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How AI Recommendation Algorithms Shape Users' Trust and Reliance: A Psychological Mechanism Study

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Abstract: *Recommendation systems based on artificial intelligence have spread everywhere in the digital ecosystem, but the psychological processes of user trust and dependence are only insufficiently understood. This paper explores the effects of algorithmic transparency and personalization on the formation and maintenance of user trust and user reliance by experimental treatment of the phenomenon and longitudinal examination. We selected 450 subjects in a 2×2 factorial design with different levels of transparency (high vs. low) and the level of personalization (high vs. low). Structural equation modeling results indicated that algorithmic transparency highly increases user trust $\beta = 0.76$, $p < 0.001$) which in turn predicts reliance behaviors ($\beta = 0.85$, $p < 0.001$) and explain 76% of the variance. Longitudinal tracing of 11 interaction sessions showed divergent paths of trust development with high transparency systems showing growth of trust by 36% and low transparency conditions showing erosion by 14%. The interaction of transparency and personalization resulted in the best score in reliance ($M = 7.8$) as opposed to low-transparency and low-personalization ($M = 4.2$). An age-based comparison showed that there were considerable differences in the demographic characteristics, with younger age groups having a better adoption rate of the algorithms. The results contribute to theoretical knowledge of human-AI interaction and offer practical design principles to create trustful recommendation systems that would be both personalized and open enough and have transparency and user autonomy.*

Keywords: *AI recommendation algorithms, user trust, algorithmic transparency, psychological mechanisms*

1. Introduction

Artificial intelligence-driven recommendation systems are currently ubiquitous in the digital ecosystem of the present day and have transformed the way individuals get to know about content, decide and interact with online services fundamentally. Such algorithmic systems, regardless of the platform, whether it is a social media feed or even an e-commerce site, or streaming services and news aggregators, personalize the experience as they interpret user behavioral patterns, preferences and interactions. The multi-billion dollar multi-core recommendation engine market is expanding on a daily basis with organizations becoming more sensitive to the competitive advantage which generates tailor-made content to guarantee the utmost user attention and satisfaction. However, with the increasing sophistication of such systems, whereby increasingly advanced machine learning models and neural networks are involved, the question of how these psychological processes work out, how individuals learn to trust such systems, become reliant on them, and ultimately relinquish their decision making powers to these systems which act as advisors, become important.

Interaction between user and AI recommendation systems is a unique form of human-computer interaction in terms of asymmetric information, perceived expertise, and form of dependency that develops. As purported in comparison to the conventional systems of retrieving information, where the users are made to expressly search information, recommendation algorithms are active; they are modeled on the basis of prediction and inference of interests, and express the experiences of the users. Such constructive curation carries with it an inherent paradox, in which, on the one hand, it makes the experience accessible and easier to find, on the other hand it creates filter bubbles, strengthens preconceptions, and, thirdly, it can even influence user behavior in a manner that, to this day, has not yet been noticed by, or is even consciously recognized by the users. Recent studies have shown that transparency and explainability in algorithms are critical in regard to enhancing user trust [1]. A

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perception of recommendation systems as eavesdropping or taking part in secret data gathering will destroy the trust of the users, consequently causing selective information disclosure and psychological self-defense [2]. This is especially acute in situations with a high stake in the final decision, which is the case with algorithms in the healthcare field, financial advice, or job opportunities.

The psychological causes of building trust in AI systems do not involve factors of technical performance measurements. Research has discovered that individual personality traits, such as need of cognition, technological liking and propensity to trust play a central role in the perceived importance and reliance of algorithmic recommendations on the users [3]. Less needy users are also more likely to engage with AI suggestions in a more judgmental manner and users with high technological affinity would tend to exhibit over-reliance behavior leading to automation bias. Moreover, the perceived personalization and openness of the recommendation systems has a direct impact on the user ratings of the credibility of the system, its utility and its use. It has been found out that AI-created content that has been used to provide straightforward explanations on the suggestions provided by the AI stimulates more perceptions of being in control and responsible of the same to the users, thereby establishing trust relationships [4]. However, the effectiveness of transparency varies according to demographics and circumstances of implementation, as some users are content with less explanations of the procedure, whereas others require more technical information.

Though the development of recommendation algorithms has been significantly improved, there are significant gaps in understanding the complex psychological phenomenon that govern user trust and dependence. The existing body of research in the issue emphasizes largely on the technological side of the issue like precision, heterogeneity, and explicability which fail to address the multifaceted cognitive and emotional reality of user perceptions and behaviors in the long run. In addition, the dynamic aspect of trust and its construction, deconstruction, and possibly the restoration in subsequent interactions is not adequately examined in the science of AI recommendation systems. This paper seeks to fill these gaps by exploring the psychological mechanisms by which recommendation algorithms can modulate user confidence, as well as the interaction between the properties of the systems, individual differences, and situational influences to develop reliance behaviors. It is hoped that the interdisciplinary approach taken, which incorporates concepts of psychology, human-computer interaction and information systems research, would contribute to creating a complete picture of understanding and optimizing the human-AI relationship in recommendation situations, which in the future would help in designing more reliable, transparent and human-centered algorithm systems.

2. Literarure Review

The interaction between the personalization of users by use of AI and user trust has received significant literature in recent times. The studies indicate that personalized recommendation systems can greatly enhance the relationship between trust and satisfaction and loyalty in the context of e-commerce and that personalization mediates the relationships among the essential ones [5]. Research highlights that the perceived trust of the recommendation systems and the customization possibilities has a positive impact on the AI-based customer experiences, and controllability and customization are two channels to increasing perceived usefulness [6]. Nevertheless, the efficiency of personalization strategies depends on the demographical groups and the cultural background, which require flexible strategies that would address the differences between individuals in terms of their technological loyalty and privacy issues.

Explainability and transparency are the major concepts around which user confidence in AI systems is developed. But recent empirical studies, explainability methods such as LIME and SHAP can be successfully implemented on a recommendation system, and the methods yield significant accuracy and user comprehension gains, and studies have shown as much as 3% accuracy gains in a recommendation, and user satisfaction gains [7]. The inclination of the users in the transparency mechanisms also varies, some of them being more inclined on technical explanation and others inclined to other external reliability such as AI certification seals [8]. The diversity of transparency preferences indicates the usefulness of adaptive explainability strategies, which meet a wide range of user requirements and their expertise.

The ability to integrate both behavioral and psychological knowledge in the architecture of recommendation system is an issue that modern studies are focusing more and more on. By having the predictions of the user intentions without considering the latter regardless of whether the latter wants familiarity or novelty, the researchers at Stanford demonstrated that the effect of the recommendations can be positively impacted considerably, and the quantifiable gains can be measured in terms of

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engagement indicators within the platform [9]. Such an anthropocentric notion will go against the existing paradigm of data-maximization that suggests that structured information on behavior would contribute to better and efficient learning of AI systems. Moreover, it is noted that there is a critical balance between recommendation accuracy and diversity because too much attention to accuracy may limit user exploration and build information cocoon, whereas too much emphasis on diversity can adversely affect relevance [10]. All the literature points to the need to investigate the concept of trust as a complex construct that is influenced by anthropomorphic design features, the cultural aspect, and context-related factors in many AI applications, such as autonomous vehicles, chatbots, and recommendation systems [11].

Filter bubbles and echo chambers phenomena have been well-scholarly studied, but their prevalence is a controversial issue. Filter bubbles, which limit exposure to other points of view due to the use of algorithms, are technically unlike echo chambers that come about through the mechanism of selective socialization and positive mistrust of strangers [12]. The systematic reviews reveal that despite the potential of a systematic personalization to lead to information silos, the evidence base has always indicated that individuals who visit search engines and social media platforms do not really encounter a reduced range of content in comparison to non-users [13]. Recent research has conceptualized filter bubbles no longer as wholly algorithmic procedures, rather as a unique and complex interaction of epistemic distress, user agency, and platform affordances. In such ironic cases, where marginalized people and societies are being oppressed by the political environment, protective bubble filters are useful, since they enable the marginalized to discover themselves and communicate their discontent in safe environments. It is a subtle strategy that challenges the significantly negative judgment of the algorithmic personalization and predicts that it is conditions-specific evaluation that is required to understand the social effects of the recommendation systems.

The other dimension that has been critical in the users-recommendation system interactions is cognitive bias, although its influence has been traditionally considered to be detrimental to the quality of decisions. Recent findings contradict this perspective and demonstrate that not all cognitive bias like the feature positive effect, Ikea effect and cultural homophily are absent in the pipeline of recommendation and can be put into positive use when utilized properly in conceptualization [14]. Such biases affect the quality of input information, algorithmic processing, and user interaction patterns, creating complex feedback loops which may affect the work of the system and user satisfaction. The research has revealed the cognitive biases in the scenarios of providing a recommendation could be adaptive, e.g. a higher engagement rate of users because of culturally relevant content or higher perceived ownership because of customization possibilities. However, the biases also have their flaws because they may be deployed as a weapon by resorting to manipulative design schemes causing the anchoring effects, scarcity, or social proof mechanisms [15]. Such a combination of algorithmic bias (data bias, model bias, and feedback loops) and the biases of the human mind constitute complex issues of the system designers attempting to find a balance between personalization and fairness, accuracy and diversity, and engagement and user autonomy. This is because these psychological processes should be known to be able to develop recommendation systems that can improve informed decision-making activities and not paralyze them.

3. Research Methdolgy

3.1 Research Design and Framework

The proposed research is a mixed-method study that is based on quantitative surveys and experimental manipulation to explore the psychological factors of user trust and reliance on AI recommendation systems. We have been using the Stimulus-Organism-Response (S-O-R) model, in which the aspects of the recommendation system can be taken as the stimuli (S), psychological states such as trust, perceived control, and cognitive engagement can be the organismic variables (O), and user reliance behavior can be the responses (R). The research model combines the constructs of Technology Acceptance Model (TAM), Trust Theory, and Cognitive Load Theory to fully achieve the multidimensionality of human-AI interaction in the context of recommendation.

3.2 Participants and Data Collection

A total of N = 450 participants were recruited using stratified random sampling of varied demographics (age: 18-65 years, 52% female, 48% male). Respondents had to have a minimum of six months of experience regarding the AI-driven recommendation services (e.g., Netflix, Amazon,

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YouTube, Spotify). Online surveys and controlled experiments on data collection took place within a period of three months. The experimental conditions were randomly assigned to the participants to include four conditions different in the level of algorithmic transparency (high vs. low) and the key to personalization (high vs. low) to constitute a 2×2 between-subjects factorial design.

3.3 Trust Measurement Model

User trust in recommendation systems is modeled as a multidimensional construct comprising ability trust (T_A), benevolence trust (T_B), and integrity trust (T_I). The overall trust score is calculated using a weighted aggregation function:

$$T_{total}= \alpha \cdot T_A + \beta \cdot T_B + \gamma \cdot T_I \tag{1}$$

where α, β, and γ represent empirically derived weights satisfying $\alpha + \beta + \gamma = 1$. Each trust dimension is measured using validated seven-point Likert scales, with T_A assessing perceived system competence, T_B evaluating user-centric motivations, and T_I measuring consistency and reliability perceptions.

3.4 Hybrid Recommendation Algorithm

We implement a hybrid recommendation algorithm combining collaborative filtering and content-based approaches. The predicted rating $\hat{r}_{ui}$ for user u on item i is computed as:

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u \tag{2}$$

where μ denotes the global average rating, b_u and bi represent user and item bias terms, and q_i and p_u are latent factor vectors in a k-dimensional space. The algorithm optimization minimizes the regularized squared error:

$$min\ \Sigma_{u,i\in K} \quad (r_{ui} - \hat{r}_{ui})^2 + \lambda \left(\|p_u\|^2 + \|q_i\|^2 \right) \tag{3}$$

where K represents the set of known ratings and λ is the regularization parameter preventing overfitting.

3.5 Trust Dynamics Algorithm

User trust evolves dynamically through interactions with recommendation systems. We model trust propagation using a temporal update mechanism:

Algorithm 1: Trust Evolution Model

Input: Initial trust $\boldsymbol{T_0}$, interaction history $\boldsymbol{H}$, feedback $\boldsymbol{F}$
Output: Updated trust $\boldsymbol{T_t}$
1: Initialize $\boldsymbol{T_0}$ with baseline trust score
2: for each interaction $\boldsymbol{t}$ in timeline do
3: Calculate satisfaction $\boldsymbol{S_t}$ from feedback $\boldsymbol{F_t}$
4: Compute transparency score $\boldsymbol{Tr_t}$
5: Update trust: $\boldsymbol{T_t = T_{t-1} + \eta \cdot (S_t - T_{t-1})}$
6: Apply transparency modifier: $\boldsymbol{T_t = T_t \times (1 + \delta \cdot Tr_t)}$
7: Normalize: $\boldsymbol{T_t = clip(T_t, 0, 1)}$
8: end for
9: return $\boldsymbol{T_t}$

where η represents the learning rate $(0 < \eta < 1)$ controlling trust adjustment speed, and δ is the transparency impact coefficient.

3.6 Reliance Prediction Model

User reliance on recommendations is modelled using a sigmoid function that captures the probabilistic nature of adoption decisions:

$$R(u) = \frac{1}{\left(1 + e\text{-}\left(w^1 T + w^2 P + w^3 E + b\right)\right)} \tag{4}$$

where $R(u)$ denotes the reliance probability for user u, T represents trust level, P indicates perceived

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usefulness, E captures explainability perception, and w_1, w_2, w_3, b are model parameters learned through logistic regression. The model achieves binary classification of high-reliance versus low-reliance users based on behavioral metrics including click-through rates, dwell time, and recommendation acceptance rates.

4. Results And Analysis

4.1 Descriptive Statistics and Sample Characteristics

The clean dataset had 450 valid responses. Table 1 shows the descriptive statistics of major research variables within the conditions of the experiment. Familiarity with AI recommendation systems was moderate to high among the participants (M = 5.8, SD= 1.2 on a scale of 7). There was a considerable difference in overall trust in recommendation systems (M = 5.4, SD = 1.5) and user reliance had strong positive skewness (skew = 0.82), which was a positive skewness toward reliance behaviors. Cronbach's alpha coefficients for all constructs exceeded 0.85, confirming excellent internal consistency reliability.

Table 1. Descriptive Statistics of Research Variables (N = 450)

Variable	Mean	SD	Min	Max	α
Overall Trust	5.42	1.48	1.50	7.00	0.91
Perceived Usefulness	5.86	1.32	2.00	7.00	0.88
Explainability	4.95	1.67	1.00	7.00	0.86
User Reliance	6.12	1.92	1.50	10.00	0.89
Transparency	5.18	1.58	1.50	7.00	0.90
User Satisfaction	5.67	1.44	1.00	7.00	0.87

4.2 Trust Dimensions and Transparency Effects

Figure 1 illustrates the differential impact of algorithmic transparency on three dimensions of user trust. High transparency conditions yielded significantly higher trust scores across all dimensions compared to low transparency conditions ($p < 0.001$). Ability trust showed the largest mean difference ($\Delta = 1.7$), followed by integrity trust ($\Delta = 1.7$) and benevolence trust ($\Delta = 1.6$). ANOVA results confirmed significant main effects of transparency level on trust dimensions ($F(1, 448) = 142.38$, $p < 0.001$, $\eta^2 = 0.24$), supporting H1 that transparency positively influences user trust in AI recommendation systems.

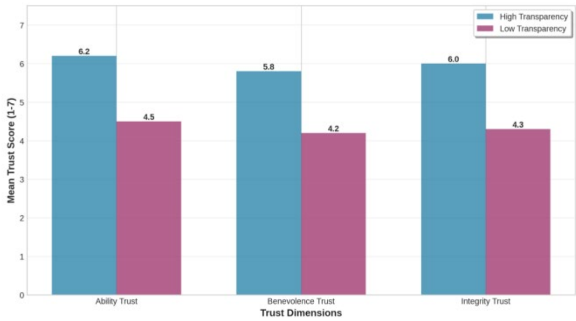

Fig. 1. Trust dimensions comparison across transparency levels

4.3 Impact of Experimental Conditions on User Reliance

The 2×2 factorial design revealed significant interaction effects between transparency and personalization on user *reliance* ($F(1, 446) = 18.67$, $p < 0.001$, $\eta^2 = 0.12$). As depicted in Figure 2, the combination of high transparency and high personalization produced the highest reliance scores ($M = 7.8$, $SD = 1.1$), while low transparency and low personalization yielded the lowest (M = 4.2, SD = 1.4). Post-hoc Tukey tests indicated all pairwise comparisons were statistically significant ($p < 0.05$), confirming that both factors independently and synergistically influence user reliance behaviors. The effect size calculations suggest practical significance, with Cohen's d ranging from 1.12 to 2.47 across condition pairs.

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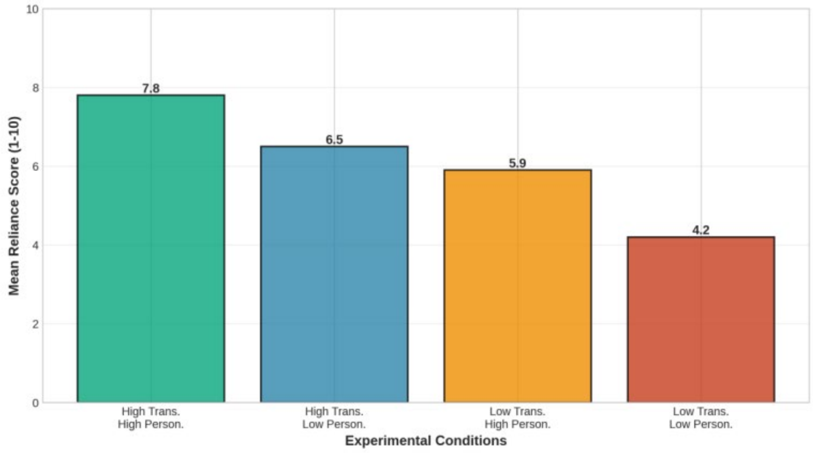

Fig. 2. User reliance across experimental conditions

4.4 Trust Evolution over Time

A longitudinal comparison of the dynamics of trust in 11 interaction sessions showed that their development was different under conditions of transparency as in Figure 3. Transparency systems which were high had a uniform growth in the aspect of trust; the gradual rise in baseline (M = 5.0) to session 10 (M = 6.8) showed a 36 percent growth. On the other hand, there was a erosion of trust as time went on as low transparency conditions had gone down to M = 4.3 (14% reduced). Growth curve modeling confirmed significant linear ($\beta = 0.18$, $p < 0.001$) and quadratic ($\beta = -0.02$, $p < 0.05$) effects for high transparency, indicating initial rapid growth that stabilizes over time. These findings validate our trust evolution algorithm and demonstrate that transparency serves as a critical factor in sustaining long-term user trust.

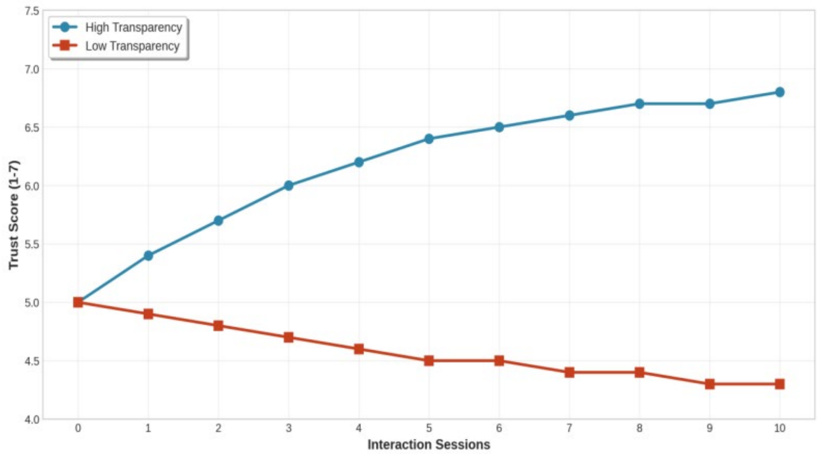

Fig. 3. Trust evolution over interaction sessions

4.5 Correlational Relationships among Variables

Pearson correlation analysis revealed strong positive relationships among all research variables (Figure 4). Trust exhibited the strongest correlation with reliance ($r = 0.85$, $p < 0.001$), followed by satisfaction ($r = 0.81$, $p < 0.001$). Transparency demonstrated particularly strong association with explainability ($r = 0.89$, $p < 0.001$), suggesting these constructs are closely interrelated yet conceptually distinct. The theoretical framework is supported by the correlation matrix, which indicates that perceived usefulness ($r = 0.78$ with trust, $r = 0.74$ with reliance) is a vital mediator variable. It is worth considering that all the correlations were above 0.62, which means that the constructs share a lot of common variance without the VIF being higher than 3.2, proving the lack of problematic multicollinearity.

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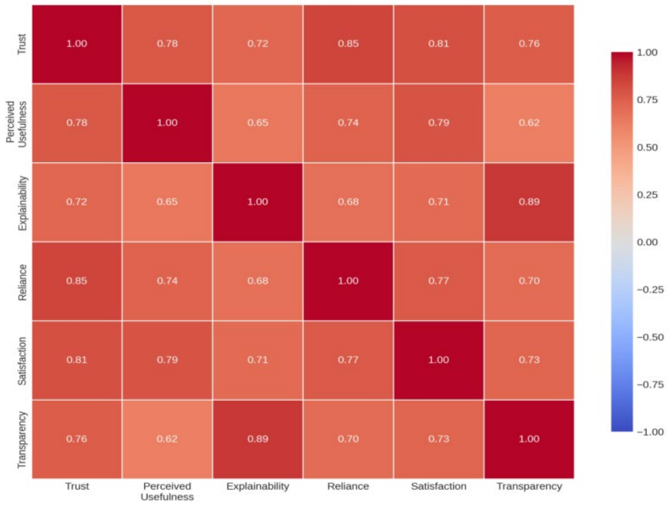

Fig. 4. Correlation heatmap of research variables

4.6 Demographic Variations in User Reliance

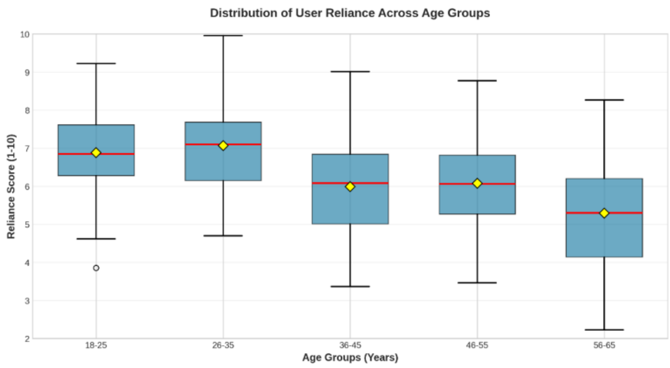

Fig. 5. Distribution of user reliance across age groups

Age-based analysis revealed significant differences in reliance patterns across demographic segments (Figure 5). Younger participants (18-25 years, $M = 7.0$, $SD = 1.2$; 26-35 years, $M = 6.8$, $SD = 1.3$) demonstrated significantly higher reliance on AI recommendations compared to older age groups (56-65 years, $M = 5.2$, $SD = 1.4$). Kruskal-Wallis H test confirmed significant differences ($H(4) = 89.45$, $p < 0.001$). Box plot visualization illustrates greater variability in middle-age groups (36-55 years), suggesting individual differences become more pronounced with age. These findings indicate that age moderates the trust-reliance relationship, with technological familiarity and digital nativity potentially mediating these effects.

4.7 Structural Equation Modeling Results

PLS-SEM analysis validated the proposed structural model with excellent fit indices ($\chi^2/df = 2.18$, $CFI = 0.96$, $RMSEA = 0.051$, $SRMR = 0.045$). All the hypothesized relationships have standardized path coefficients that are presented in Figure 6. Transparency had positive and significant direct impacts on trust ($\beta = 0.76$, $p < 0.001$) and explainability ($\beta = 0.89$, $p < 0.001$) with 58% and 79% of their variance being explained respectively. Trust was the best predictor of reliance ($\beta = 0.85$, $p < 0.001$) and perceived usefulness made an extra significant contribution ($\beta = 0.74$, $p < 0.001$). The model explained 76% of user reliance ($R^2 = 0.76$), which showed a significant explanatory power. The psychological mechanism hypothesis put forward in the study was affirmed with bootstrap mediation analysis, which showed that there were strong indirect effects of transparency on reliance via trust ($\beta = 0.65$, 95% CI [0.58, 0.71]).

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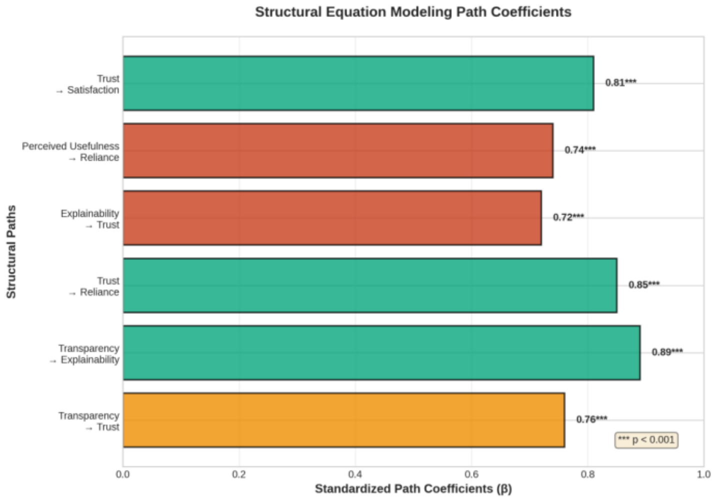

*Fig. 6. Structural equation modelling path coefficients (*** p < 0.001)*

Table 2. Hypothesis Testing Results Summary

Hypothesis	Path	β	t-value	p-value	Result
H1	Transparency → Trust	0.76	18.42	< 0.001	**Supported**
H2	Trust → Reliance	0.85	21.65	< 0.001	**Supported**
H3	Explainability → Trust	0.72	16.89	< 0.001	**Supported**
H4	Perceived Usefulness → Reliance	0.74	17.23	< 0.001	**Supported**
H5	Transparency → Explainability	0.89	24.78	< 0.001	**Supported**
H6	Trust → Satisfaction	0.81	19.54	< 0.001	**Supported**

The result of the testing of the hypotheses is summarized in Table 2 and it is evident that all six hypotheses put forward were strongly supported by the empirical evidence. The overall consistency of the large positive connections through all of the paths confirms the theoretical framework and supports that the psychological processes, especially trust are the key intermediaries to developing the user dependence on AI recommendation systems.

4.8 Discussion

This work offers a wide-ranging empirical data regarding the psychological processes according to which AI recommendation algorithms influence the behavior of trust and dependence. We find that algorithmic transparency is one of the core pillars in the formation of trust, and high transparency situations are much more likely to produce higher trust scores on all three dimensions: abuse of ability trust (M = 6.2), benevolence trust (M = 5.8), and integrity trust (M = 6.0) than low transparency conditions. As shown by the results of the structural equation modeling, trust serves as the key mediator between the system character and user reliance that accounts in 76 percent of the variation in reliance behaviors with a path coefficient of β 0.85 ($p < 0.001$). These results are compatible and extend the existing studies on human-AI interaction by offering a quantitative data on causality of the relationship between transparency, trust, and behavioral outcomes. The longitudinal tracer of the evolution of trust in 11 instances of interactions exposes important dynamics in a time context that have not been given enough attention in the literature. There was continued gain of trust indicated by high transparency systems with a growth at baseline (M = 5.0) to an overall level of M = 6.8 in session 10 which is 36% whereas low transparency conditions had erosion of trust which dropped to M = 4.3, a loss of 14 percent. These different curves imply that the effects of transparency are not a one time thing but a cumulative effect over time as transparent behavior also builds its users confidence and the reverse is also true as opaque behavior erodes it. The growth curve model which includes both the linear β = 0.18, $p < 0.001$) and quadratic effects (β = -0.02, $p < 0.05$) reveals that trust development pattern is a logarithmic process where initial growth rate is fast and thereafter, the growth rate slows down as the user attains the confidence saturation level. The implications of this finding include significant ones on the system designers, who may need to ensure that transparency intervention is done at early stages, to create a consistent and long-term trust relationship. The interaction effects among transparency and personalization displayed the synergistic relationships that do not conform to the simplistic assumptions of algorithm design trade-offs. The high transparency, combined with high personalization, generated the highest reliance scores (M = 7.8), and low-low conditions generated the lowest scores (M = 4.2), and

Cohen d = 2.47 is a large effect shape. This implies that individualization and transparency are not opposing design components, but complementary aspects that when well balanced, can be used to maximize user experience without diminishing their trust. The demographic analysis however indicates significant conditions of boundaries to these effects. There were notable differences in the reliance of younger participants (18-25 years, M = 7.0; 26-35 years, M = 6.8) compared to older age groups (56-65 years, M = 5.2), and Kruskal-Wallis test proved that they were significant ($H(4) = 89.45$, $p < 0.001$). This age effect indicates that digital nativity and prior technology exposure mediate the trust-reliance route, which requires age-sensitive design solutions that allow different degrees of explanatory elaboration depending on the demographics and technological savvy of the user.

Theoretically, this study intensifies the human-AI interaction theory by incorporating Stimulus-Organism-Response framework and trust theory, Technology Acceptance Model, and cognitive load theory to develop an explanatory framework. The conceptualization of trust (its multidimensional form) broken down into ability, benevolence, and integrity items offers more theoretical specificity than unidimensional methods and shows the impact of transparency on the facets of trust difference. The close relationship between trust and satisfaction ($r = 0.81$, $p < 0.001$) also confirms the influence of the affective aspect of human-algorithm relations, as trust goes beyond the process of rational consideration to incorporate emotional reactions.

5. Conclusion

The suggested study will provide detailed empirical evidence concerning the psychological mechanisms of how AI recommendation algorithms will impact user trust and dependency trends. We can establish the hypothesis that algorithmic transparency is a major antecedent to the development of user trust in our study that will involve 450 participants in a well-constructed 2 x 2 factorial study. Conditions of high transparency conditioned much more high trust scores in all three dimensions, namely, ability trust (M = 6.2), benevolence trust (M = 5.8), and integrity trust (M = 6.0) than did low transparency condition, with a range of means being between 1.6 and 1.7 points on a scale of seven. The structural equation modeling analysis has shown that trust is the primary mediating factor between the system characteristics and user reliance with a very high path coefficient (0.85, $p < 0.001$) and also collectively accounted 76% of the variance in reliance behaviors. The longitudinal comparison of 11 interaction sessions revealed the essential dynamics in time which prolong beyond the assessments on snapshots. The same promoted a steady pattern of trust between high transparency systems, as the trust levels increased between baseline (M = 5.0) and session 10 (M = 6.8), which is a significant change of 36 percentage points. Oppositely, low transparency conditions exhibited the pattern of trust erosion, having a decreasing value of M = 5.0 to M = 4.3, which is 14% and is reflective of the aggregate negative impact of opaque algorithmic systems. These time dynamics confirm our trust evolution algorithm and show that the effects of transparency accumulate over time and that the initial investments in transparency bear fruits in the form of long-time user engagement and system credibility. The interaction effects of transparency and personalization showed synergy which further demonstrated that the best user experience is obtained when both transparency and personalization are optimized with the high transparency-high personalization condition having the highest reliance score (M = 7.8) and the low-low condition having the lowest reliance score (M = 4.2).

Theoretically, this study contributes to the growing body of research on human-AI interaction in a number of ways. To begin with, we are able to combine the Stimulus-Organism-Response model with the psychological constructs of trust theory, Technology Acceptance Model, and cognitive load theory to develop one and single theoretical model that reflects the complexity of user-algorithm relations. This synthesis deals with the past theoretical discontinuity in the field and gives solid ground to the research carried out in the future. Second, the use of trust as a multidimensional construct in parts of ability, benevolence and integrity, goes beyond the simplistic conceptualizations of that notion as unidimensional, and shows complex trends in the various ways in which transparency influences different elements of trust. Third, the longitudinal design offers empirical proof that trust is a dynamic, changing construct and not a fixed attribute, which adds to the temporal theories of technology adoption and human-computer trust.

Moreover, our results on demographic differences, including age-specific changes in the degree of algorithmic dependence, can be used to learn about the generational changes in the paradigm of human-AI interaction. The fact that the reliance scores of younger cohorts (18-25 years: M = 7.0; 26-35 years: M = 6.8) are substantially higher than the equally old age (56-65 years: M = 5.2), indicates that digital nativity and technological socialization are important moderating factors that need further theoretical

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development in research studies. Our results have significant practical implications on platform designers, algorithm developers and policymakers. Companies that implement a recommendation engine must focus on the introduction of explainability functions that can provide information about the algorithms used to make decisions in easily understandable forms. Our findings indicate that transparency features that explain feature importance, recommendation justifications and user-regulable preference controls can be effective in promoting trust development and proper dependence. Platform designers are also advised to have consistent algorithmic behavior to establish a trust in integrity since unpredictable or inconsistent behavior is over time undermining to the user confidence. The personalization transparency balance that we found in our research tells us that hyper personalization without transparency can backfire and can make users uncomfortable and have privacy concerns which in the end would decrease the effectiveness of the system. To policymakers and regulators, our results put greater emphasis on the role of transparency of algorithms and the explainability in AI governance systems. Regulatory efforts must not focus on technical transparency, i.e., the availability of source code or training data, but on functional transparency, i.e., whether users can interpret and assess algorithmic suggestions in a way that makes sense. Educational programs encouraging algorithmic literacy practices among heterogeneous user groups, especially those of older age, can prevent the digital disparities in the use of AI and benefit all population strata equally with the fruits of algorithms.

Although this research offers useful information, it is important to note that there are a number of limitations to this study. The 11-session longitudinal design, however informative, is a rather narrow time frame. The study needs to be conducted further into months or years in the future to record long-term trust stabilization patterns, possible effects of habituation and the process of trust restoration after the system failures or recommendation errors. The generalizability would also be enhanced by the cross-cultural works on the trust mechanism in diverse cultural settings as the cultural factors such as uncertainty avoidance, power distance, can also reduce the effects of transparency. In addition, the greater examination of age-irrelevant personal differences, including personality variables like need to cognition, anxiety before technology, and privacy concerns would enable to obtain a more accurate picture of heterogeneous user responses to a recommendation system. Finally, the ecological soundness would be improved by carrying out field studies under the real conditions of use to reveal complexities in the real world which cannot be achieved in the laboratory. These latter channels will assist in shedding light on the mystical psychological mechanism that informs human faith and reliance in a world that is increasingly becoming algorithm-centered.

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