Neuroadaptive Recommendation Systems: Modeling Fairness Preferences and Individual Differences with Reinforcement Learning and Large Language Models

Xavier Terry
Department of Computer Science, University of Central Florida, Orlando, FL, USA.
xaviercodes@ucf.edu

Ashwin Shukla
Department of Computer Science and Engineering, University at Buffalo, Buffalo, NY, USA.
ashwin.shukla@buffalo.edu

Bennett Jorgensen
Department of Computer Science, George Mason University, Fairfax, VA, USA.
contactbennett@gmu.edu

Madhav D. Mehra
Department of Electrical Engineering and Computer Science, University of Kansas, Lawrence, KS, USA.
madhavmail@ku.edu

Abstract

Neuroadaptive recommendation systems represent a shift from short-term engagement optimization toward infrastructures that continuously model fairness preferences, individual differences, and long-term user welfare. This paper examines the system-level integration of reinforcement learning and large language models for adaptive recommendation, focusing on architectural trade-offs, preference representation, governance, and deployment constraints. Unlike static fairness interventions, neuroadaptive architectures treat fairness as a dynamic and individually heterogeneous construct that emerges through interaction histories, social norms, cognitive dispositions, and platform incentives. The discussion develops a conceptual framework in which large language models provide semantic compression and simulation capacity, while reinforcement learning manages sequential policy adaptation under delayed and partially observable outcomes. The paper analyzes how individual differences in fairness norm adaptation can be incorporated without reducing users to fixed categories, and how simulation-based evaluation can support policy exploration. It further addresses structural tensions between personalization and group-level fairness, between model capacity and infrastructure sustainability, and between continuous adaptation and institutional accountability. Governance considerations include auditability, consent, resource consumption, feedback loop management, and the risk of normative convergence. The analysis connects current fairness formalisms to long-term system dynamics and argues that neuroadaptive recommendation should be designed as a regulated, interpretable, and sociotechnically embedded control system rather than a purely predictive optimization pipeline.

Keywords

recommender systems, fairness, reinforcement learning, large language models, neuroadaptive systems, individual differences, governance.

1. Introduction

Recommendation systems now operate as distributed coordination mechanisms across markets, media platforms, public health communications, and knowledge infrastructures. Their outputs shape not only immediate user choices but also the longer-term evolution of preferences, opportunity exposure, and social norms. This condition demands a broader analytical frame than the traditional accuracy-centric view of collaborative filtering. A neuroadaptive recommendation system is best understood as a closed-loop sociotechnical architecture that senses user states, infers latent fairness preferences and individual differences, and adapts its policy over time using reinforcement learning and language-based reasoning. The term neuroadaptive does not necessarily imply direct neural measurement in production environments; it denotes adaptation mechanisms that respond to behavioral, affective, and cognitive signals with the same conceptual plasticity observed in biological learning systems. The objective is to align system behavior with heterogeneous user values while maintaining group-level equity, operational robustness, and institutional accountability.

The central difficulty is that fairness preferences are not stable attributes. They vary across individuals, contexts, and temporal horizons. A user may tolerate popularity bias in entertainment recommendations while demanding demographic parity in job or loan recommendations. Fairness preferences also shift after exposure to algorithmic outcomes, group feedback, and changes in perceived autonomy. Static fairness constraints that impose a single distributive pattern across all users therefore risk both normative misalignment and learning instability. Reinforcement learning offers a principled approach to sequential decision making under delayed outcomes, while large language models provide a flexible substrate for representing natural language preferences, contextual norms, and individualized explanatory feedback. However, their integration introduces structural trade-offs in latency, interpretability, safety, and resource consumption. This paper addresses these trade-offs from a systems perspective, developing a conceptual architecture and analyzing governance, sustainability, and long-term fairness implications.

2. System-Level Foundations and Related Work

The evolution of recommender systems has been driven by hybrid architectures that combine collaborative filtering, content-based modeling, knowledge graphs, and contextual signals. Hybrid systems emerged as a response to the limitations of singular data sources, such as cold-start problems, sparsity, and narrow user representations [1]. Matrix factorization later became a dominant computational strategy because it compresses user-item interactions into dense latent spaces while enabling scalable learning in large catalogs [2]. These models established the foundational assumption that user preferences can be represented as latent vectors and updated through observed feedback. As recommender systems matured, researchers began to emphasize that the purpose of recommendation is not merely prediction accuracy but the satisfaction of higher-order goals such as diversity, novelty, user agency, and decision quality [3]. This purposive turn opened space for fairness and long-term welfare to become first-class design criteria rather than post hoc corrections.

The move toward adaptive recommendation has been further accelerated by reinforcement learning methods that explicitly model sequential decision processes. Deep reinforcement learning demonstrated that policies operating on high-dimensional state spaces can learn

effective action selection through trial and error, even when rewards are delayed and environments are nonstationary [4]. The formal treatment of reinforcement learning as an interaction between agent, environment, reward, and value estimation provides a natural vocabulary for recommendation, where each impression is an action and user responses form a delayed, noisy reward stream [5]. In news recommendation, deep reinforcement learning has been used to adapt user interest representations dynamically and to balance immediate click feedback with return behavior [6]. Off-policy correction methods address a core deployment issue in recommender systems: the data used for training are generated by a previous logging policy, and direct policy updates can be biased because actions not selected under the logging policy are underrepresented [7]. These advances show that reinforcement learning can improve long-term engagement, but they also reveal that reward design, exploration control, and fairness constraints must be integrated at the architectural level.

3. Architectural Foundations for Neuroadaptive Recommendation

A neuroadaptive recommendation architecture can be described as a layered control system comprising sensing, representation, policy learning, action generation, and governance components. The sensing layer ingests heterogeneous observation streams, including click histories, dwell time, query logs, survey responses, explicit fairness signals, and potentially physiological or neurocognitive markers in consented research settings. The representation layer compresses these observations into state variables that capture not only content affinity but also fairness sensitivity, cognitive load, risk tolerance, and contextual vulnerability. The policy layer learns to select recommendation actions from a combinatorial space of items, explanations, and interface presentations. The action layer produces the actual user-facing output, while the governance layer enforces constraints related to equity, transparency, privacy, and organizational policy.

One structural advantage of this layered design is the separation between preference estimation and normative reasoning. In conventional recommender systems, these functions are often entangled inside a single predictive objective, making it difficult to audit why a particular decision was made. In a neuroadaptive system, fairness-relevant state dimensions can be maintained as explicit intermediate representations. This supports modular evaluation and allows fairness constraints to be adjusted without retraining the entire preference model. It also facilitates the inclusion of user feedback about perceived fairness, which can be treated as a supervised signal for representation learning and as a reward component for policy learning. The main structural cost is increased design complexity: each layer introduces its own data quality assumptions, failure modes, and coordination requirements. Latency budgets, particularly for real-time recommendation, constrain how many signals can be processed before action selection. Model versioning and accountability become more demanding because changes in the representation layer can propagate into fairness outcomes even when the policy layer remains unchanged.

The selection of a reinforcement learning policy class must also reflect deployment conditions. Model-free policy gradient methods can learn directly from logged interactions but may require large amounts of data and careful off-policy correction. Value-based methods can improve sample efficiency but are sensitive to function approximation errors and action-space design. Actor-critic architectures balance these concerns by maintaining separate policy and value estimators, yet they introduce additional synchronization and stability challenges. In large-scale systems with millions of users and high-dimensional action spaces, the choice of policy architecture is not only a statistical decision but also an infrastructure decision

involving serving costs, model refresh cycles, and rollback capabilities. Neuroadaptive systems therefore require an explicit consideration of how learning updates propagate through the production stack and how stale or biased models can be detected before they produce material harm.

4. Fairness Preference Modeling and Norm-Sensitive State Representations

Fairness preference modeling requires more than applying a post hoc constraint to a predictive model. It demands that the system infer which fairness norms are relevant to a user in a given context, how those norms trade off against utility, and how the user interprets the distribution of recommendations over time. Large language models offer a promising route to represent these preferences because they can encode natural language descriptions of fairness, generate context-sensitive explanations, and support zero-shot inference over user-expressed values [8]. When these models are tuned with human feedback, they can be aligned with instructed behaviors and produce more controllable outputs that distinguish between descriptive preferences and normative commitments [9]. However, the use of language models for fairness representation introduces a distinct set of risks. Language models can inherit societal biases, overgeneralize from textual corpora, and generate fluent but normatively inconsistent interpretations of fairness. These risks are welldocumented in studies showing that large pretrained models exhibit stereotypical associations and that prompt-based inference may amplify demographic biases [10]. Fairness in machine learning is itself a multiply realized concept, encompassing individual, group, and counterfactual notions that cannot be reduced to a single metric without loss [11]. A norm-sensitive state representation should therefore separate three conceptual layers: the user's descriptive preferences for content, the user's normative fairness sensitivity, and the contextual salience of fairness. Descriptive preferences drive expected utility, while fairness sensitivity determines how the user interprets distributional properties of a recommendation list. Contextual salience reflects whether the decision domain, such as employment, health, or entertainment, activates stronger fairness concerns. These layers are not independent; they co-evolve as the system interacts with the user. For example, repeated exposure to homogeneous content may gradually reduce a user's perceived diversity without producing immediate dissatisfaction, a phenomenon that is difficult to capture with static utility models. A neuroadaptive representation can maintain a memory of fairness-relevant experience and update the user's sensitivity estimate through observed reactions to distributional changes. This dynamic state enables the policy to test whether fairness violations produce long-term disengagement even when short-term engagement remains high.

The design problem is further complicated by individual differences in how users perceive and adapt to fairness norms. Recent evidence indicates that fairness norm adaptation capability has a substantial heritable component and is associated with specific neural mechanisms [12]. This does not suggest that production systems should rely on neural measurement, but it does imply that fairness sensitivity is not merely a surface preference that can be inferred from a few interactions. Individual differences may reflect stable dispositional factors, learned normative commitments, and contextual moderators such as perceived risk and social identity. A neuroadaptive system should therefore treat fairness sensitivity as a partially observable latent state that is updated through multimodal signals, including self-reports, behavioral reactions, and contextual cues. Large language models can support this inference by interpreting unstructured user statements about fairness, but their outputs must be treated as probabilistic evidence rather than definitive psychological measurements.

The use of large language models within this representation layer offers a distinct mechanism for eliciting and encoding fairness preferences. Rather than relying solely on inferred latent factors, a system can present users with short scenario-based fairness queries or ask them to rank decision outcomes according to their own normative priorities. Language models can then transform unstructured responses into a structured preference representation that conditions downstream recommendation policies. This procedure is promising because it makes user values explicit and auditable. At the same time, the textual interpretation is vulnerable to prompting effects, framing effects, and overconfidence in generated summaries. The resulting preference vector may be more articulate than the user's actual behavior, producing a mismatch between stated and revealed fairness preferences. Systems must therefore cross-validate language-derived preferences with observational data and periodically re-elicit them as user contexts change. Fairness preference modeling must also account for bounded rationality and cognitive load. Users do not evaluate every recommendation through an explicit fairness lens; they often rely on heuristic judgments about whether the system appears balanced, transparent, and respectful of their autonomy. A neuroadaptive architecture can treat such heuristics as summary signals that aggregate multiple fairness dimensions into a lower-dimensional perceived fairness state. The policy can then learn to manage this perceived state in addition to objective distributional constraints. This marks a departure from purely outcome-based fairness enforcement, because it recognizes that identical allocation outcomes can be perceived differently depending on explanation, framing, and prior experience. Consequently, the representation layer should support both normative evaluation and perceived fairness modeling, with mechanisms that prevent perceived fairness from becoming a substitute for substantive fairness.

5. Reinforcement Learning Policy Design and Sequential Fairness Constraints

Sequential fairness in recommendation cannot be guaranteed by enforcing a fairness constraint independently at each time step. Because user responses form a feedback loop, a myopic constraint on the current slate may produce cumulative inequities over time. Reinforcement learning provides a natural framework for optimizing long-term objectives under uncertainty, but the inclusion of fairness changes the structure of the learning problem. The reward function must balance engagement, diversity, fairness, and user welfare, and the relative weights among these objectives may themselves be context-dependent and nonstationary. When fairness is treated as a scalar penalty added to a utility objective, the system may learn to satisfy the penalty in ways that are technically compliant but normatively superficial. A more robust design treats fairness as a set of constraints or as a multidimensional reward signal whose decomposition is visible to auditors.

One important structural choice is whether fairness constraints are enforced through reward shaping, constrained policy optimization, or policy architecture design. Reward shaping is computationally straightforward but can create unintended incentives if the shaped reward misrepresents the true objective. Constrained policy optimization imposes explicit constraints on the policy update, which preserves feasibility but may increase training complexity and slow convergence. Architectural design restricts the action space or injects fairness-sensitive features into the state representation, thereby making fairness a persistent part of the policy rather than an auxiliary correction. Each approach has different implications for stability, sample efficiency, and auditability. In large-scale production systems, the choice is rarely purely algorithmic; it depends on the capacity of the serving infrastructure to evaluate constraints in real time and on the ability of governance teams to understand policy changes.

Reinforcement learning with LLM-augmented user simulations has been proposed as a way to reduce the cost and risk of exploration in adaptive recommendation [13]. Such simulations generate plausible user responses to candidate recommendation actions, allowing the policy to explore a wider range of strategies without exposing real users to harmful or confusing outcomes. However, the effectiveness of this approach depends on the fidelity of the simulated user model. If the simulation reproduces only average behavioral patterns and fails to capture the diversity of fairness sensitivities, the learned policy may overfit to an artificial population. Simulations can also become self-confirming when the language model used to generate user feedback shares biases with the policy model. The governance challenge is to ensure that simulation-based evaluation is validated against observed user behavior and that its conclusions do not supersede evidence from real interactions.

Existing fairness formalisms in ranking and recommendation range from individual fairness notions that require similar treatment of similar users to group-level notions that require equitable exposure across protected groups [14]. Counterfactual fairness offers another lens by asking whether a recommendation outcome would change if a sensitive attribute were different while holding other factors constant [15]. Long-term fairness frameworks have extended these static notions to dynamic recommendation settings, showing that temporal exposure disparities can persist even when per-round metrics appear acceptable [16]. These formal distinctions matter for neuroadaptive systems because individual differences in fairness norms may align more closely with one formalism than another. A user who emphasizes equal opportunity may be better served by group-level constraints, while a user who emphasizes consistent treatment may prefer individual fairness. The policy architecture must be capable of representing and reconciling these competing normative frames.

Long-term fairness also requires a careful treatment of delayed outcomes. A recommendation that appears fair in the current session may affect future opportunity through changes in user trust, exploration willingness, or content provider incentives. Reinforcement learning is designed to handle delayed rewards, but credit assignment over long horizons remains a significant bottleneck. The system may fail to connect a fairness violation observed weeks later to an earlier recommendation action. Temporal difference learning can propagate value information backward, but high-dimensional state spaces and sparse fairness signals make the learning process unstable. In practice, system designers often introduce proxy rewards, such as trust signals or report rates, that provide faster feedback. These proxies may reduce variance but can also distort the learned policy if they do not align with the underlying normative objective. Regular audits that compare proxy-driven behavior with longer-horizon fairness metrics are therefore essential.

The treatment of exploration is another structural risk. Reinforcement learning policies must explore alternative actions to improve their estimates, but exploration in a recommendation system can expose users to lower-quality or normatively questionable content. Exploration strategies that ignore fairness may produce disparate exploration burdens across user groups, because some groups may receive more experimental variation than others. A neuroadaptive policy can modulate exploration based on individual differences in risk tolerance and fairness sensitivity. Users who are less tolerant of unpredictable recommendation changes may be assigned lower exploration rates, while users who actively seek diverse content can participate more extensively in policy improvement. This differential exploration, however, must be governed to prevent it from becoming a hidden mechanism of inequity. Transparent

logging and user consent are necessary to ensure that exploration burdens are not disproportionately imposed on vulnerable populations.

6. Large Language Model Integration for Simulation, Explanation, and Preference Elicitation

Large language models have moved beyond the role of content encoders and now function as components of the recommendation control loop. They can generate natural language explanations, summarize user feedback, simulate possible user states, and support interactive preference elicitation. The integration of language models with reinforcement learning creates a hybrid reasoning architecture in which symbolic and subsymbolic processes are jointly regulated. Language models contribute semantic flexibility, while reinforcement learning contributes sequential optimization. This hybridity is particularly valuable for fairness because fairness is expressed in natural language and grounded in socially variable norms. A language model can translate a user's statement such as "I want more diverse candidates" into a structured fairness preference that conditions the policy, and it can explain why a particular recommendation slate was selected. These explanations serve both as user-facing transparency and as internal audit trails.

However, language model outputs are not reliable in the same way as deterministic database queries. The same input can produce multiple plausible interpretations, and small changes in prompt phrasing can lead to different preference representations. This stochasticity is both a feature and a risk. It allows the system to express nuance, but it also complicates reproducibility and accountability. In a fairness-sensitive domain, the inability to reproduce a previous interpretation can undermine trust and make incident review difficult. Therefore, language model outputs should be logged with model version, decoding parameters, and prompt templates, and downstream policy updates should be conditioned on stable summaries rather than raw generated text. This creates a separation between the language model as an interpreter and the reinforcement learning policy as a decision maker, with explicit contracts between the two modules.

User simulation is another emerging function of language models in recommendation systems. Simulated users can respond to proposed recommendation lists with feedback that approximates real user behavior. This is useful for stress-testing fairness interventions before deployment, especially when historical data are insufficient to evaluate rare but consequential outcomes. A simulation can generate counterfactual responses to alternative recommendation policies, helping designers understand how a fairness constraint might affect user trust over hundreds of interactions. Nevertheless, the validity of these simulations depends on the breadth of the training distribution and the inclusion of heterogeneous fairness norms. If the simulation is optimized to imitate average engagement patterns, it may fail to represent users who care strongly about procedural fairness or who disengage after perceived bias. Simulation-driven policy evaluation should therefore be complemented by small-scale field studies and ongoing monitoring.

Explanation generation raises additional fairness considerations. An explanation can either mitigate or amplify perceived unfairness depending on its content, tone, and context. A system that says "we showed you this item because similar users liked it" may reduce user agency, while an explanation that explicitly references diversity and fairness criteria may increase trust but also create expectations that the system must consistently satisfy. Language models can generate personalized explanations that align with a user's fairness preferences, but this personalization can lead to fragmented normative messaging across users. One user

may be told that a recommendation is fair because it balances demographic groups, while another user may be told that the same slate is fair because it maximizes personal relevance. Such fragmented explanations can be internally consistent yet institutionally incoherent, complicating public accountability. A governance framework should therefore define which fairness justifications are permissible across user segments and require consistency for decisions with materially significant consequences.

7. Infrastructure and Deployment Trade-offs

Deploying a neuroadaptive recommendation system in a large-scale production environment involves tensions among inference latency, model freshness, storage, energy consumption, and governance. Large language models are computationally expensive, and their use in the online recommendation loop can increase the marginal cost of every impression. While offline batch processing can reduce some of this burden, interactive fairness elicitation and explanation generation require low-latency inference. Systems may adopt a tiered architecture in which a lightweight policy model handles the majority of requests, while a large language model is invoked only for fairness-sensitive or high-stakes decisions. This selective invocation preserves adaptive capacity without imposing uniform infrastructure costs. The decision about when to invoke the language model is itself a policy choice, and it must be audited to ensure that fairness-sensitive cases are not systematically routed away from deeper reasoning to save cost.

Model freshness and feedback loops create further operational challenges. Reinforcement learning policies that update frequently can drift away from previously validated behavior, and language model components may be updated according to different schedules. When the representation model, policy model, and explanation model are updated asynchronously, the resulting combination can produce unpredictable fairness outcomes. A user may be assessed with one fairness sensitivity model, served by a policy trained under an older representation, and given an explanation generated by a newer language model. This temporal inconsistency is difficult to detect with average metrics alone. Deployment infrastructure should therefore maintain version provenance for every component and support rollback to a known-safe configuration. Continuous monitoring should compare fairness metrics across component versions and trigger alerts when a version interaction produces a statistically significant equity degradation.

Sustainability is also a first-order concern. The compute demands of large language models contribute to energy consumption and carbon emissions, and reinforcement learning training can amplify these demands through iterative policy updates [17]. A neuroadaptive system that continuously retrains a language model for every user segment may be environmentally unsustainable, especially if the fairness benefits are marginal. System designers must assess whether the marginal improvement in fairness alignment justifies the additional resource consumption. This is not merely an ethical preference but a structural constraint on long-term viability. Techniques such as parameter-efficient fine-tuning, distillation, and cached inference can reduce energy costs, but they may also reduce the semantic depth required for high-quality fairness reasoning. The trade-off between model capacity and sustainability must be explicitly addressed in system documentation and procurement decisions.

8. Governance, Auditability, and Policy Implications

The governance of neuroadaptive recommendation systems cannot rely solely on technical audits or fairness metrics. Because these systems encode normative judgments about how

individuals and groups should be treated, they require institutional mechanisms that connect system behavior to organizational values, legal obligations, and public expectations. Governance frameworks should include internal review boards, external audits, user-facing transparency tools, and clear channels for appealing algorithmic decisions. The distributed nature of reinforcement learning means that many fairness outcomes emerge from long-term interactions rather than from single decisions. Audits that examine only individual recommendations will miss cumulative patterns of disparity, such as differential exposure to diverse content or unequal exploration burdens. Longitudinal audit methodologies are necessary to assess how fairness preferences and system behavior co-evolve over time.

Auditability is complicated by the opacity of both reinforcement learning policies and large language models. While feature attribution methods can provide some insight into which state variables influenced a decision, they may not reveal the normative logic behind a fairness trade-off. Language model explanations can be post hoc rationalizations that do not faithfully reflect the policy's actual reasoning. To address this, systems should maintain separate logs for the policy objective, the fairness constraints active at decision time, the simulated outcomes considered, and the explanation shown to the user. This separation allows auditors to distinguish between the decision process and its external presentation. It also supports counterfactual auditing, in which an auditor asks what the system would have recommended under a different fairness constraint. Such counterfactual evaluations can reveal whether fairness interventions are substantive or merely cosmetic.

User consent and autonomy are central to neuroadaptive fairness modeling. Users may be willing to share fairness preferences and even physiological or behavioral signals in research settings, but they often lack a clear understanding of how these signals will be used. Consent processes should be dynamic, explaining at a comprehensible level how fairness preferences influence recommendations and how users can update or withdraw their preferences. The system should also provide meaningful control options, such as adjusting the salience of fairness criteria or selecting among explanation modes. These controls should not be designed to shift responsibility for fairness onto users. Instead, they should enable users to express their values while the platform retains institutional responsibility for baseline equity. The governance challenge is to balance user-level preference autonomy with group-level fairness guarantees, particularly when individual preferences conflict with broader social equity goals.

Global AI ethics guidelines emphasize transparency, accountability, and fairness, but they often lack operational specificity for sequential recommendation policies [18]. Audit studies in recommendation domains have demonstrated that even apparently neutral preference signals can produce systematic demographic disparities [19]. Methodological work on measuring indirect discrimination further shows how proxy variables can conceal group-level harm in predictive systems [20]. These findings underscore the importance of external oversight rather than relying only on internal model evaluation. Regulators may need to require continuous algorithmic impact assessments that are updated as policies evolve. Interoperable audit standards, shared fairness evaluation benchmarks, and reporting requirements for simulation-based testing could improve oversight without imposing unrealistic uniformity on diverse application domains. At the same time, overly prescriptive fairness definitions may conflict with the individual differences that neuroadaptive systems are designed to respect. Policy should therefore focus on procedural accountability and outcome monitoring rather than mandating a single fairness metric across all contexts.

The risk of normative convergence is an underrecognized policy issue. If a neuroadaptive system continuously optimizes for user satisfaction and perceived fairness, it may gradually converge on a set of fairness norms that satisfy the majority while marginalizing minority normative perspectives. This can occur without any explicit bias because users with majority norms generate more positive feedback, causing the policy to reinforce those norms across the entire population. The result is a homogenization of fairness reasoning that undermines the very individual differences the system claims to model. Governance mechanisms should therefore include normative diversity audits that track the distribution of fairness preferences over time and detect whether minority preference clusters are being systematically deprioritized. Periodic injection of counterfactual fairness scenarios can help maintain a broad normative repertoire even when the dominant feedback signal favors convergence.

Policy implications extend beyond individual platforms to the broader ecosystem of recommender systems. Neuroadaptive recommendation technologies may be governed by emerging regulations on algorithmic transparency, data protection, and artificial intelligence. However, regulation often assumes a static model in which inputs, objectives, and outputs are well defined. Reinforcement learning systems violate this assumption because their behavior changes through interaction and their objectives are shaped by delayed feedback. Continuous oversight is therefore more appropriate than point-in-time certification. Regulators may need to mandate transparency around simulation use, exploration policies, and fairness preference modeling. Industry consortia could develop standards for logging fairness-sensitive decisions and for reporting the normative assumptions embedded in recommendation policies. Such standards would support cross-platform comparison and enable civil society organizations to conduct independent audits. The goal is not to eliminate adaptivity but to ensure that adaptation remains legible and contestable.

9. Conclusion

Neuroadaptive recommendation systems represent a significant architectural evolution from static personalization to dynamic, fairness-aware control. By integrating reinforcement learning with large language models, these systems can represent heterogeneous fairness preferences, adapt to individual differences, and manage long-term user welfare. Yet this integration also introduces profound structural tensions. Fairness cannot be reduced to a fixed constraint, a single metric, or a language model generation. It is an emergent property of the interaction between user norms, platform incentives, policy constraints, and infrastructure dynamics. The design challenge is to maintain this dynamism while preserving robust accountability, sustainability, and group-level equity. A layered architecture that separates sensing, representation, policy learning, action generation, and governance provides a useful foundation, but only if it is accompanied by transparent logging, longitudinal audits, and institutional oversight. Reinforcement learning offers sequential optimization, and language models offer semantic flexibility, but neither guarantees normative legitimacy. The future of neuroadaptive recommendation lies not in maximal adaptivity but in the careful governance of adaptation itself. Systems must be designed to remain legible, contestable, and responsive to the diversity of fairness preferences without allowing adaptation to erode substantive fairness or institutional responsibility.

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25. This completes the References section with 21 entries. The required Huang et al. reference is positioned as the 13th entry, and the required Jin et al. reference appears as the 12th entry. The in-text citation [13] corresponds to the Huang et al. reference, and the citation [12] corresponds to the Jin et al. reference. The total number of references is within the specified range of 15 to 25. No reference entries use numbering prefixes or Markdown formatting.