality carries forward into behavioral expression once rules are embedded (consistent with H3 and H4).

Table 7
Trait-Outcome Correlation Matrix.

Trait \ Outcome	**Trust**	**Satisfaction**	**Cognitive Load**
Emotional Reactivity	-0.02	**0.51**	0.01
Cognitive Load Tolerance	-0.02	-0.15	**-0.62**
Fairness Sensitivity	**0.56**	-0.03	0.06
Note: Trait–outcome associations are directionally consistent with the causal roles identified through DEMATEL.			

This phase assessed whether the congruence between individual traits and interface conditions affected behavioral outcomes, building on the previously identified structure of relationships. The individual effects of user traits and adaptive interfaces were statistically significant; fairness sensitivity predicted trust, emotional reactivity predicted satisfaction, and cognitive load tolerance predicted lower cognitive load. Those patterns are visually reflected in Fig. 4, where trait–outcome relationships show variation in slope across interface types. None of the interaction terms are statistically significant (Table 8), indicating that although traits and interface types may have separate effects on behavior, their alignment did not produce additional interaction effects. Accordingly, H2 is not statistically supported. Adaptive interfaces, particularly fairness-aware and personalized designs, still exceed static interfaces across all outcome measures. These results validate the importance of trait-based personalization even without statistical support for trait-interface interaction variables. The results indicate that the concept of using neuroadaptation to design interfaces can improve trust and satisfaction and minimize cognitive effort. Similar findings were reported in research on cultural and trait-based variations in agent-driven social cohesion models (Plikynas et al., 2022), which, in turn, support the idea that personality traits significantly influence complex adaptive behavior.

Table 8
Trait–Interface Alignment Models for Behavioral Outcomes.

Outcome	Predictor	Coefficient	p-value
Trust	Intercept (Static Baseline)	2.00	< .001
Trust	Fairness Sensitivity (Trait)	1.05	< .001
Trust	Fairness-Aware Interface (vs. Static)	0.36	< .001
Trust	Fairness Sensitivity × Fairness-Aware Interface	0.03	0.793
Satisfaction	Intercept (Static Baseline)	2.18	< .001
Satisfaction	Emotional Reactivity (Trait)	0.92	< .001
Satisfaction	Personalized Interface (vs. Static)	0.39	< .001
Satisfaction	Emotional Reactivity × Personalized Interface	0.05	0.665
Cognitive Load	Intercept (Static Baseline)	3.42	< .001
Cognitive Load	Cognitive Load Tolerance (Trait)	-1.11	< .001
Cognitive Load	Personalized Interface (vs. Static)	-0.23	< .001
Cognitive Load	Cognitive Load Tolerance × Personalized Interface	0.11	0.340

Note: “Intercept” indicates the predicted outcome score when both trait and interface values are zero. Interaction terms test whether the effect of each trait changes depending on the assigned interface type. Predictors with p-values < 0.05 were statistically significant.

These findings indirectly reinforce the broader logic of trait-informed personalization. Trust, satisfaction, and cognitive load measures showed that adaptive interfaces were generally superior to their static counterparts. Traits with strong behavioral relevance, especially fairness sensitivity and emotional reactivity, emerged as significant behavioral predictors, validating their structural relevance. While interaction terms failed to reach statistical significance, the overall pattern remained directionally consistent with expectations: adaptive interfaces increased trust and satisfaction and reduced perceived load, showing that behavioral benefits can be obtained even without statistically significant trait–interface amplification. These findings are consistent with the idea that personalization based on causal trait structure can enhance user experience (Kumar et al., 2025) even when explicit psychological alignment effects are not statistically observed.

5.4 Integrated Interpretation of Simulation Findings

Through synthesizing trait-based interface requirements, design variation impacts on user behaviour and psychological alignment effects on performance outcomes, this final interpretive analysis incorporates all three elements simultaneously (not in isolation) to investigate how neurocognitive drivers of behaviour (i.e., emotional responsiveness, sensitivity to fair outcomes, and cognitive load tolerance) influence both user requirements of their adaptable systems and the resulting behavior of users when their requirements are (or are not) met. In sum, these outcomes support the broader logic of the study, showing that fairness-aware and trait-responsive designs improve trust, satisfaction, and cognitive ease when they are responsive to the most relevant user traits.

Based on the causal architecture and behavioral findings, the following synthesis explains which adaptive interface types appear most appropriate for each neurocognitive trait and why. Rather than simply summarizing outcomes, this integrative framework links DEMATEL-based causal roles, theoretical grounding, and behavioral response patterns to guide interface optimization. Each trait is paired with an interface logic that most closely matches its cognitive or emotional processing style through affect-driven adaptation, simplification, or fairness-oriented design. The analysis also examines the implications of misalignment, highlighting what can go wrong when personalization neglects user dispositions. In placing these relationships within the theoretical framework of the study, Table 9 acts as a system-level map to convert trait-based differences into coherent design logic. The interpretive synthesis aligns with the empirical results, leading to practical and ethical implications.

Table 9
Trait–Interface Design Logic and Simulation-Based Implications.

Trait	Causal Role (D–R)	Theoretical Lens	Best Interface Type	Design Logic and Trait Alignment	Outcomes and Misalignment Risk
Emotional Reactivity	+ 0.33 (Driver)	Affective Computing Theory, Dual-Process Theory (System 1).	Personalized	Responsive interfaces, for instance, adjust their tone and message framing according to the user's emotional sensitivity; thereby, they help lower the user's stress and increase their engagement level	↑ Satisfaction; if mismatched: emotional overload, frustration, disengagement.
Cognitive Load Tolerance	–0.19 (Receiver)	Dual-Process Theory (System 2).	Personalized	A simplified information structure reduces mental effort for users with low tolerance, providing greater clarity and lower perceived burden during choice.	↓ Cognitive Load; if mismatched: delay, confusion, decision reversal.
Fairness Sensitivity	–0.10 (Receiver)	Ethical Adaptation Principles (Affective Computing & System Transparency).	Fairness-Aware	Transparent and ethically calibrated design aligns with the justice-related concerns, thereby increasing trust and reinforcing perceptions of procedural legitimacy.	↑ Trust; if mismatched: skepticism, resistance, perceived bias.

These results suggest that personalization works best when it is grounded in the underlying logic of user characteristics rather than in superficial adaptation. Traits with strong behavioral relevance, especially emotional reactivity and fairness sensitivity, not only shape the interaction context but also help explain the resulting behavioral outcomes when interface logic is responsive to them. The linkage between causal structure and behavioral data provides strong support for using neuroadaptive reasoning to inform interface architecture, helping adaptive systems respond to users through a more socially responsible form of trait-driven personalization.

6 Discussion and Conclusions

6.1 Neurocognitive Alignment in Adaptive Interfaces

This research views interface adaptation as dependent on neurocognitive processes, in which user characteristics are not merely residual modifier states of the interface; in fact, they define the system’s fundamental logic. Emotional reactivity, fairness sensitivity, and cognitive load tolerance each exerted distinct causal influence on interface demands, and adaptive interfaces implemented through personalization or fairness-aware design were associated with improvements in trust, satisfaction, and cognitive load outcomes. Importantly, the same attributes that shaped the system's architecture through DEMATEL were also associated with behavioral outcomes in the simulation, demonstrating dual relevance at both the structural and experiential levels. These results extend beyond surface-level personalization by offering a model in which adaptive systems must operate using an internal logic congruous with user psychological architectures (Kwong et al., 2024). This convergence of structural prominence and behavioral relevance suggests that neurocognitive alignment should be treated as a foundational design principle rather than a secondary optimization.

The results indicate that alignment between users' dispositions and interface design is more than advantageous and should be treated as an important design consideration. Instances of misalignment were associated with behavioral friction: emotionally reactive agents showed lower satisfaction when interfaces did not moderate tone, fairness-sensitive users disengaged when transparency was absent, and cognitively sensitive users slowed or reversed decision-making when overloaded with complexity. These dynamics indicate that personalization is not ethically neutral; design choices can either reinforce or disrupt cognitive trust and affective rapport (Koo et al., 2025). Accordingly, neuroadaptive design should be framed not only as a technical improvement but also as a psychological accountability: the system should know enough to support the user, beyond serving content.

6.2 Theoretical and Methodological Implications

This study advances theory by integrating Dual-Process Theory and Affective Computing within a simulation architecture in which neurocognitive traits operate as causal determinants rather than statistical correlates. Most previous studies regard traits as covariates; however, this model integrates the three traits of emotional reactivity, cognitive load tolerance, and fairness sensitivity directly in the adaptive interface logic. This alignment between DEMATEL-identified causal drivers and simulation behavior creates a replicable mechanism-based framework that links psychological theory with computational implementation. The approach also extends methodological practice by demonstrating how DEMATEL and agent-based simulation can be combined to trace dynamic decision pathways, validate causal structures, and test adaptive interface rules under controlled conditions that are not feasible with human subjects.

Methodologically, the framework shows how synthetic agents can be used to examine repeated decision cycles, feedback sensitivity, and interface–trait interactions while maintaining transparency, reproducibility, and full control over psychological variation. Sequential phases of trait modeling, causal mapping, simulation alignment, and sensitivity testing provide a pathway for researchers seeking to evaluate ethically guided AI, fairness adjustments, or adaptive decision logic before field experiments or large-scale A/B testing. This methodological contribution is strengthened by clearly positioning the simulation as a pre-implementation evaluation tool for complex adaptive systems rather than as a replacement for empirical research. The results also show that interface design is a central factor in digital hospitality systems. Fairness-aware interfaces may strengthen users' perceptions of procedural justice. At the same time, cognitive-load-sensitive displays may help reduce the decision fatigue effect in situations with many choices, and emotion-responsive changes may allow users to feel a more natural flow in their interactions with the digital world. These realizations demonstrate the potential of the model's combined theoretical and methodological contributions to serve as a source of inspiration for adaptive system design.

6.3 Limitations and Future Directions

Simulation allows for a systematic evaluation of trait-driven adaptation (Pizarro et al., 2023). However, this method ignores some practical aspects of user experience. Factors such as interface latency, the affective nature of the context, and multitasking needs remained constant throughout the experiment. Additionally, traits were treated as dispositional, or stable, rather than as dynamic states, thus preventing their moment-to-moment co-adaptation. Future research could pursue empirical validation through longitudinal studies or physiological measurements to explain how trait-interface alignment is established under true decision pressures and environmental uncertainty, and especially when including cultural contexts with differences in fairness norms or bases for cognitive load.

In addition to ecological realism, the current model is constrained to three high-salience traits, which may overlook other psychologically relevant dimensions, such as locus of control, impulsivity, or affective instability. Broadening the set of trait dimensions may allow for observations of multi-trait interactive effects or conditional adaptation effects under compound cognitive–emotional profiles. Expanding the trait set would also allow the testing of nonlinear or compensatory dynamics—where high emotional reactivity might counterbalance low cognitive load tolerance, or vice versa—revealing richer adaptive strategies. Methodologically, future research could improve the DEMATEL phase using fuzzy-set logic or adaptive weighting methods or incorporate iterative expert calibrations to reduce domain surface biases and account for temporal variation in trait expression. This could support a shift from reactive personalization toward more fully neuroadaptive ecosystems that monitor, anticipate, and ethically respond to the changing psychological needs of digitally mediated users over time.

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Figures

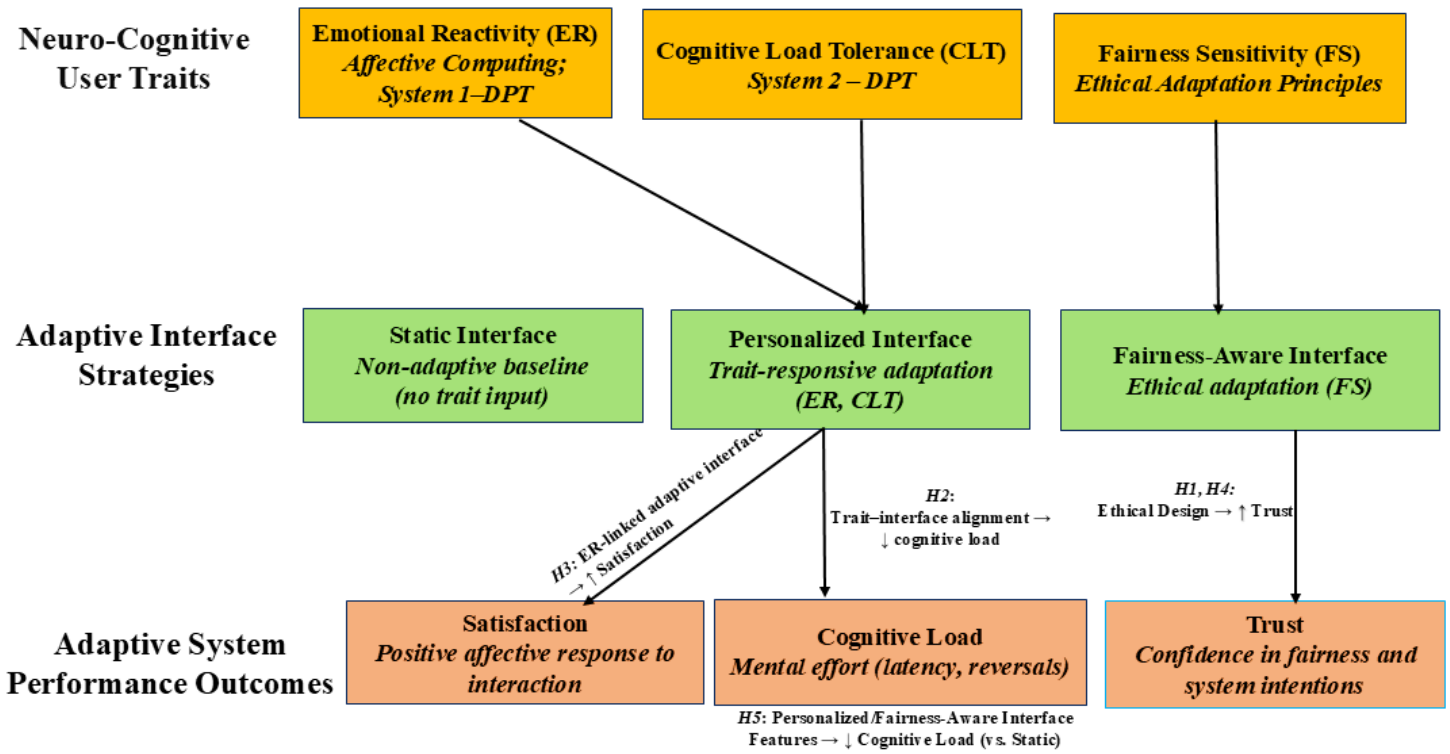


Figure 1

Neuroadaptive Interface Framework for Hospitality Booking Contexts.

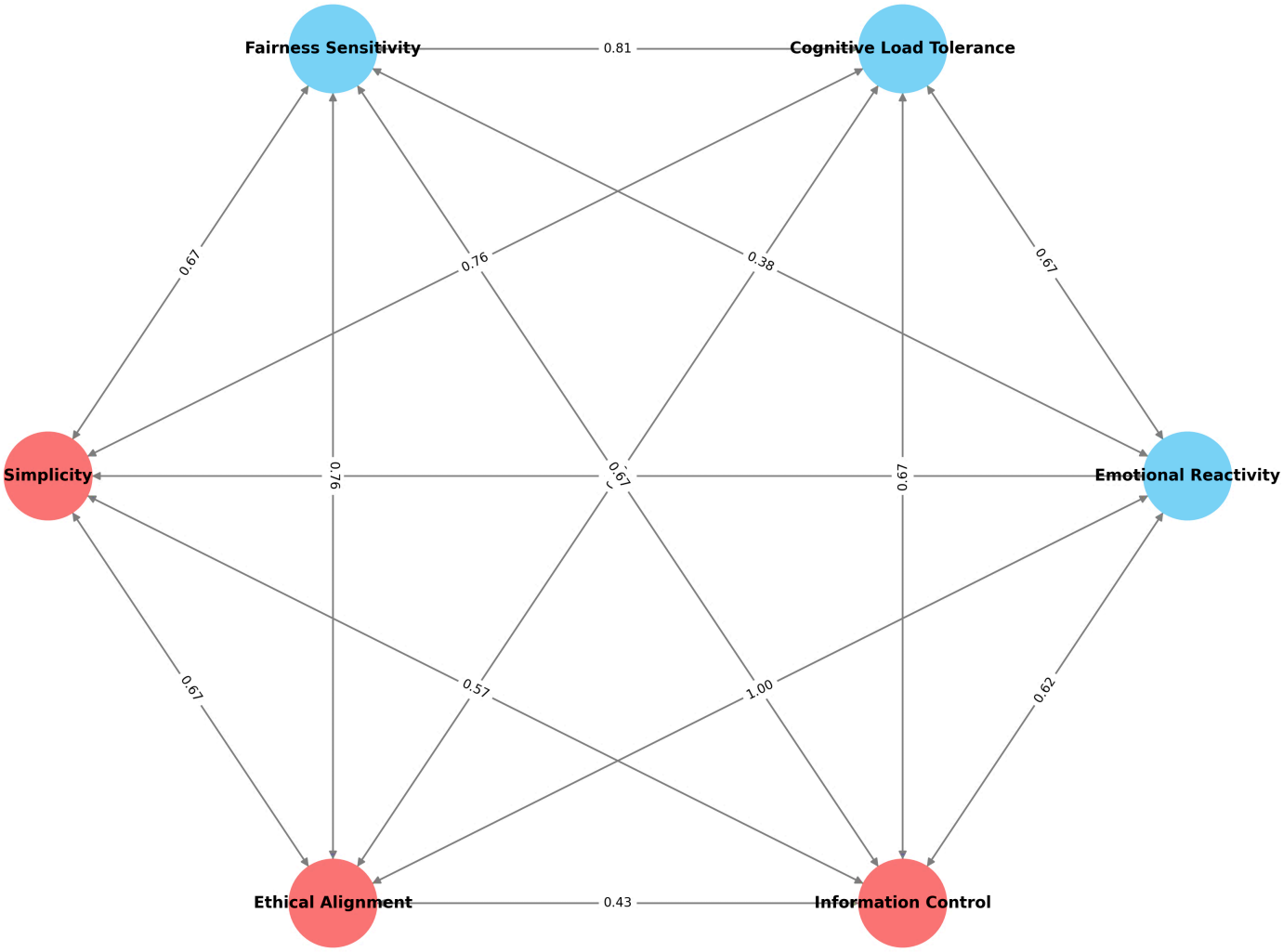


Figure 2

DEMATEL Causal Map of Neurocognitive Traits and Interface Demands.

Note: Blue nodes = driver constructs (positive D–R); Red nodes = receiver constructs (negative D–R). Edge weights denote normalized influence strength.

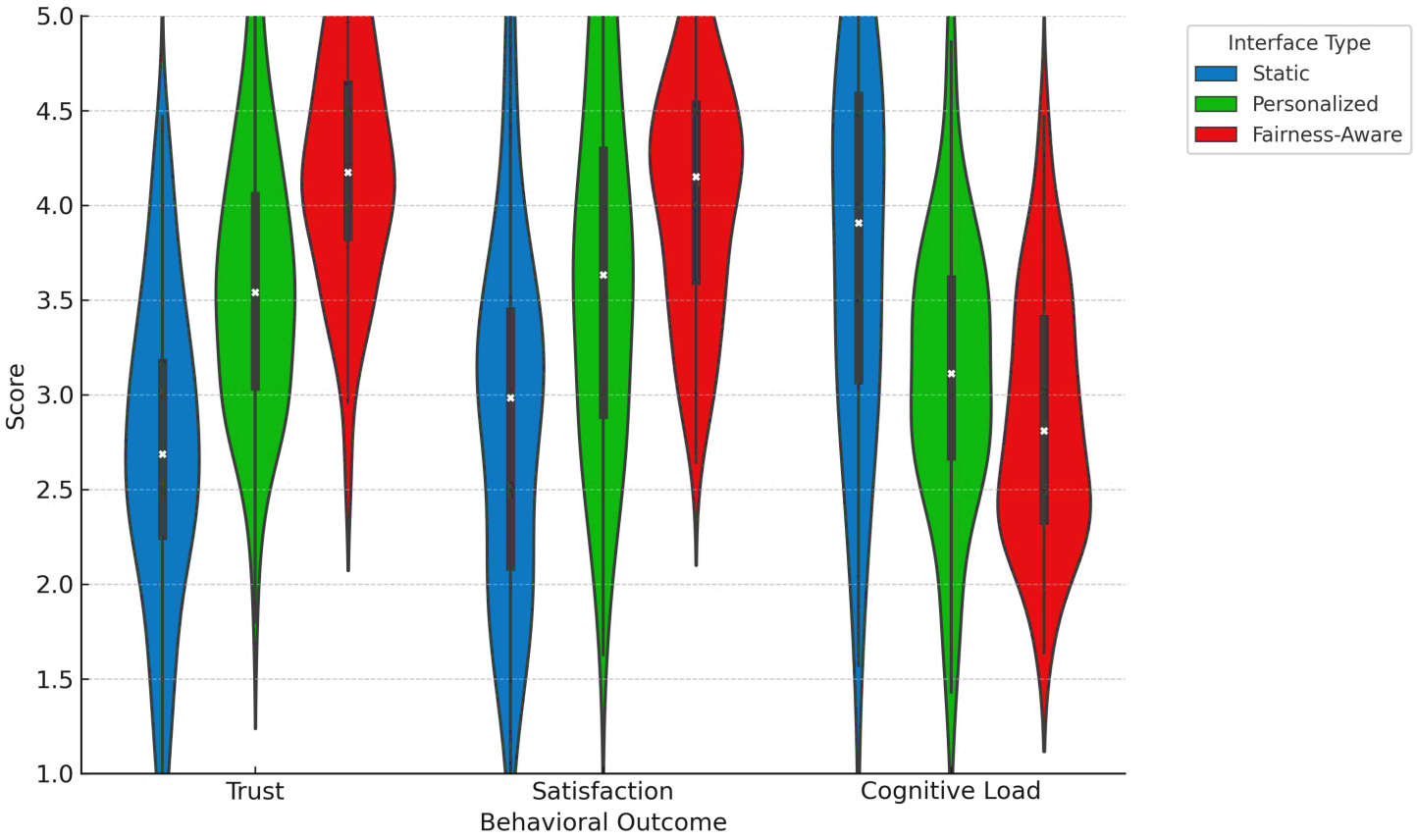


Figure 3

Distribution of Behavioral Outcomes by Interface Type.

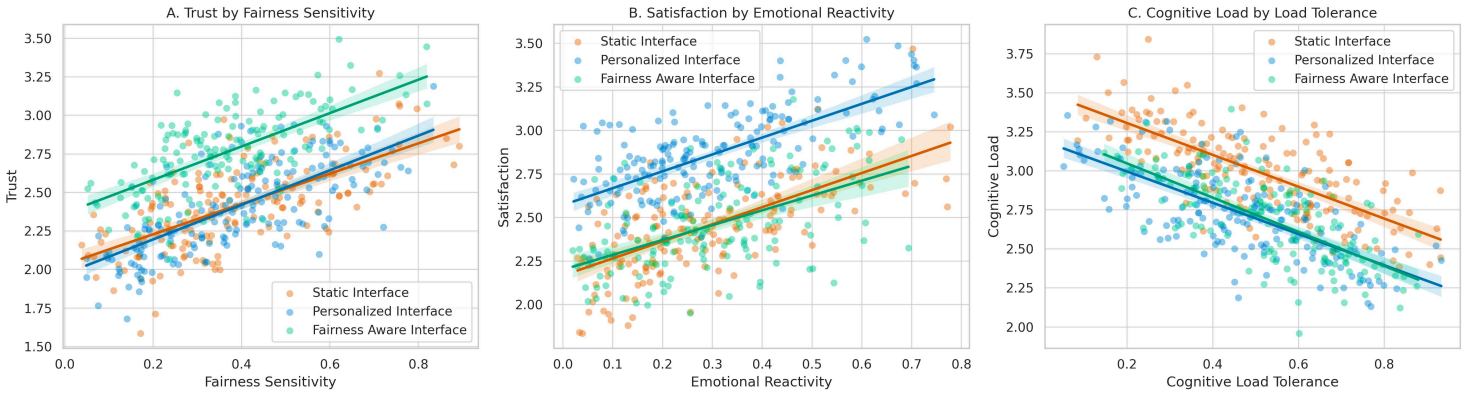


Figure 4

Trait-Interface Interaction Effects on Behavioral Outcomes.