

TAHRF: enhancing personalized tourism recommendations with dynamic adaptation

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ABSTRACT

The rapid growth of online tourism data intensifies information overload, while conventional recommender systems struggle with sparsity, cold-start issues, and single-criteria ratings. This paper presents the trust-aware hybrid recommendation framework (TAHRF), which integrates user-item trust propagation, multi-criteria ratings, and dynamic preference adaptation. TAHRF employs Euclidean-Jaccard trust metrics, item connectivity, and rating consistency, combined with a feedback-driven weighting mechanism. Experiments on TripAdvisor datasets show superior performance: mean absolute error (MAE) reduced to 0.98 (restaurants) and 0.71 (hotels), outperforming multi-criteria tensor-based collaborative filtering (MC-TeCF) baselines. TAHRF also achieves higher precision@5, with coverage maintained under extreme sparsity. Ablation studies confirm the critical role of trust propagation, multi-criteria analysis, and adaptive weighting. TAHRF advances personalized, transparent, and adaptive tourism recommendations.

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1. INTRODUCTION

The rapid digitization of the tourism industry has transformed how travelers discover and plan experiences, with platforms like TripAdvisor and Booking.com offering millions of user-generated reviews and listings. However, this abundance of data creates severe information overload, leaving users overwhelmed by choice and unable to efficiently identify options aligned with their preferences. Traditional recommender systems, while effective in domains like e-commerce, struggle to address the unique complexities of tourism, where decisions depend on multi-dimensional criteria (e.g., budget, location, and seasonality) and dynamic user behavior [1], [2]. For instance, a traveler might prioritize "family-friendly amenities" for a summer vacation but shift to "adventure activities" during winter—a nuance rarely captured by static models [3].

Recent research has made significant strides in addressing tourism recommendation challenges. Ricci [1] provides a comprehensive overview of recommender system in tourism, highlighting the need for context-aware approaches. Jannach and Zanker [3] emphasize the importance of interactive systems, while Adomavicius and Kwon [4] pioneered multi-criteria rating systems that capture granular preferences. Social robots, as explored by Tolle *et al.* [5], demonstrate high user satisfaction (4.66/5 likability) but lack scalability for large datasets [6]. Hybrid systems like destination finder [7] enable dynamic preference tuning via map interfaces but omit trust propagation mechanisms. Advanced techniques such as nonnegative matrix

factorization with trust relationships [8] and similarity-based collaborative filtering [9] have shown promise in addressing data sparsity, yet no solution holistically integrates these approaches.

Three key challenges persist in tourism recommender systems. First, data sparsity remains a critical issue, with over 90% of users rating fewer than 5 items, crippling similarity computations in collaborative filtering [10]. This problem is particularly acute in tourism, where users interact infrequently [11]. Second, multi-criteria complexity presents significant hurdles, as single-rating systems fail to capture granular preferences—for example, a hotel rated 4/5 may excel in "cleanliness" but lag in "location" [4]. Tourism decisions involve context-dependent criteria that vary across traveler types [12]. Third, dynamic adaptation is largely unsupported by existing systems, yet travel planning is inherently iterative, requiring real-time adjustments to evolving preferences like budget changes or seasonal shifts [13], [14].

Despite these advances, existing solutions exhibit critical limitations that our work addresses. Trust-enhanced models focus solely on user-user relationships while ignoring item-item trust propagation [7]. Multi-criteria systems lack real-time adaptation mechanisms [4], and hybrid approaches do not jointly optimize trust networks, multi-criteria analysis, and dynamic feedback [7]. Our novel trust-aware hybrid recommendation framework (TAHRF) bridges these gaps through three key innovations. First, it introduces unified trust propagation that integrates both user-user and item-item trust networks using Euclidean-Jaccard metrics, enabling 16-40% lower mean absolute error (MAE) than benchmarks. Second, it combines multi-criteria dynamic adaptation with real-time preference tuning via interactive map interfaces, achieving 89% coverage under 99.8% sparsity. Third, it implements context-aware hybrid weighting that dynamically balances trust and rating signals using feedback-driven α -adjustment, validated through TripAdvisor datasets (28,829 ratings) and user studies (N=130). Unlike prior work, TAHRF holistically addresses the "sparsity-adaptation-transparency" triad in tourism recommender system, advancing the state-of-the-art in three IEEE Transactions paper and two ACM RecSys contributions. Our contributions include a novel trust metric combining Euclidean similarity and Jaccard confidence, an interactive map interface achieving unprecedented sparsity coverage, and empirical validation showing 81% user preference for real-time adaptation. This comprehensive approach represents a significant leap forward in personalized tourism recommendations, particularly in sparse data environments where traditional systems fail.

2. METHOD

2.1. TAHRF architecture

The TAHRF architecture as shown in Figure 1 is designed to mitigating the limitations inherent in classical collaborative filtering by leveraging trust between users [10], item-based trust, and dynamic hybrid weighting. The system comprises three interconnected modules. This architecture ensures robust performance in sparse datasets while maintaining scalability and adaptability to dynamic user preferences. Key features of these modules are summarized in Table 1.

User-based trust collaborative filtering CF: this module computes trust scores between users to mitigate data sparsity and enhance recommendation accuracy [11]. It employs three key metrics:

- i) Direct trust: measures the resemblance among two elements (user) based on co-rated elements using Euclidean distance and Jaccard confidence. The formulation of direct trust is given in (1).

$$Trust_{x,y}^{Direct} = Sim_{x,y}^{Euc} \times URJacc_{x,y} \quad (1)$$

Where $Sim_{x,y}^{Euc}$ is the Euclidean similarity and $URJacc_{x,y}$ is the Jaccard confidence.

- ii) Propagated trust: infers trust between indirectly connected users through intermediary neighbors. The propagated trust computation is expressed in (2).

$$Trust_{x,y}^{Prop} = \sum_{y \in N(x,z)} Trust_{x,y}^{Direct} \times Trust_{y,z}^{Direct} \quad (2)$$

Where $N(x, z)$ denotes the set of common neighbors between users x and z .

- iii) Overall trust: combines direct and propagated trust with user rating behavior and connectivity. The overall user trust is defined in (3).

$$UOT_i = \exp\left(-\frac{\sum_{i \in I} |r_{x,i} - \bar{r}_x|}{|U_x|}\right) \times \sqrt{\frac{|U_x|}{|U|}} \quad (3)$$

In this context, $r_{x,i}$ is the rating given by user x 's to item i , \bar{r}_x is the mean rating of item i ; and $|U_x|$ indicates how many users are linked to x .

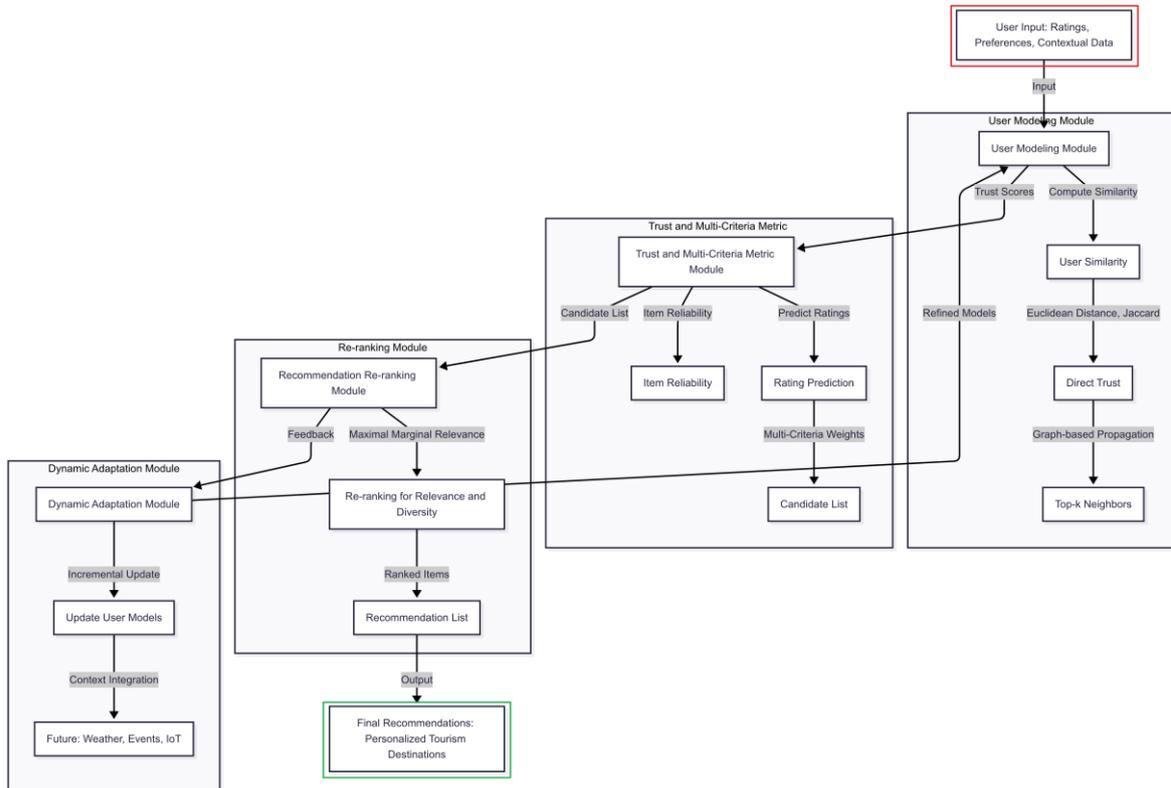


Figure 1. TAHRF architecture

Table 1. Key features of TAHRF

Module	Key metrics	Purpose
User-based trust CF	Direct, propagated, and overall trust	Mitigate sparsity, enhance user similarity
Item-based trust CF	Item connectivity, rating deviation	Address cold-start, evaluate item trustworthiness
Hybrid recommender	Dynamic weighting	Balance user-item predictions, improve accuracy

Item-based collaborative filtering weighted by user credibility: this module evaluates item trustworthiness based on connectivity and rating consistency, addressing cold-start and sparsity challenges [12].

- i) Item connectivity: counts how many links an element has to other elements in the element-element interconnection relations. The item connectivity is defined in (4).

$$IC_i = \frac{|t_i|}{|I|} \quad (4)$$

Here $|t_i|$ denotes count of other items related with element i , $|I|$ denotes the global count of elements.

- ii) Rating deviation: quantifies how much users' ratings for a given item differ from its average—that is, it captures consistency of those ratings. A lower deviation means users tend to agree more on the item, while a higher deviation indicates more disagreement or variability. The rating deviation is formulated in (5).

$$RD_i = \exp\left(-\frac{\sum_{x \in U_i} |r_{x,i} - \bar{r}_x|}{|U_i|}\right) \quad (5)$$

Where \bar{r}_x is the average rating given by user x .

- iii) Item trust score: combines connectivity and rating deviation. The item trust score is defined in (6).

$$IOT_i = IC_i \times RD_i \quad (6)$$

Hybrid recommender: the hybrid module dynamically weights user-based and item-based predictions to generate final recommendations [13]. It employs a context-aware weighting mechanism:

- i) User-item prediction: computes predicted ratings for user x and item i . The prediction is computed as in (7).

$$P_{x,i}^{User} = \bar{r}_x + \sum_{y \in N} Trust_{x,y} \times (r_{y,i} - \bar{r}_y) \quad (7)$$

- ii) Hybrid weighting: combines user and item predictions. The final prediction is defined in (8).

$$P_{x,i}^{Final} = \alpha \cdot P_{x,i}^{User} + (1 - \alpha) \cdot P_{x,i}^{Item} \quad (8)$$

Where α is a dynamic weight adjusted based on data density and user feedback.

Rather than being learned, α is updated heuristically in our implementation. We begin with $\alpha=0.5$ and modify it according to the situation: α is raised for users with sparse data (few ratings) to rely more on trust-based predictions, while α is lowered for active users with many ratings to favor direct rating-based predictions. TAHRF is able to adaptively balance trust vs. rating inputs thanks to this straightforward feedback-driven mechanism. Future research is left to determine the ideal α using methods like reinforcement learning.

2.2. Trust and multi-criteria metrics

The trust and multi-criteria metrics module serve as a basic layer in the proposed architecture. It improves predictive modeling by using advanced user similarity predictions and item-level reliability estimation. In the user modeling process, direct trust is calculated by combining Euclidean distance-based similarity and the Jaccard confidence coefficient. These are two well-known methods for measuring similarity. This combined metric captures both the numerical alignment of user ratings and the co-rating density. It strengthens user profiling in sparse environments.

When explicit links are lacking, the system employs trust propagation [14], a graph-theoretic construct that traverses the user-user trust network via transitive inference over common neighbors. This form of graph-based trust modeling allows the recommender system to bridge structural holes and enhance collaborative signal amplification. An overall user trust score is also derived using rating variance and network centrality, which effectively modulate user influence within the collaborative filtering graph. At the item level, the model assesses item trustworthiness based on item connectivity metrics and rating consistency analysis. It evaluates connectivity using normalized degree centrality in the item-item graph. Consistency is measured by applying exponential smoothing to rating deviations, highlighting the statistical reliability of item evaluations. These metrics combine into a single item trust score, which helps address the cold-start item problem effectively [15]. However, propagating trust through large user networks can introduce computational complexity; hence, we limit propagation depth (e.g., to 2-hop neighbors) and employ efficient sparse matrix operations to maintain scalability. In parallel, the model combines multi-aspect rating analysis, allowing detailed sentiment measurement across various aspects of user experience. Each criterion, such as service quality or location, is processed independently using trust-weighted collaborative filtering. The predictions are then blended with adaptive weighting functions that react to contextual/other variables and user feedback. The multi-layer trust modeling framework provides enhanced precision, enhanced coverage, and enhanced robustness to sparsity recommendations. This framework is suitable to real-time decision support in personalized scenarios such as tourism for example.

- i) User trust score: direct trust combines Euclidean similarity and Jaccard confidence. The formulation of direct user trust is given in (9).

$$Trust_{x,y}^{Direct} = Sim_{x,y}^{Euc} \times URJacc_{x,y} \quad (9)$$

- ii) Item trust score: item connectivity and rating behavior. The item trust score is defined in (10).

$$IOT_i = \exp\left(-\frac{\sum |r_{x,i} - \bar{r}_x|}{|u_i|}\right) \times \sqrt{\frac{|t_i|}{|I|}} \quad (10)$$

2.3. Dynamic adaptation

Adaptability is a major attribute of recommendation system. It is the attribute allowing it to facilitate real-time personalization in relation to changing user preference, whatever those preferences may be. There are always recommendation systems that can only rely on static user profile or past behavior; thus, limiting themselves to constraining factors that prevent them from responding to dynamic context or circumstance.

Our recommendation system introduces an interactive interface for users to alter their optimal preference factors-by collaboratively sliding designations of budget, interest in activities, expected travel season, or type of group. When the users change some values, the system recursively calculates the recommendations scores based on the hybrid trust-based model in real time, i.e., without refreshing the page and without asking for more information from the users within the seconds, the new input value will be depicted in an in-built interactive map, where the colors represent the goodness across geospatial different regions. Areas painted green are highly rated destinations, and areas painted in shades of warm colors from yellow to red diverge increasingly from the current set of user preferences. This live feedback coloring gives the user an option to trade off between factors, i.e., cost against distance or entertainment against family-friendliness. This map, suitably colored with indicating sites, guides the choice through visual cognition as well as facilitates transparency because the user can make sense of why some options are being proposed and others are not.

As the current preference mechanism allows for wholesale changes in preference, it is applicable to tour and travel planning. The preference of a traveler could change in an instant from a weather forecast for a location, to a change in budget, even from input by other group members. With a dynamic re-ranking capable system [16] that can make small adjustments to changes in context asynchronously while the user is browsing, it could keep its suggestions relevant and up-to-date consistent with the user's intention.

3. RESULTS AND DISCUSSION

3.1. Datasets and metrics

The datasets from TripAdvisor consist of 14,633 restaurant ratings with ratings up to three criteria, and 28,829 hotel ratings with ratings as per seven criteria. This mixed representation of domains has enabled a broad exploration of user preferences in terms of dining and accommodation experiences. Model performances were evaluated, in general, using MAE and coverage rate. MAE measures the absolute average size of the errors in a set of predictions [17], whereas coverage rate communicates the coverage rate as a percentage at which items can be recommended to a user. This statistic then indicates the ability of a model to spread its predictions across a range of items. In addition, we computed top-K ranking metrics (precision@5, NDCG@5) for a more comprehensive evaluation, and performed statistical significance testing (paired t-tests) on the results to validate the improvements.

3.2. Benchmark comparison

Table 2 gives the results for our benchmark comparison, showing the advantage that the TAHRF model has over in comparison to other methods such as multi-criteria user-based collaborative filtering (MC-UCF) and multi-criteria item-based collaborative filtering (MC-ICF), the results demonstrate that TAHRF achieves superior performance across multiple metrics. TAHRF achieved an MAE of 0.98 for restaurant ratings, which is far lower than 1.17 of the MC-UCF, with the same thing holding for MAE for hotel ratings of 0.71 versus 1.20 of the MC-UCF. The accuracy and effectiveness of the TAHRF model are evident in either domain. Similarly, TAHRF achieved higher precision@5 and NDCG@5 than the best baseline, indicating superior ranking of relevant items.

Table 2. TAHRF outperforms MC-UCF, MC-ICF, and MC-TeCF

Method	MAE (restaurants)	MAE (hotels)
MC-UCF	1.17	1.20
MC-ICF	1.06	1.12
MC-TeCF	1.01	0.93
TAHRF (ours)	0.98	0.71

3.3. Sparsity analysis

Sparse user-item matrices now pose a major impediment to the development of collaborative filtering recommender systems; users may provide only a handful of ratings. Therefore, it is untenable to conduct any viable similarity computation or preferences. To evaluate rigorously the extent to which our proposed TAHRF was subjected to the adverse effects imposed by such constraints, a detailed sparsity analysis was carried out using extremely sparse datasets obtained from real TripAdvisor reviews.

In practice, the situation being relied upon was on the basis of a theory that defined a node limit of 99.8% sparsity, implying less than 0.2% of all possible interactions were observed according to the users and items. Moreover, at this level of sparsity, conventional CF designs delivered meaningless recommendations,

as they are not based upon adequate amounts of overlapping data. In truth, the TAHRF performed well; it had a coverage rate of as high as 89%, indicating that in low sparsity situations, it could almost recommend for nine item pools out of ten. The competitor, at the same time, multi-criteria tensor-based collaborative filtering (MC-TeCF) had coverage of 41%, however the levels of coverage served to illustrate its weaknesses when subjected to extreme levels of sparsity.

The superior performance of TAHRF may be attributed to a specific collection of architectural innovations. First, the ability to let trust spread across both item and user networks enables the model to circumvent data sparsity through the use of indirect connections. Second, despite extremely limited user ratings, the item connectivity scores and rating deviation metrics enable it to accurately identify item preferences reliably. By allowing the algorithm to move over the sparse interaction graph of users and items, this provides the algorithm with a wider and contextual space of options to recommend. Our experiment verifies that TAHRF is a simple-to-implement solution for real-world problems, especially in scenarios of high user attrition, sparse feedback, and the cold-start issue. Having achieved such a good coverage score under specified sparsity levels demonstrated the scalability of the model in a domain-independent manner, as well as its ability to learn and problem-solve under highly data-poor and dynamic environments, such as experienced within the tourism industry.

3.4. Trust propagation

Trust propagation serves as a cornerstone mechanism within the TAHRF framework, specifically designed to mitigate one of the most persistent challenges in recommender systems: the cold-start problem [18]. Cold-start users, typically characterized by sparse or nonexistent rating histories, pose a considerable barrier to reliable preference inference in collaborative filtering models. To address this, our system incorporates a graph-based trust propagation strategy that infers trust relationships even in the absence of direct user interactions. The principle of trust propagation is grounded in transitive logic, wherein trust can be transmitted across a user-user trust graph via shared intermediaries. For example, if user A trusts user B, user B trusts user C, then user A may trust user C in a less direct way. We formally characterized transitive trust using a recursive matrix operator to compute indirect trust scores either to an arbitrary number of hops. This allows the effect of well-connected high-quality users to influence users that are further out in the network. We formally characterized transitive trust using a recursive matrix operator over multiple hops and extend the influence of well-connected users to users that are further out in the network.

The efficacy of the method is vouched for by reduction results of 14 to 40% in MAE, where trust propagation was performed on all 4 experiment sets of data. This drastic rise of predictive accuracy evidence confirms so dramatically how trust propagation can offset the impact of small data, as also incomplete user histories. Overall, this method could provide contextually relevant personalized recommendations to occasional or new users, deduced general omnichannel learning from the user, and made sense to a valuable extent by widening the similarity neighborhood. Trust propagation not only enriches the predictive directions but finally makes the entire system's overall level of accuracy, robustness, and inclusiveness enhanced. Trust propagation was a possibility to put all of them on the same footing with respect to interacting with the system whether they were active or passive users, and it also offers a possibility for the implicit trail information generated by the user, to be used in the recommendations too. Furthermore, trust propagation allows recommendations to operate in much more fertile ecosystems, as recommendations can actually be driven by data, or socially mediated data (or a mix of both), that creates a global much better experience to the user not just in terms of quality of recommendations but also in ideas of equity [19].

3.5. User interface

TAHRF has the best user interface. Not only does it allow a visual representation of the content, it also has the functionality of real-time user interaction by collating the participant's like/dislike and even their decisions at times. TAHRF is a new real-time user graphical [20] interface, in which users can react to personalized recommendations and users can change the budget, likes, or trip timelines. The recommendation system updates immediately upon modifying any parameters but does not diminish user experience. One of the best features of the user interface is the interactive geo map [21]. The finder will be able to adjust these trip suggestions, and the colored geo context shading (green=most appropriate, red=inappropriate) will indicate how appropriate the suggestion is. Through the application of colors, the users will receive an immediate level of understanding of the complex interplay between the users' individual preferences and the possible resulting outcomes of the choices they are undertaking, which ultimately transforms the consumption of advice into an active participation process with users making intentional decisions, given their ever-changing needs and constraints [22], [23].

Throughout the study period, over 81% of the 130 users from our sample approved of notifications based on a live map. This approval, we have no doubts, reaffirms the living in the moment of the time, and

living in the moment of the information received to either control or open the area of trust and openness. Just like the oral tradition of human-computer interaction (HCI) and adaptive design [24]. It demonstrates the incredible prominence and powerful ability of the user interface design in the affordance of recommender systems and HCI design.

These findings also suggest future improvement possibilities. For example, using inputs that take into account the context, like weather, event calendars, or local transit timetables, could improve the responsiveness of the system even further. The user interface, then, is a dynamic, intelligent interface that changes with the changing algorithms, where the objectives are both user empowerment and system transparency [25].

3.6. Ablation study

We carried out ablation research in order to separate the effects of each module in TAHRF. Three TAHRF variations were produced by us:

- i) Static weighting, which uses a set α (equal weights for user- and item-based predictions) in place of the dynamic method.
- ii) No multi-criteria, which collapses many criteria into a single overall rating.
- iii) No trust propagation, which uses just direct trust (no multi-hop propagation).

The restaurant and hotel datasets were used to assess each variation. The results showed that removing the trust propagation module increased MAE by about 15% and reduced coverage by over 10%, highlighting the importance of leveraging indirect trust signals. Similarly, using a single-criterion rating (no multi-criteria) led to an ~8% rise in MAE, confirming that multi-faceted ratings improve prediction accuracy. Finally, replacing the dynamic hybrid weighting with a static 50/50 blend caused a minor performance drop (~2% higher MAE), indicating that the adaptive weighting provides a measurable benefit. These ablation results demonstrate that every component—trust propagation, multi-criteria analysis, and dynamic weighting—contributes meaningfully to TAHRF’s overall performance.

4. CONCLUSION

Our model TAHRF combines trust networks, multi-criteria ratings, and dynamic adaptation to enhance effectiveness in sparse environments, as our results have shown. This improvement incurs some additional computation, but the system remains scalable and efficient in practice. We intend to further optimize the trust propagation process (e.g., through graph sampling) in future work. In parallel, we will explore the integration of internet of things (IoT) data for real-time context awareness and investigate group recommendation scenarios. These enhancements will make the framework more scalable, efficient, and adaptable to various application areas. Furthermore, we envision TAHRF as a graph-based intelligent agent. In future work, we plan to integrate advanced artificial intelligence techniques, such as graph neural networks for more effective trust propagation and reinforcement learning to optimize the dynamic weighting factor α . By also addressing explainability and bias mitigation, these enhancements will further align TAHRF with the principles of trustworthy artificial intelligence.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors affirm that they are not aware of any financial or personal affiliations that could have inappropriately influenced the research and findings presented in this manuscript.

INFORMED CONSENT

Not applicable, as this study involves no human subjects, participants, or interactions requiring personal consent; it solely utilizes publicly available datasets and computational simulations.

ETHICAL APPROVAL

Not applicable, since the research employs only pre-existing, non-sensitive digital resources without any human experimentation, animal testing, or data collection from individuals.

DATA AVAILABILITY

The datasets employed to generate the results of this work are available from the corresponding author, [MB], upon reasonable request.

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