

MUSIC RECOMMENDATION APPS: PERCEIVED TRUST-WORTHINESS AMONG INDIAN LISTENERS

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Abstract

Music is usually said to be a medium that connects people regardless of creed, social standing, communal background, or any other categories in human society, music unites. While being representative of an individual's legacy and heritage (de Alwis, 2025), it also allows one's eyes to look outward, understanding different cultures and traditions as far as they can be defined, thus broadening perspectives. Apart from the sociocultural benefits, music can heal (Dias & Nettavong, 2016) on a more personal level. Having experienced the therapeutic effects of music, people integrate it almost completely with their daily routines—walking or working; it is exceedingly rare to find an individual who is not consuming music. In a country like India, which is inherently diverse and where each regional language is rich in its contribution to musical expressions, exploration and discovery form a key part of a listener's musical journey. It therefore becomes vital to identify the factors some people look for in their music recommendations and to assess their perceptions of the existing systems based on how well they cater to their needs. The present paper, mostly as a quantitative projection, undertakes an exploration of the recommendation systems employed by music streaming apps used in India to study the perceived trustworthiness of music apps and the factors driving the adoption of these applications, which are mainly made for music consumers. However, the results may apply to many other cultural responsibilities.

Keywords

Music recommendations, music streaming apps, trustworthiness of recommendations, Indian music listeners, ethical AI

INTRODUCTION

With the onset of artificial intelligence (AI) technology that utilizes content-based and collaborative mechanisms, music enthusiasts are spoilt for choice when it comes to consuming newer genres and varieties of music every day. We have just entered the future that humankind has long dreamed of. AI applications have transformed the world of music. We rely on algorithms to ensure that we get the best outcome from everything that we do, and music is no exception. This is where recommendation systems or recommender engines have made themselves fit into our wish-lists perfectly. The etymology of the word “recommend” has its roots in the Latin re- + commendāre from con- + mandāre, which means to commit to one's care or entrust (en.wiktionary.org). Thus, the term recommendation inherently implies a suggestion that one would consider trustworthy and reliable. Earlier, the word recommendations was used for more serious aspects of living, such as educational streams, career paths, life partners, investment planning, and the like. However, in the present context, recommendations play a role in almost every day-to-day activity that we are involved in. From ordering dinner, deciding on a workout for reducing weight, hiring employees at our workplace, or listening to music while driving, these systems have integrated themselves into our daily routine, without much ado. We trust them enough to follow their recommendations when we find it beneficial, and at least give them consideration most of the time before rejecting the suggested content. So, what makes us trust and accept the suggestions given by these systems? Is it because they explain in a straightforward manner the rationale behind the recommendations, or do we believe that they know us well enough to recommend what we might want? This paper attempts to answer these questions.

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RESEARCH PURPOSE

This research aims to identify the factors that influence listener-perceived trustworthiness of music recommendation apps from earlier studies and chart out a framework for these factors with respect to music recommenders. The study also aims at determining the extent of influence that these factors have on the adoption of music recommendation systems by Indian listeners, through the mediating effect of trustworthiness.

Perceived trustworthiness of these AI apps among users will naturally increase their adoption of the recommendation system, thereby alleviating the user cold start problem, characteristic of classical recommendation systems as described in teaching books. This study delves into the working of music recommendation systems, to understand its working and study the users' perceptions on the role that factors such as content correctness (accuracy), privacy, algorithmic fairness, diversity, and transparency (explainability) play in the trustworthiness, and consequent decisions on adoption of the recommendation app.

THEORETICAL BACKGROUND

Trust in technology has been defined as the belief of the users that a specific technology has the necessary attributes to produce the expected outcome in a given situation in which negative consequences are possible (McKnight et al, 2011). What are these attributes, and what is their specific role in building user trust? Prior researches have established the role of information quality, perceived explainability, and anthropomorphism as attributes that define trust (Prakash & Das, 2024) in information systems (IS).

TRUST IN AI-BASED INFORMATION SYSTEMS

The need to differentiate between traditional IS and AI-based IS in this regard can be summarized as follows:

- The trust-related challenges created by AI systems are qualitatively different from traditional IS, and if they do not prove themselves to be worthy of trust, their acceptance and adoption will be hindered, since trust is vital for the continued social license of AI-based IS (Lockey, Gillespie, Holm, & Someh, 2021).
- The advantages of AI-based IS are manifold, including but not restricted to
 - (i) cheaper processing infrastructure,
 - (ii) growth of data availability,
 - (iii) greater connectivity between technologies that combine data, algorithms, and computational power,
 - (iv) capability of being like human beings while achieving specific tasks,
 - (v) improved prediction of results over its conventional counterparts,
 - (vi) optimized operations and customized service deliveries (Magrani & da Silva, 2024).
- Thus, AI contributes to social and economic well-being and is therefore naturally expected to be more trustworthy than traditional IS, failing which the complete benefits of AI-based IS can never be fully realized.
- Studies have shown that people over-rely on AI systems to the extent that they follow the suggestions of the AI system, even when the suggestion is wrong (Buçinca, Malaya, & Gajos, 2021). It is a generally accepted fact that the overreliance on AI-based systems is several times higher than in the case of traditional information systems, making it all the more unsafe when AI systems display a breach of trust.

For these reasons, it becomes imperative to pay special attention to the factors of trust in AI-based IS and warn users about the signs they need to look out for before trusting AI-based systems.

TRUST IN RECOMMENDATION SYSTEMS

Earlier, the IS landscape in a business environment had Expert Systems, which would recommend or suggest courses of action to people when in doubt. These systems were trained by human experts and were tested thoroughly for false positives/negatives. If the system was found to be inaccurate in its

suggestions, the incorrectness was identified and corrected through rigorous re-training and regression testing. However, in cases like a music recommendation system, where AI systems are used for personal consumption and have subjective outcomes, the technology provides no scope for fault identification, since it becomes the burden of the individual to bear the consequences of following an incorrect recommendation. Users hardly read the fine print before using these apps, casually agree to the terms and conditions, and are therefore liable for the outcomes of incorrect recommendations.

Recommendation systems use a few standard algorithms such as content-based filters and collaborative filters or hybrid filters (which combine the capabilities of both content-based and collaborative filters) to produce a highly subjective outcome for the listener. Terms such as “since you liked this item before” (content-based) or “people who liked this item, also liked this item” (collaborative) ensure that the app gains the trust of the casual user, who may have no means of verifying the authenticity or correctness of the recommendation.

TRUST IN MUSIC RECOMMENDATION SYSTEMS

After an elaborate survey of literary work specifically on the area of music recommendation systems, the following attributes were identified as influencers of user-perceived trustworthiness and subsequent adoption of music apps. While influencers of trust are referred to by different names in different studies, for the purpose of this study, we have identified them as the following:

- Explainable recommendations (also referred to as transparency)
- User data privacy (also referred to as user data security/confidentiality/data protection)
- Correct recommendations (also referred to as accuracy/precision)
- Display of diversity (also referred to as inclusive/inclusion)
- Fair recommendations (also referred to as unbiased)

EXPLAINABILITY OF RECOMMENDATIONS

Several studies have been dedicated to the study of relationship between transparency and trust (Felzmann, Villaronga, Lutz & Tamò-Larrieux, 2019; Kyosuke et al, 2023; Ge Yingqiang et al, 2024). Researchers have demonstrated that providing users with explanations lead to favorable outcomes such as improved user comprehension and increased trust. It also facilitates detection and correction of system errors while calibrating appropriate reliance on decision aids (Vorm & Miller, 2018). When a recommendation system algorithm does not clearly identify the reasons for the recommendation provided by it, several questions arise as to the reason for this “opacity.” The algorithm being proprietary could be a reason. Or it could be the technical complexity. In some cases, however, it could be an indication of the corporation’s concealment.

Recommendation systems are expected to strike the right balance between optimization of machine learning algorithms and the demands of human-level reasoning and semantic interpretation (Burrell, 2016). The explicit stating of the reasoning behind the recommendation not only allows the user to understand the cause for the recommendation but also effectively explains how the system works (Guesmi et al, 2023). Users cannot be expected to trust something the working of which they do not understand. A recent study has proved that character traits-based personalization, along with explanations, were preferred over non-personalized, non-explained recommendations by participants (Elazab et al, 2023). Recommendation systems that lack transparency could be viewed as “black boxes” where the methods and features used to arrive at the recommendations are concealed for whatever reason. However, there are studies that refute the role of explainability on the reliance of people on AI systems as well, suggesting that in spite of explainable modules, which would help people identify situations where AI suggestions should be disregarded, people may still over-rely on AI even when the suggestions are wrong (Buçinca, Malaya, & Gajos, 2021).

PROTECTION OF USER DATA PRIVACY

The deployment of AI-based algorithms, especially recommendation systems, has come under the scanner in the past decade for ethical concerns that accompany the use of these systems, specifically regarding the surveillance of user data (Gonçalves-Sá & Pinheiro, 2023). Dissemination of inappropriate content, data protection and privacy concerns (Ge Yingqiang et al, 2024), sale of personal data to third parties that causes infringement of individual privacy, autonomy and identity (Senthilkumar

et al, 2024), and anxiety of users regarding data privacy lapses (Liu Jen-Yu & Yang Yi-Hsuan, 2012) have all been focused on, in literary and academic conversations. The medium- and long-term consequences of recommendation systems, therefore, constitute an ethical gray area and require our immediate attention (Bonicalzi, De Caro & Giovanola, 2023).

Legal issues such as breaches of privacy and misuse of user data may also arise due to the continual user tracking, prediction, and inference of user behavior through analysis of personal data, construction of user behavioral profiles, and microtargeting for more accurate and personalized recommendations (Magrani & da Silva, 2024). With the large-scale prevalence of cybercrimes where criminals build trust among victims by displaying knowledge of their private data during the act of the crime, users are becoming more and more reluctant to divulge their information to untrustworthy sources. App developers would want to keep this in mind if they are banking on user trust for their growth and sustenance, as seen in the case of recommendation systems.

CORRECTNESS OF RECOMMENDATIONS

The most basic feature with which any technology, in general, and recommendation systems, in particular, can increase perceived trustworthiness by being correct and relevant in its track suggestions from the user's perspective. It is a simple and straightforward connection. Technical expertise in delivering recommendations and use of appropriate models establishes credibility, which improves trustworthiness (Shani & Gunawardana, 2011; Pu Pearl, Chen Li & Hu Rong, 2012). Numerous studies have contributed to the establishment of factors that improve accuracy: number of ratings to provide accurate predictions (Ahmadian, Ahmadi & Ahmadian, 2022), feature selection strategies in multicriteria recommendations (Jannach, Karakaya & Gedikli, 2012), solutions to sparsity and cold start problems in unsupervised learning systems (Bakshi et al, 2014), leveraging missing ratings (Ying Yuanping, Feinberg & Wedel, 2006), and filtering approaches based on rating variances (Adomavicius, Kamireddy & Youngok Kwon, 2007), to name a few. Irrespective of the mechanisms used and the tools deployed, at the end of the day, the user must feel that the list of items aligns accurately with their present disposition, interests, and preferences, as if the system were designed with just them in mind. If users begin to wonder why a certain recommendation was made for them (add to this the opacity of the algorithm), it beats the purpose of the system in question. There is a reason why researchers have concluded that accuracy and trustworthiness go hand in hand in the recommendation landscape (Hyan Yoo Kyung & Gretzel, 2008). Explicit feedback such as adding to playlists and implicit feedback such as skipping tracks after a short duration should typically find their way into future recommendations, making it more and more accurate, relevant, context-aware, and personalized.

DISPLAY OF DIVERSITY

Fairness and diversity can be viewed as two sides of a coin. While there are differences between the two concepts, one can argue that diversity or inclusion would automatically reduce bias and discrimination and therefore lead to fairness, thereby improving the ethical alignment of the system (Milano, Taddeo & Floridi, 2020). Extant literature has explored and established the impact of diversity on the performance of music recommender engines (Farrahil, Schedl, Vall, Hauger & Tkalčič, 2014) and has suggested mechanisms to increase diversity in these algorithms (Jones, 2010) using, for instance, knowledge graphs (Bertram, Dunkel & Hermoso, 2023). In fact, a study has revealed that diversity has a longstanding impact on listener attitudes, viz., deconstructing pre-existing implicit attachments and stereotypes (Porcaro, Gómez & Castillo, 2024). User trust may be lost if the system consistently promotes a narrow set of artists or genres, especially when the motives are commercial.

FAIRNESS OF RECOMMENDATIONS

Fair, bias-free, and non-discriminatory systems are beneficial to all stakeholders, which makes fairness-awareness a direct influencer of perceived trustworthiness by the users (Jin Di, Wang Luzhi, Zhang He, Zheng Yizhen, Ding Weiping, Xia Feng & Pan Shirui, 2023). From a user perspective, an ethical system would encompass a just and discrimination-free application; thus, any form of overrepresentation or under-representation of items in the recommendations would naturally lead to unjust and discriminatory consequences (Sonboli et al, 2021). There are several components to fairness, viz., ridding the system of popularity bias for instance, which could affect the way users perceive the ethical alignment of recommender algorithms, inclusion of artists from different sectors, which could

make the recommendations balanced in terms of genre of tracks and artists (as mentioned earlier, diversity contributes to fairness but is not the sole component), correctness of recommendations, which itself is a measure of fairness because the reasons why the suggestions are made is objective in the sense, can be explained with definite causes. Introducing recommendation system users to emerging artists, combined with preference-based recommendations, can serve well to demonstrate the system's impartiality. In a focus group discussion with eight participants that was also conducted as part of this study to get an overall idea of what listeners liked and disliked most in music apps, the parameter that most participants mentioned under "disliked" was the promotion of specific artists for commercial purposes. It was evident from the discussion that users are aware of the biases that music apps propagate for financial reasons.

METHODS AND MATERIAL

From the literature study, the factors that contribute to the listener-perceived trustworthiness of music recommendation systems were found to be (i) content correctness, (ii) explainability, (iii) privacy, (iv) fairness, and (v) diversity, though equivalent terms are used.

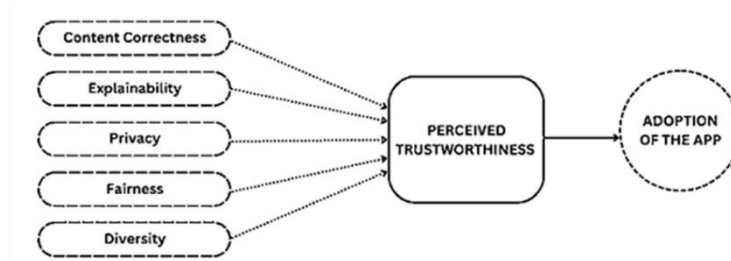


Figure 1: Factors that influence perceived trustworthiness and adoption of music recommendation systems.

A framework was created to study the exact effect of these factors on listener-perceived trustworthiness of music recommendation systems and in turn their effect in the adoption of these systems by Indian consumers. The framework has been drawn from various previous research work (Fernando, Ameeta & Shanthi Venkatesh, 2025) and aspires:

- To illustrate the factors that influence the listener-perceived trustworthiness and perceived ethical alignment of music recommendation systems.
- To study if trustworthiness has a mediating effect between these factors and the user acceptance and adoption of the recommendation system.

While some other aspects such as consistency, cross-platform reliability, user control, and listener experiences also feature in researches pertaining to music recommendation systems, these other aspects have not been included in the current study either since they fall under the broad categories that have been identified below directly or indirectly or do not have sufficient theoretical backing to establish the relationship they have on the user-perceived trustworthiness and adoption of these systems. Figure 1 illustrates the theoretical framework indicating the factors that have been found to influence user-perceived trustworthiness of music recommendation systems.

Going further, a pilot study was conducted, and responses were elicited for a 38-item questionnaire. An exploratory factor analysis was performed. The reliability of the questionnaire was ascertained using the Cron Bach's alpha value which was 0.921. The Varimax Rotation Method (EFA) was used to determine the validation and the items that were not found to be valid were removed for the final study. The final questionnaire with 31 items was floated among Indian music app listeners who were 18 years or older. The factors that emerged aligned with the factors identified by earlier research as being influential in the perceived trustworthiness of recommendation systems.

SURVEY INSTRUMENT

The data was collected using a structured questionnaire circulated among music recommendation app listeners in India through WhatsApp messages. The questions were framed with simple, non-technical terms wherever possible so as to ensure genuine and correct answers. The answers were elicited using a five-point Likert scale ranging from Strongly Disagree to Strongly Agree (1 = “Strongly Disagree” to 7 = “Strongly Agree”). A screenshot of the Google Form used for data collection has been provided in Figures 2 and 3.

The Effect of Perceived Trustworthiness and Ethical Alignment on the Adoption of Music Recommendation Systems

This study aims to find the factors that affect the consumer-perceived trustworthiness and ethical orientation of music recommendation systems, an increase of which is expected to be the determinant of higher acceptance of such applications.

The tracks recommended for me by the app are correct most of the time *

1 2 3 4 5

Strongly Disagree Strongly Agree

The app suggests music genres that match my current mood or preferences. *

1 2 3 4 5

Strongly Disagree Strongly Agree

Figures 2 (left) and 3 (right): Survey instrument screenshot; questions for content correctness screenshot.

The questionnaire was circulated through multiple channels, with a request to forward it to other music app listeners, and hence the sampling technique was a combination of convenience and snow-ball methods. The number of listeners who responded to the questionnaire was 430.

RESULTS

DEMOGRAPHY SAMPLE

Figure 4 indicates the frequency and percentages across the value ranges for the different categories of demographic information.

S. No	Variable	Values	Frequency	Percentage
1	Age (in years)	18–24 25–34 35–44 45–54 55–64 65+	135 111 88 59 34 3	31.4 25.8 20.5 13.7 7.9 0.7
2	Gender	Male Female	211 219	49.1 50.9
3	Occupation	Student Employed (full-time/part-time) Unemployed Other (please specify)	106 273 28 23	24.7 63.5 6.5 5.3
4	Frequency of use of music platform	Multiple times a day Daily Weekly Rarely	189 198 38 5	44.0 46.0 8.8 1.2
5	Most preferred music app	Spotify Jio Saavn Amazon Music YouTube Music Apple Music Others (please specify)	311 1 7 104 4 3	72.3 0.2 1.6 24.2 0.9 0.7

Figure 3: Sample demography.

RELIABILITY

Figure 5 displays the outcomes of the reliability analysis conducted via Cronbach’s alpha for each multi-item scale. Results indicate good reliability across the scale.

Variables	No. of items	Mean	Cronbach's alpha
Content correctness	6	4.27	0.890
Fairness	4	4.40	0.928
Diversity	3	4.34	0.817
Explainability	5	4.30	0.800
Privacy	4	4.27	0.830
Trustworthiness & alignment	6	4.27	0.917
Adoption of the App	3	4.42	0.825
Overall	31	4.31	0.914

Figure 4: Reliability analysis.

EXPLORATORY FACTOR ANALYSIS

A principal components analysis with varimax rotation using SPSS 25.0 was used in this study to discern the underlying dimensions of multi-item measurement scales, including the explainability of recommendations, protection of user data privacy, correctness of recommendations, display of diversity, and fairness of recommendations. A minimum Eigenvalue of 1.0 was applied to ascertain the total number of factors for the scales, with loadings above 0.40 on a single factor being retained. The EFA aimed to uncover the factors influencing the adoption of the app, utilizing data obtained from 430 respondents. The Kaiser–Meyer–Olkin (KMO) test was conducted to gauge how well the collected data conformed to factor analysis criteria. The value derived from this test satisfies the condition for an adequate sample for the entire model as well as the individual variables. The outcome of the KMO test for sampling adequacy is given in Figure 6.

Kaiser–Meyer–Olkin measure of sampling adequacy		.816
Bartlett's test of sphericity	Approx. Chi-square	9967.043
	df	465
	Sig.	.000

Figure 5: KMO Test for sampling adequacy.

Initially, thirty-one items were subjected to factor analysis, resulting in the reduction of these items into seven factors. These factors generated from the exploratory factor analysis correspond to the results of the literature survey. Identification of variables within a factor was performed with the help of Varimax with Kaiser normalization. The Eigen values were generated, revealing the extraction of seven factors, aligning with the conceptualized dimensions.

CONFIRMATORY FACTOR ANALYSIS

Variables			Unstandardized coefficient	S.E.	Standardized coefficient	p-value
Item 28	←	Trustworthiness	1.000		0.780	
Item 27	←	Trustworthiness	1.171	0.058	0.889	<0.001**
Item 26	←	Trustworthiness	1.134	0.059	0.965	<0.001**
Item 25	←	Trustworthiness	1.023	0.058	0.779	<0.001**
Item 24	←	Trustworthiness	0.968	0.044	0.748	<0.001**
Item 23	←	Trustworthiness	0.955	0.058	0.721	<0.001**
Item 6	←	Content correctness	1.000		0.661	
Item 5	←	Content correctness	1.089	0.077	0.755	<0.001**
Item 4	←	Content correctness	1.034	0.076	0.689	<0.001**
Item 3	←	Content correctness	1.175	0.077	0.821	<0.001**
Item 2	←	Content correctness	1.101	0.069	0.739	<0.001**
Item 1	←	Content correctness	1.194	0.074	0.887	<0.001**

Item 10	←	Fairness	1.000		0.899	
Item 9	←	Fairness	1.011	0.033	0.900	<0.001**
Item 8	←	Fairness	0.911	0.038	0.780	<0.001**
Item 7	←	Fairness	1.039	0.033	0.922	<0.001**
Item 18	←	Explainability	1.000		0.898	
Item 17	←	Explainability	0.846	0.046	0.710	<0.001**
Item 16	←	Explainability	0.870	0.046	0.747	<0.001**
Item 14	←	Explainability	0.619	0.054	0.531	<0.001**
Item 21	←	Privacy	1.000		0.781	
Item 20	←	Privacy	0.953	0.052	0.837	<0.001**
Item 19	←	Privacy	0.869	0.053	0.760	<0.001**
Item 13	←	Diversity	1.000		0.776	
Item 12	←	Diversity	1.022	0.061	0.785	<0.001**
Item 11	←	Diversity	0.981	0.059	0.778	<0.001**
Item 31	←	Adoption	1.000		1.022	
Item 30	←	Adoption	0.719	0.043	0.710	<0.001**
Item 29	←	Adoption	0.655	0.046	0.642	<0.001**

Note: 1. ** Denotes significance at 1% level

Figure 6: Confirmatory factor analysis.

A Confirmatory Factor Analysis was performed to examine the theoretical interdependence between seven factors, and the results have been tabulated in Figure 7. The first-order model for the seven factors has been depicted in Figure 8.

The fit indices indicate that it is a **good** fit as the factors are found to be significant at $p < 0.05$.

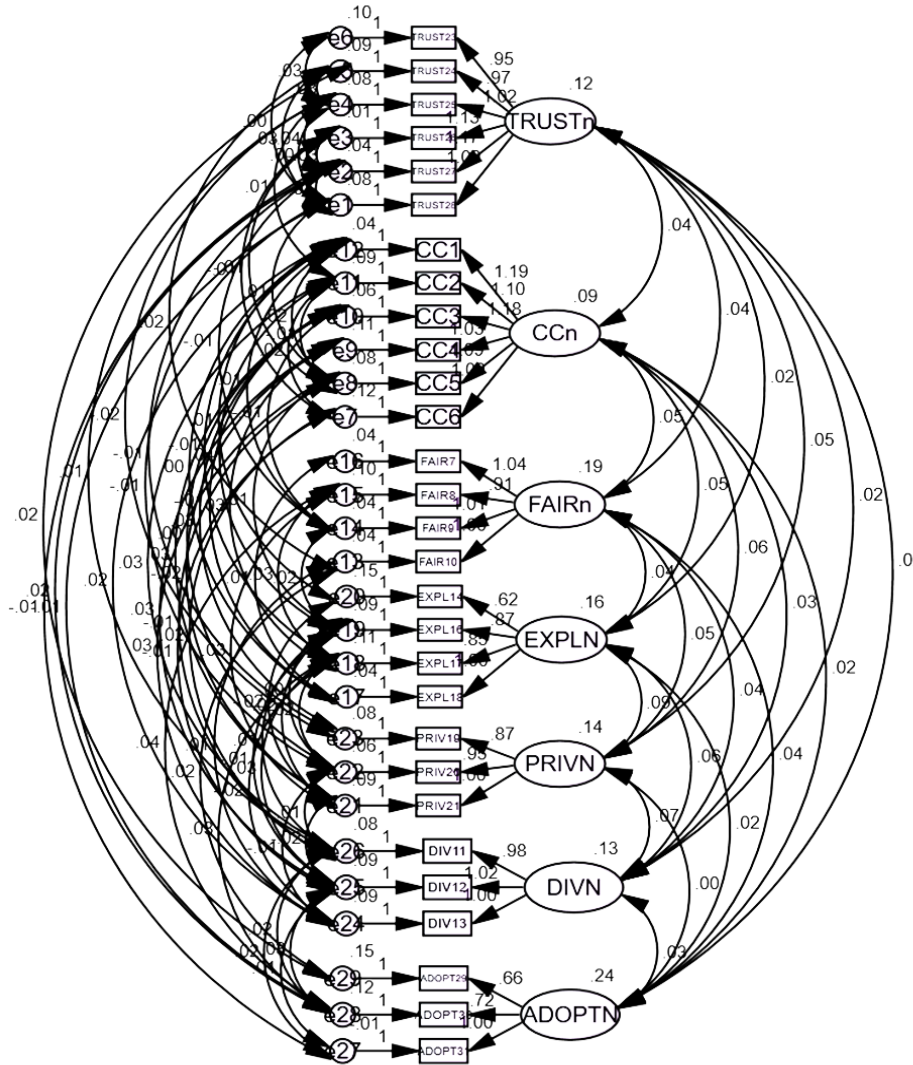


Figure 7: First-order model for explainability, data privacy, correctness of recommendations, display of diversity, fairness of recommendations, trustworthiness, and adoption of the app.

MEDIATION TESTING

The mediation analysis is conducted by treating content correctness, fairness, explainability, diversity, and privacy as independent variables, adoption of the app as dependent variable, and trustworthiness as mediator. An analysis of indirect effects that is based on the guideline proposed by Baron and Kenny (1986) was the basis for the mediation analysis. The effect of the factors on the adoption of the app, when mediated by perceived trustworthiness, has been depicted in Figure 9.

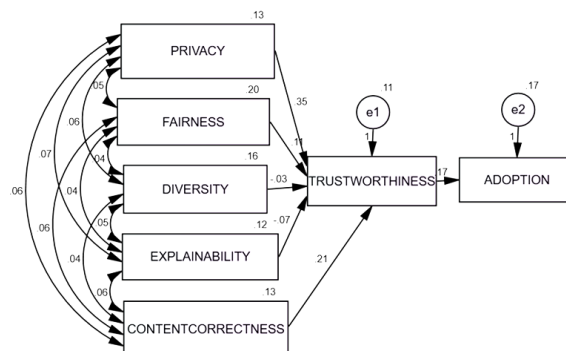


Figure 8: Second-order model for explainability, data privacy, correctness of recommendations, display of diversity, fairness of recommendations, trustworthiness, and adoption of the app.

The results of the Mediation Analysis have been provided in Figure 10.

Path			Total effects	Direct effects	Indirect effects	Remarks
Trustworthiness	←	Diversity	-.029	-.029		Rejected
Trustworthiness	←	Explainability	-.070	-.070		Rejected
Trustworthiness	←	Content Correctness	.206**	.206**		Accepted
Trustworthiness	←	Fairness	.109*	.109*		Accepted
Trustworthiness	←	Privacy	.349**	.349**		Accepted
Adoption	←	Trustworthiness	.173**	.173**		Accepted
Adoption	←	Content Correctness	.036**		.036**	Accepted
Adoption	←	Privacy	.061**		.061**	Accepted
Adoption	←	Fairness	.019*		.019*	Accepted
Adoption	←	Explainability	-.012		-.012	Rejected
Adoption	←	Diversity	-.005		-.005	Rejected

**p<0.01, *p<0.05

Figure 9: Mediation analysis.

The results of this analysis indicate that perceived trustworthiness is, in fact, partially mediating the relationship connecting content correctness and adoption of the app as indirect effects are statistically significant ($\beta=0.036$, $p<0.01$). Also, trustworthiness is found to be partially mediating the relationship between privacy and adoption of the app, as here too, indirect effects are statistically significant ($\beta=0.061$, $p<0.01$). In the case of fairness also, the same result is obtained, indicating the mediating role of trustworthiness as the indirect effects are found to be statistically significant ($\beta=0.019$, $p<0.05$). However, in the case of explainability and diversity, the results vary, demonstrating a lack of mediating influence of trustworthiness in the adoption of the app since the indirect effects prove insignificant.

DISCUSSION

This is a significant finding for the academic community and AI enthusiasts alike. While most of the world surrounding the ethics of AI systems speaks of eradicating the “black box” nature of algorithms, here we have a study that establishes that explainability, after all, may not be a thing at all for users. Several follow-up questions arise at a glance at these results, the primary ones among them being, “Is this good or bad?” or “Why is that a bad thing?”. Let us have a look at the probable causes for this effect to answer these questions. In the following section, we aspire to uncover probable reasons for this lukewarm attitude of users toward the explainability of music recommendation engines.

WHY EXPLAINABILITY MIGHT NOT MATTER

There may be several reasons why users may not pay attention to explainability of the algorithm while using music recommendation engines:

CONVENIENCE OVER EXPLAINABILITY

Users may prioritize enjoyment and the convenience of listening to a huge database of music over the transparency of its operation. When it comes to recreational applications, they may be happy that their favorite tracks can be listened to anytime, anywhere for free (or for a subscription), and this freedom may be considered much more important than a few poor recommendations for whatever reason.

TRUST IN TECHNOLOGY

Consumers often trust verified platforms that deploy sophisticated algorithms, which, according to them, will provide correct recommendations without the need to explain them. Anthropomorphism is real, and since the rapport that these tools build with the consumer is so human-like and natural, users may be led to believe the apps’ recommendations beyond a shadow of doubt.

ALGORITHMIC AVERSION

Users may not feel the necessity to understand the dynamics of preference mapping and mechanics of the algorithms (such as content-based or collaborative) due to its complexity. There are several

factors that lead to a user liking or disliking a song, which they may not be aware of themselves. Analyzing these factors may be left best to the algorithm according to them. Aversion to algorithms and information overload is a concept that has been researched in the past. Detailed explanations could sometimes be overwhelming for users who would prefer straightforward suggestions to detailed ones.

LACK OF AWARENESS

Several consumers fall under the category of naïve users (as against knowledgeable users) who are not aware of the need for algorithms to explain suggestions to them. They are happy if their requirements are met by the application. Listeners typically from non-technical or non-computer science backgrounds may fall under this category. They have not been formally trained on technology (such training would typically cover pitfalls or limitations of technology as well) nor have they been exposed to the ill-effects of trusting technology too much, through social media or everyday news. Then there are a few listeners who do not **want** to believe that technology can go wrong—skeptical even, about research on the unethical aspects of IS. These are the users who are not fully aware of the other side of the two-edged sword that is called technology.

CRITICALITY OF THE APPLICATION

A music recommendation system will fall under the least critical systems, where an error in recommendation accuracy, even if huge, will only lead to the user listening to the wrong track. This could be the reason why users are not worried about how the song was recommended to them. However, in apps that are more critical, and the consequences of failure are high, this attitude could lead to disasters. Would a career recommendation system that suggested an educational path that did not turn out to be lucrative for the user be viewed at the same level of gravity as a music recommendation system that suggested a wrong song? But do users differentiate between applications that way before deciding to trust the system less (in the first case) and more (in the second)?

DEMOGRAPHIC PROFILE OF LISTENERS

Further research may be required to find out if this trend of lukewarmness to explainability is an Indian-listener feature. If so, identifying the reasons behind this trend may make for an interesting topic. Likewise, age group or profession may also reveal patterns in this aspect. This could be considered as the future scope of this research.

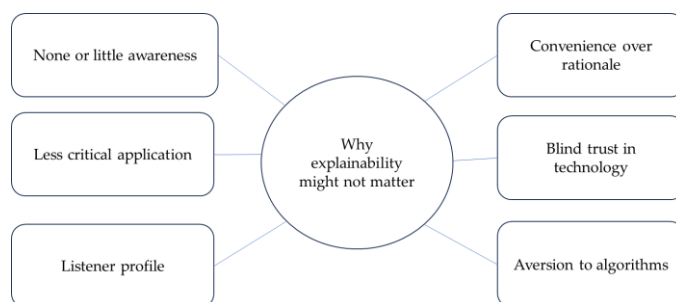


Figure 10: Reasons why explainability might not matter.

If, by further probe, we can establish that the criticality of the system is the primary reason for this indifference to transparency, it means that users are prudent enough to differentiate the need for explainability in high-criticality systems (such as healthcare recommendations) versus low-criticality systems (such as music or movie recommendations). However, if users choose to ignore the explanations given by the recommendation facility due to reasons such as complexity of the explanations or prioritizing convenience over transparency, that could be a cause for concern. If users were to blindly trust recommendations of critical applications using the same yardstick, it could lead to distrust and even a total aversion to AI-based recommendations in case they encounter incorrect recommendations. Figure 11 summarizes the various reasons why users disregard explainability as a trust factor.

CONTRIBUTION OF THE STUDY

With AI applications finding their way into every sphere of business and personal automation, industry and academia equally bear the burden of ensuring a smooth transition for consumers from non-AI

into AI environments, at the same time, educating them about the importance of attributes such as transparency, privacy, and diversity over mere convenience and cost-effectiveness. While the advantages that contemporary AI systems have showcased can never be undermined, it becomes imperative for industry and academia to instruct users about the pitfalls of such systems and the consequences of blindly believing their outcomes in order that AI-based systems enjoy continued social acceptance (as already discussed earlier. This path of discovery on what exactly are the attributes that influence the quest for explainability in AI systems from user perspectives is the future scope of this study and may throw light on some pivotal user behavior aspects that may decide the future of AI application design and deployment.

SUGGESTIONS TO THE INDUSTRY

Though this study was centered around music listeners, research is required in business landscapes too in this regard. Studies that throw light on the factors that influence the trust levels of AI systems in enterprises are very limited in number. Organizations should develop frameworks that guide them while deploying AI-based IS instead of blindly joining the bandwagon of AI-adopters. Some of the frameworks that have been developed by organizations include variants of the Repeatability-Criticality framework (which indicate the level of trust that can be had in AI systems under a spectrum of repeatability and criticality of the applications) (Wanner et al, 2020) and the Objectivity-Subjectivity framework, in which case, the decision to rely on the AI system will depend on whether the input and output are objective or subjective in nature (Abhigyan, [2026]). In either case, business domains will have to lay down ground rules for trust in AI-based IS, especially recommendation systems, factoring in parameters such as content correctness, explainability, privacy, diversity, and fairness.

SUGGESTIONS TO INDIVIDUAL CONSUMERS

As mentioned in the Discussion section, a follow-up study could reveal why users are not interested in knowing why tracks are recommended to them. Depending on such findings, certain courses of action could be taken. Whether it is prioritizing convenience or algorithmic aversion, consumers need to be aware of the pitfalls of their own sluggishness when it comes to paying attention to critical parameters such as transparency or privacy. When a healthcare app recommends a certain medication to a user, wouldn't he/she be invested in determining the reason for the recommendation? What about allergies and/or contraindications? Wouldn't the user want to know if these parameters were factored in before the recommendation was given? Similarly, while investing huge amounts in financial instruments, wouldn't users want to know the rationale behind the recommendation given by an AI-based financial advisor app? Would they blindly trust such systems without paying heed to whether the system took into consideration the number of dependents of the investor, the number of remaining years they can be employed, and so on?

With the advent of newer technology come newer problems—cybercrimes being a classic example! Consumers should be prudent enough to gauge the level to which recommendation systems, or for that matter, any information system, can be trusted. If users are prudent enough to customize their trust levels based on how critical the app is, their lack of attention to one or two of the trust parameters may not be even significant in systems such as music recommendations. However, if users lack this trait and trust all systems equally without paying attention to the transparency of recommendations or the diversity of suggestions, then that could lead to undesirable results in more critical systems.

CONCLUSION

We are currently living in an era where perceptions are questioned more than ever. In this context, there are several debates and discussions on whether AI is something that should be trusted at all. In this context, apart from the accuracy of the system itself, an AI-driven system should also display some ethical standards such as explanation of rationale in its suggestions, inclusion of different artists and genres, protection of user data, and fairness in its recommendations. A recommendation system that takes into consideration only some of these factors while ignoring the others cannot be trusted in its delivery of recommendations in the light of ethical considerations.

Lack of ethical alignment in AI systems may prove harmful to consumers. If users use the same yardsticks to trust more critical systems, AI applications could be doubted and scrutinized to a point where its use may be limited to just music recommendations and nothing more—unless we wake up

and teach users to trust AI the way it is supposed to be trusted: with caution and conditions of ethical behavior encompassing factors such as explainability and diversity.

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