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Analysis of the Effect of AI Personalization on User Trust and Perceived Price Value and Its Implications for Subscription Intention to Music Streaming Services

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Abstract

Background: Despite high adoption of music streaming in Indonesia, the subscription conversion rate is still low. This reveals an opportunity to understand how AI personalization influences trust and leads to subscriptions. This study explores the impact of AI-based personalization systems as well as the role of trust on music streaming subscription intention in Indonesia.
Objective: The research objectives include analyzing the impact of personalization on Price Value, Performance Expectancy, and Trust in AI, as well as the mediating effect of Trust in AI and Performance Expectancy on Intention to Subscribe.
Methods: This research employed a quantitative study design, and a questionnaire was purposively administered to active users of Spotify and YouTube Music in Indonesia. A total of 420 valid responses were collected and utilized for the final data analysis from both free and premium users. PLS-SEM via SmartPLS software was used to analyze the data.
Results: The results show that AI Personalization has a significant effect on Trust in AI and Price Value. Trust in AI serves as a mediating variable that reinforces both Performance Expectancy and Effort Expectancy. Price Value is most influential in determining subscription intention, followed by Performance Expectancy and then Habit.
Conclusion: The greater the trust users place in AI, the more they value security, transparency, and control. This study extends UTAUT2 through the integration of Personalization and Trust in AI within the context of AI-driven digital subscriptions.

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INTRODUCTION

Over the last few decades, the music industry has undergone a monumental change, driven by rapid advances in digital technology. Globally, the internet, mobile devices, and music streaming platforms have altered how music is produced, distributed, and consumed worldwide. Digital formats, especially music streaming, constitute the primary revenue driver of the music industry as we know it today (IFPI, 2024).

The IFPI Global Music Report 2024 reports that global music industry revenues surged to US$28.6 billion in 2023 (+10.2% YoY). The music streaming share was 67.3% of total revenue, with subscription streaming growing by 11.2%, achieving a 48.9% share globally (IFPI, 2024). Paid subscription streaming users climbed to 667 million, signifying increasing demand for and user engagement with digital music formats (IFPI, 2024).

With the expansion of the music industry worldwide, personalization plays a major role in providing a better user experience and satisfaction on music platforms. Prior research investigating music streaming adoption used constructs from UTAUT2 (performance expectancy, effort expectancy, and habit; Risanti (2022) and Barata (2021) and the effects of personalization on user behavior (Cheng et al., 2020; Halim et al., 2022). In contrast, the integration of AI personalization and trust in AI within UTAUT2's expanded constructs through mediation analysis in the context of music streaming subscriptions has not been systematically studied in Indonesia.

The originality of this study lies in examining AI personalization quality and its effects on the intention to subscribe through trust and value perception pathways, validated in Indonesia. Personalization helps users find music that fits their tastes, their moods, or what they are doing in a certain context, thus improving user engagement and retention (Schedl et al., 2018).

Data is essential to achieving the vision of successful music personalization. Analyzing user data (listening history, liked tracks, and playlists) helps understand users' music preferences and consumption patterns. One way to do this is by utilizing music metadata (genre, tempo, and lyrics), which helps identify similarities and categorize music into playlists (Herlocker et al., 2004).

Internet and mobile device penetration also drive a dynamic, evolving music industry in Indonesia. Indonesians increasingly prefer to listen through music streaming platforms such as Spotify, YouTube Music, and Joox (IFPI, 2024). Indonesia has one of the most dynamic and varied music industries in Southeast Asia. This sector, sustained by its large population and high interest in music, has expanded considerably over the years, mainly due to digital technology development along with music streaming platforms (Khutami et al., 2024).

Since the advent of music streaming platforms, Indonesian listening behavior has changed significantly. As a result, millions of songs are easily accessible through applications, offering personalized perspectives and playlists for users through algorithms that generate recommendations for each of them (Syahraihan et al., 2024). Music streaming has become the main choice for many Indonesians, while physical formats, such as CDs, are increasingly being abandoned (IFPI, 2024).

Based on data from We Are Social in 2023, Indonesia ranks first as the country with the highest percentage of music streaming platform users globally, sharing this position with Brazil at the same percentage of 50.3%.

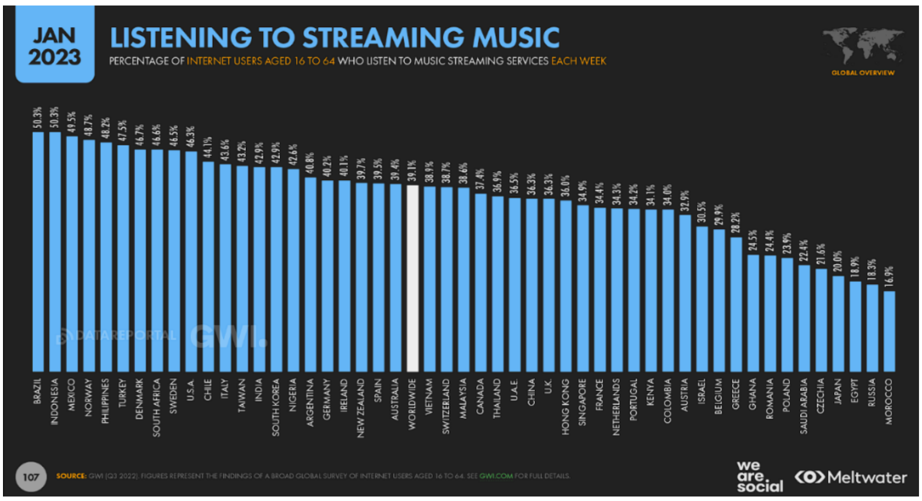

Figure 1. Percentage of Music Streaming Platform Users
source: We Are Social (2023)

This usage is also expected to continue increasing annually. According to an analysis by Statista, revenue in the "Music Streaming" segment of the digital media market in Indonesia is projected to continue growing between 2024 and 2027, with a total increase of 46.8 million US dollars (Statista, 2023).

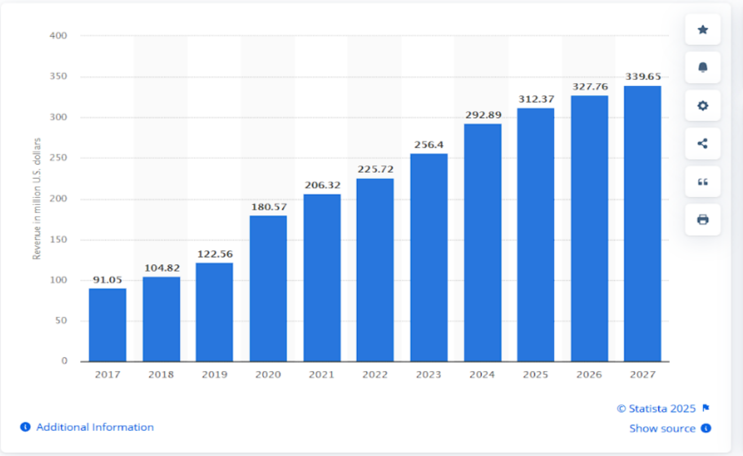

Figure 2. Projected Growth of the Music Streaming Industry in Indonesia
source: Statista (2023)

Most of the music streaming market share is still controlled by two major platforms. The Indonesian Internet Service Providers Association (APJII) in its 2023 Indonesian Internet Penetration Survey report outlined the music platforms most frequently used by the public in 2023. YouTube Music ranked first with 67.62% of respondents, followed by Spotify with 28.27%. Other platforms like Joox recorded 7.96% of respondents, while Apple Music only reached 1.77% of respondents APJII (2024), although Apple Music usage figures might be influenced by iOS usage, which only covers 7.3% of the mobile operating system market share compared to Android's 92.63% in Indonesia in 2024.

Music is not only a form of entertainment but also an integral part of cultural identity, self-expression, and social interaction. Traditional music, such as *gamelan* and *keroncong*, is still preserved and appreciated, while popular music, including pop, rock, and dangdut, dominates the charts and streaming platforms (Jakpat, 2024).

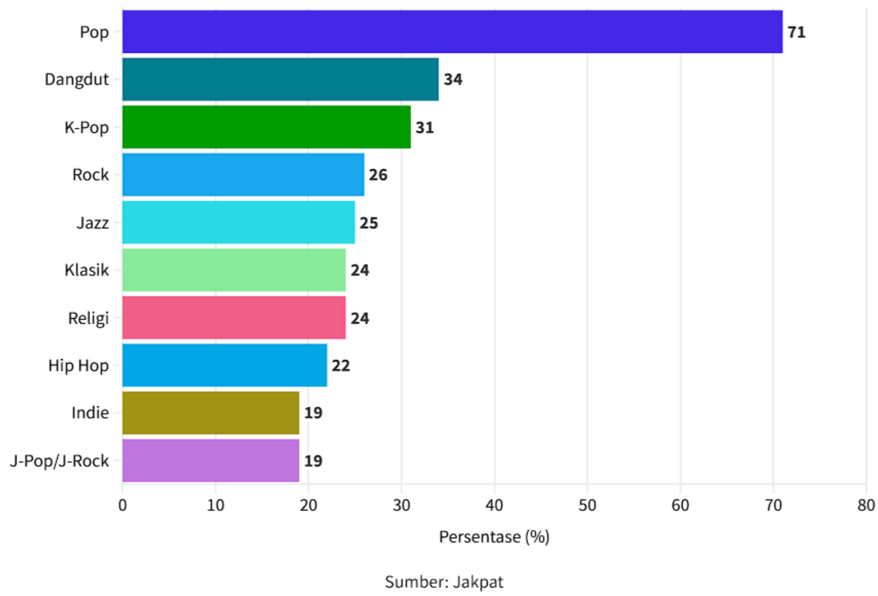

Figure 3. Popular genres on music streaming platforms in Indonesia
source: Jakpat (2024)

Pop is the favorite genre among Indonesians, as stated by 71% of respondents in the Jakpat 2024 survey. *Dangdut* follows in second place, favored by 34% of respondents, while K-pop ranks third, liked by 31%. Rock is preferred by 26% of respondents, and jazz by 25%. The same report also shows that music streaming has become part of daily habits (Jakpat, 2024).

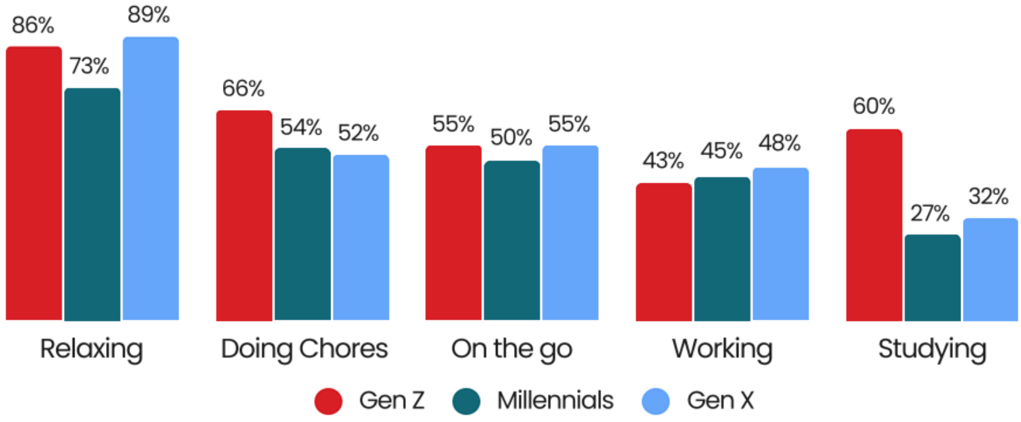

Figure 4. Music Streaming Usage Habits in Daily Activities
source: Jakpat (2024)

Overall, music usage in Indonesia is highest during leisure activities, followed by doing housework, traveling, working, and studying. Leisure activities top the list with an average usage of around 83%, indicating that music is strongly associated with relaxation. Meanwhile, listening to music while studying has the lowest average, around 40%, but still shows a significant role, especially among the younger generation. These data confirm that music has become part of the daily habits of Indonesians, with usage levels varying depending on the context of the activity (Jakpat, 2024).

Although the usage rate of music streaming platforms in Indonesia is very high, a survey conducted by Jakpat revealed that 45% of streaming platform users plan to cancel their subscriptions, with the main reasons being dissatisfaction with the platform's service and expensive subscription costs (Jakpat, 2024). These data are also supported by Spotify's annual reports, which show that the percentage of Spotify Premium (paying) users has steadily declined, from 44.9% in 2020 to 39.0% in 2024 (Spotify, 2025). For YouTube Music, although paying subscribers reached 125 million in 2025 Google (2025), this number is still very small compared to YouTube's total monthly active users exceeding 2 billion Dongre (2023), meaning the conversion rate to subscription is below 10%. This indicates a challenge in retaining users to continue subscribing and increasing the conversion rate for users to start subscribing to music streaming platforms in Indonesia.

The objective of this research is to analyze the influence of Personalization on Price Value, Performance Expectancy, and Trust in AI in music streaming platforms. The usefulness of this research is to offer strategic recommendations to music streaming service providers for improving Price Value, Performance Expectancy, ease of use, and Habit through the level of influence of the personalization factor and Trust in AI. While adoption of music streaming and AI personalization has received increasing attention in the literature, substantial research gaps exist.

Earlier works have studied the UTAUT2 constructs in a broader context of digital services generally Venkatesh (2012), but have not yet thoroughly explored the various forms of AI-led personalization specifically in Indonesian music streaming contexts. Although Trust in AI has been the focus of several research papers Sousa (2024) and Choung (2023), other studies have not examined its mediating role between personalization quality and subscription intention. This study, therefore, addresses these gaps by incorporating Personalization and Trust in AI as additional factors within an integrated UTAUT2 framework based on the Technology Acceptance Model (TAM) and AI trust theory.

METHOD

This research employed a quantitative explanatory approach aimed at analyzing the effect of AI-based personalization on customer subscription intention among music streaming service users in Indonesia. The research was directed toward the relationships between variables in a user behavior model, using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework expanded with Personalization and Trust in AI constructs as its theoretical artifact.

This approach was chosen because it explains causal relationships between constructs in a measurable way through hypothesis testing.

Conceptually, the research began with preliminary research to identify the main issues underlying the study, namely the low subscription intention of users toward music streaming services in Indonesia despite the increasing use of digital music platforms. This preliminary investigation provided the basis for the construction of a problem statement, as well as an adequate literature review prior to proposing a research model—one combining core UTAUT2 constructs with two additional ones: Personalization and Trust in AI. This model then informed the hypotheses and research instruments developed.

This study employed a content analysis approach to cluster user reviews of music streaming platforms for the development of the Personalization and Trust in AI constructs. A qualitative content analysis was performed on 65 user reviews from Spotify and YouTube Music that were collected from online discussion channels related to the use of both applications, as well as in-app reviews, focusing on users' lived experiences with AI personalization. The output of this analysis was used to confirm that the indicators developed were not merely theoretical, but also accurately reflected what users experienced.

Recommendation Relevance, Context Suitability, User Control, and System Flexibility led to the formation of the Personalization construct. The dimensions of system reliability, AI consistency, algorithmic transparency, and recommendation fairness were used to formulate the items of the Trust in AI construct. Drawing on the theoretical framework as well as construct development results, eleven hypotheses were formulated in this study: Hypothesis 1 addressed the direct effect of Personalization on Trust in AI and Price Value; Hypothesis 2 addressed the influence of Trust in AI on Performance Expectancy and Effort Expectancy; Hypotheses 3–6 addressed the effects of Price Value, Performance Expectancy, Effort Expectancy, and Habit on Subscription Intention. This study also tested the mediating role of Price Value, Performance Expectancy, and Effort Expectancy in the relationships between the main variables in the model.

This research focused on AI-based music streaming platforms, specifically Spotify and YouTube Music, including personalization features such as song recommendations, shuffle, automatic playlist creation, and AI DJ. The respondents of the study were active Spotify and YouTube Music users in Indonesia. Respondents were selected based on the following criteria: aged 18 years or above, at least three months of usage on the platform, having listened to music at least seven times a week, and including both free-tier and premium-tier users.

The research population was drawn from data published by the Indonesian Internet Service Providers Association (*Asosiasi Penyelenggara Jasa Internet Indonesia* [APJII]) for 2024, which reported that the number of people connected to the internet in Indonesia reached 221,563,479, with 56.07% accessing music content online. Of this group, Spotify and YouTube Music together accounted for a 95.89% market share, meaning the estimated number of active users across both platforms was 119,164,999.

Purposive sampling was implemented as the sampling technique, selecting respondents based on criteria aligned with the research objectives. The Slovin formula was used to calculate the minimum sample size, with a margin of error of 5%, yielding a minimum required sample of approximately 398.6, which was rounded up to 399 respondents. Ultimately, a total of 420 valid responses were collected, exceeding this minimum requirement. This approach was considered appropriate given that the research required actual users of music streaming services who were exposed to AI personalization features.

The research instrument was an online structured questionnaire administered via Google Forms. The questionnaire measured all research constructs, including Performance Expectancy, Effort Expectancy, Price Value, Habit, Personalization, Trust in AI, and Subscription Intention. A five-point Likert scale was used to measure each indicator, ranging from 1 = strongly disagree to 5 = strongly agree, to quantify the extent of respondent agreement with each statement and facilitate comparison across response items.

Each construct was operationalized using four indicators based on a five-point Likert scale, drawing from validated studies and a content analysis of 65 prior user reviews. Data were collected through an online structured questionnaire administered to participants via social media platforms and user forums.

Data collected in this study were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with the SmartPLS software. This approach was selected because it is capable of examining simultaneous relationships between latent variables, including predictive models and those involving mediating variables. The analysis consisted of two main stages: outer model assessment and inner model evaluation. The outer model assessment was conducted to ascertain the validity and reliability of the constructs. For convergent validity, the minimum threshold was set at 0.50 for the Average Variance Extracted (AVE) value, while construct reliability was assessed using Composite Reliability and Cronbach's Alpha, each requiring a minimum value of 0.70.

The purpose of this stage was to ensure that every indicator correctly and consistently measured its respective latent construct. Subsequently, the inner model was evaluated to assess the strength of the structural relationships between constructs in the research model. Assessment was conducted using R-Square values to determine the explanatory power of the independent variables, with thresholds of 0.75 indicating a strong model, 0.50 a moderate model, and 0.25 a weak model. Hypothesis testing was then conducted using path coefficient values, t-statistics, and p-values. Relationships between variables were considered statistically significant when t-statistics exceeded 1.96 and p-values were below 0.05.

RESULTS AND DISCUSSION

Results

Results are presented in two analytical stages using SmartPLS 4 software, as described in the Methods section. (1) Measurement Model (Outer Model) evaluating validity and reliability, and (2) Structural Model (Inner Model) testing hypotheses.

Measurement Model Analysis (Outer Model)

The evaluation of the measurement model aims to ensure that the indicators used are valid and reliable in measuring the latent constructs under study. The outer model testing includes convergent validity, discriminant validity, and reliability.

Convergent Validity Test Results Using Outer Loadings

Outer Loadings assess the correlation between each indicator and its latent construct. A loading value above 0.70 indicates the latent variable explains more than 50% of the indicator's variance. The following are the results of the Outer Loading values using SmartPLS 4 software:

Table 1. Results of Outer Loadings Analysis

Variable	Indicator	Outer Loadings	Description
Price Value (PV)	PV1	0.830	Valid
	PV2	0.839	Valid
	PV3	0.847	Valid
	PV4	0.828	Valid
Performance Expectancy (PE)	PE1	0.852	Valid
	PE2	0.863	Valid
	PE3	0.795	Valid
	PE4	0.843	Valid
Effort Expectancy (EE)	EE1	0.807	Valid
	EE2	0.849	Valid
	EE3	0.832	Valid
	EE4	0.820	Valid
Habit (HB)	HB1	0.854	Valid
	HB2	0.829	Valid
	HB3	0.822	Valid
	HB4	0.808	Valid
Personalization (PS)	PS1	0.822	Valid
	PS2	0.809	Valid

Variable	Indicator	Outer Loadings	Description
	PS3	0.818	Valid
	PS4	0.810	Valid
Trust in AI (AI)	AI1	0.801	Valid
	AI2	0.820	Valid
	AI3	0.822	Valid
	AI4	0.821	Valid
Intention to Subscribe (IS)	IS1	0.813	Valid
	IS2	0.818	Valid
	IS3	0.817	Valid
	IS4	0.820	Valid

source: processed data

Based on Table 1, all indicators from the constructs Personalization (PS), Trust in AI (AI), Price Value (PV), Performance Expectancy (PE), Effort Expectancy (EE), Habit (HB), and Intention to Subscribe (IS) have good validity with outer loading values above the threshold of 0.70. The lowest recorded value is 0.795 (PE3) and the highest value reaches 0.863 (PE2).

No indicator has a value below 0.70, so no items need to be eliminated from the model. This confirms that all questions in the questionnaire are valid measures and have a significant contribution to their respective constructs.

Convergent Validity Test Results Using Average Variance Extracted (AVE)

AVE measures convergent validity at the construct level. An AVE value above 0.50 indicates that the construct explains more than half of its indicators' variance. The following are the AVE value results using SmartPLS 4 software:

Table 2. Results of AVE Analysis

Variable	AVE	Description
Price Value (PV)	0.699	Valid
Performance Expectancy (PE)	0.703	Valid
Effort Expectancy (EE)	0.684	Valid
Habit (HB)	0.686	Valid
Personalization (PS)	0.664	Valid
Trust in AI (AI)	0.666	Valid
Intention to Subscribe (IS)	0.668	Valid

source: processed data

Based on Table 2, the test results show that all research variables have good convergent validity. All constructs recorded AVE values consistently above the 0.50 threshold. The lowest value was recorded for the Personalization (PS) variable at 0.664, while the highest value was achieved by the Performance Expectancy (PE) variable at 0.703. With a range of values between 0.664 and 0.703, this indicates that the average variance explained by each construct from its indicators reaches 66% to 70%. This proves that collectively, the indicators used are valid and able to reflect the research variables very well.

Reliability Test Results: Cronbach's Alpha and Composite Reliability

Reliability is assessed using two parameters:

Cronbach's Alpha (threshold > 0.70)

Composite Reliability (CR, threshold > 0.70).

Table 3. Results of Reliability Analysis

Variable	Cronbach's Alpha	Composite Reliability	Description
PV	0.856	0.903	Reliable
PE	0.859	0.905	Reliable

Variable	Cronbach's Alpha	Composite Reliability	Description
EE	0.846	0.896	Reliable
HB	0.848	0.897	Reliable
PS	0.831	0.888	Reliable
AI	0.833	0.889	Reliable
IS	0.834	0.889	Reliable

source: processed data

Based on Table 3, the test results show a very satisfactory level of reliability for all variables. The Cronbach's alpha values for all variables are in the range of 0.831 to 0.859, far above the minimum threshold of 0.60. The CR values show even higher results, ranging from 0.888 to 0.905, exceeding the threshold of 0.70. Given that all values are above the required thresholds, it can be concluded that the measurement instruments in this study have very strong internal consistency. The indicators used are proven to be reliable in measuring their respective research variables.

Structural Model Analysis (Inner Model)

After ensuring that the measurement model meets the validity and reliability criteria, the next stage is to evaluate the Structural Model to test the causal relationships between constructs and the predictive power of the model. Inner Model evaluation includes testing R-Square (R^2) and Path Coefficients.

Analysis of R-Square (R^2) Value

The first step in evaluating the Inner Model is to look at the R-Square (R^2) value or coefficient of determination. This test aims to measure the predictive power of the structural model. The R^2 value indicates the percentage of variance in the dependent variable (such as Subscription Intention) that can be explained by the independent variables in the model (such as Price Value, Performance Expectancy, etc.). The higher the R^2 value, the better the research model's ability to predict actual conditions. The interpretation of this value refers to the criteria that values above 0.67, 0.33, and 0.19 indicate a strong, moderate, and weak model, respectively. Meanwhile, other criteria Hair (2021) set figures of 0.75, 0.50, and 0.25 as references. In this study, values significantly above the weak threshold (0.25 or 0.19) will be categorized as moderate.

Table 4. Results of R-Square (R^2) Analysis

Dependent Variable	*R-Square*	Percentage	Category
AI	0.397	39.7%	Moderate
EE	0.408	40.8%	Moderate
PE	0.424	42.4%	Moderate
PV	0.432	43.2%	Moderate
IS	0.652	65.2%	Moderate

source: processed data

Based on Table 4, the following can be concluded: 1) The Intention to Subscribe variable has an R^2 value of 0.652. This value is close to the threshold of 0.67 (or 0.75), placing it in the Moderate towards Strong category. This indicates that the model can substantially predict (65.2%) subscription intention. 2) Trust in AI R^2 = 0.397, Moderate It suggests that personalization contributes a non-negligible amount (39.7%) variance explained in the user trust. 3) Price Value variable: The R^2 of this variable is 0.432 and lays in the Moderate category; That value sits well above the weak threshold, which indicates that in terms of perception price value, the personalization system really makes a difference namely 43.2%. 4) The R^2 for Performance Expectancy is 0.424 (Moderate). User trust in AI is a significant predictor of the variance in performance expectancy (42.4%) for consumer behavior.

This means that Effort Expectancy variable with R^2 = 0.408 fall under the Moderate category It is proven that trust factor plays a considerable role (40.8%) in determining whether the ease of use will be perceived or not.

In summary, all the variables in this model has adequate predictive power (Moderate). In particular, the model does exceptionally well at explaining the key variable Intention to Subscribe based on predictive strength that approaches that of strong. Herewith confirms that the factors that are studied are significant major determinants affecting user subscribing behavior.

Path Coefficient Analysis (Hypothesis Testing)

The next stage is hypothesis testing to investigate direct effects between variables once we've established a model that has sufficient predictive power. This is done to confirm if the theoretical proposition about each independent variable influencing dependent variables (H1-H8) is supported empirically. This analysis provides the value of Path Coefficient that specifies the directionality and magnitude, with higher values (closer to +1) hooked with positive influence of one variable. Hypotheses are accepted if T-statistics > 1.96 and p-value < 0.05 (α = 0.05).

Table 5. Results of Path Coefficient Analysis

Hypothesis	Path	*Path Coefficient*	*T-statistics*	*P-value*	Decision
H1	PS → AI	0.630	14.342	< 0.001	Accepted
H2	PS → PV	0.658	15.879	< 0.001	Accepted
H3	AI → PE	0.651	16.960	< 0.001	Accepted
H4	AI → EE	0.638	15.269	< 0.001	Accepted
H5	PV → IS	0.295	5.985	< 0.001	Accepted
H6	PE → IS	0.231	4.272	< 0.001	Accepted
H7	EE → IS	0.157	2.741	0.006	Accepted
H8	HB → IS	0.213	3.982	< 0.001	Accepted

source: processed data

The following is the interpretation of the hypothesis testing results based on Table 5.

H1: Personalization → Trust in AI (Accepted)

The test output indicates that Personalization has a significant positive effect on Trust in AI (Path Coefficient = 0.630, t-statistics = 14.342, p < 0.001), as supported by the User Control indicator (PS3, Loading: 0.818). This means that user trust in AI is not merely generated through accurate recommendations but rather through the availability of features enabling users to take control over or "train" the algorithm. In contrast, Understanding Context (PS2) has the least contribution to the personalization construct, indicating that users prefer control over automatic prediction.

H2: Personalization → Price Value (Accepted)

Based on the test results obtained, Personalization significantly and positively affects Price Value, with a Path Coefficient value of 0.658 (t-statistics = 15.879; p-value < 0.001). Recommendation Relevance (PS1, Loading: 0.822) has the highest positive impact on this relationship. Personalization essentially makes the subscription cost "worth it" because, as users reported, they want a personalized mix of songs and receive relevant recommendations from the system. Price value perception is directly related to how accurately the system delivers recommendations.

H3: Trust in AI → Performance Expectancy (Accepted)

The test result indicates that Trust in AI positively and significantly influences Performance Expectancy (Path Coefficient = 0.651, t-statistics = 16.960, p-value < 0.001). Algorithm Transparency (AI3, Loading: 0.82) has a particularly high influence on this relationship. Users who understand how the AI works tend to hold higher performance expectations. Notably, transparency does affect performance expectancy more than the reliability of the AI system itself (AI1).

H4: Trust in AI → Effort Expectancy (Accepted)

Trust in AI has a positive and significant effect on Effort Expectancy, with a Path Coefficient value of 0.638, t-statistics = 15.269, and p-value < 0.001, as shown in the test results table (Table 5). The leading indicator is Recommendation Fairness (AI4, Loading: 0.821). When users perceive the system as acting "fairly" (i.e., without bias), they assume that their interactions require less effort, meaning they do not need to expend additional effort to filter out unwanted content.

H5: Price Value → Intention to Subscribe (Accepted)

Price Value has a positive and significant effect on Intention to Subscribe, based on a Path Coefficient value of 0.295, t-statistics of 5.985, and p-value < 0.001. This is driven by the Benefits–Cost Fit indicator (PV3, Loading: 0.847). Users choose to subscribe not merely because of a low price barrier, but as the result of a rational value assessment—they perceive that the personalization benefits received are at least equal to the cost incurred.

H6: Performance Expectancy → Intention to Subscribe (Accepted)

The test result shows that Performance Expectancy has a positive and significant effect on Intention to Subscribe, with a Path Coefficient of 0.231 and t-statistics of 4.272 (p-value < 0.001). The principal indicator is Experience Enhancement (PE2, Loading: 0.863). Users subscribe because they believe AI will improve their overall music listening experience (PE3), not merely help them discover new music.

H7: Effort Expectancy → Intention to Subscribe (Accepted)

Hypothesis 7 testing results show that Effort Expectancy has a positive and significant effect on Intention to Subscribe, with a Path Coefficient value of 0.157, t-statistics of 2.741, and p-value of 0.006. The driving factor is Ease of Understanding (EE2, Loading: 0.849). Users are more likely to convert to paid subscriptions when AI features are intuitive and easy to understand.

H8: Habit → Intention to Subscribe (Accepted)

Based on the test results, Habit has a positive and significant effect on Intention to Subscribe, with a Path Coefficient value of 0.213, t-statistics of 3.982, and p-value < 0.001. Daily Usage Frequency is the primary driver of this finding (HB1, Loading: 0.854). Users subscribe because the platform has become a habitual part of their routine, rather than a dependency or addiction (HB4).

Mediation Effect Analysis (Hypothesis Testing)

This study employs both direct effects tests and mediation (indirect) effect analysis to understand the mechanism or intermediary path through which independent variables affect dependent variables. This is a research design that addresses how and why a variable affects or influences other variables. Recognizing the importance of mediators—such as Price Value, Performance Expectancy, and Effort Expectancy—allows researchers to determine which variable best serves as a "bridge" in transmitting the influence of technological stimuli (Personalization and Trust in AI) into the corresponding behavioral outcome (Intention to Subscribe). Specific Indirect Effects — This output is used to conduct mediation analysis using SmartPLS. Mediation is significant if T-statistics > 1.96 and p-value < 0.05.

Table 6. Results of Mediation Effect Analysis

Hypothesis	Mediation Path	Indirect effect	T-statistics	P-value	Decision
H9	PS → PV → IS	0.194	5.164	< 0.001	Accepted
H10	AI → PE → IS	0.151	3.959	< 0.001	Accepted
H11	AI → EE → IS	0.100	2.549	0.011	Accepted

source: processed data

H9: Personalization → Price Value → Intention to Subscribe (Accepted)

The two-tailed test results indicate the significance of mediation for Price Value, where Price Value significantly mediates the relationship between Personalization and Intention to

Subscribe (indirect effect value = 0.194, t-statistics = 5.164, p-value < 0.001). This led us to the finding that AI personalization increased intention to subscribe by increasing price value perception. To put it another way, when the music recommendation feature of the AI personalization system is able to recommend relevant music that fits users' tastes and preferences, users feel as if their subscription cost is equal to the benefit gained, which in turn positively affects intention to subscribe.

H10: Trust in AI → Performance Expectancy → Intention to Subscribe (Accepted)

As per the test results, Performance Expectancy significantly mediates the relationship between Trust in AI and Intention to Subscribe (indirect effect value = 0.151, t-statistics = 3.959, p-value < 0.001). This suggests that the more trust users have in the AI (in terms of reliability, consistency, transparency, and fairness), they expect a higher performance level from the music streaming platform, which consequently results in their intention to subscribe. So, Trust in AI not only impacts directly but also creates expectations of higher performance.

H11: Trust in AI → Effort Expectancy → Intention to Subscribe (Accepted)

Results from the test indicated that Effort Expectancy has a significant mediating effect (indirect effect value = 0.100, t-statistics = 2.549, p-value = 0.011) between Trust in AI and Intention to Subscribe. This suggests that the trust placed in the AI system makes users feel, design-wise, that it is easy to use the personalization features provided by the platform, which results in an increased intention to subscribe. This mediation effect is low compared with the other two mediation hypotheses, but this path remains significant and serves an important purpose in the model.

Discussion

After hypothesis testing, it can be seen that out of the 11 hypotheses proposed, all 11 hypotheses were accepted. The following is a detailed discussion for each hypothesis:

First, based on previous hypothesis testing results, the Personalization variable on the Trust in AI variable has a p-value less than 0.05, namely < 0.001, and a t-statistic value greater than 1.96, namely 14.342. Based on these two values, it is stated that the Personalization variable has a significant influence on the Trust in AI variable. This finding is consistent with research conducted by Halim (2022), which states that personalization in AI-based services significantly influences trust. Then, based on the factor loading results in Table 1, indicator PS3 has a high value of 0.818. This aligns with the statement that the system provides a level of control to users over the personalization algorithm. Conversely, the factor loading result for indicator PS2 has the lowest value of 0.809, with the statement that the system is able to understand the context of user preferences. These results indicate that the Personalization variable significantly influences Trust in AI, emphasizing the importance of giving users control to adjust personalization algorithms to build their trust in the AI system, whereas the system's ability to understand context is less influential in increasing user trust.

Second, based on previous hypothesis testing results, the Personalization variable on the Price Value variable has a p-value less than 0.05, namely < 0.001, and its t-statistic value is greater than 1.96, namely 15.879. Based on these two values, it is stated that the Personalization variable has a significant influence on the Price Value variable. This finding aligns with research conducted by Halim (2022), which states that personalization influences users' perception of value for AI-based services.

Based on the factor loading results in Table 1, indicator PS1 has a high value of 0.822. This aligns with the statement that the system is able to provide relevant and varied recommendations. Conversely, the factor loading result for indicator PS2 has the lowest value of 0.809, with the statement that the system understands the context of user preferences for content type. These results indicate that the Personalization variable significantly influences the Price Value variable, emphasizing the importance of recommendation relevance and variety so that users feel the subscription cost is comparable to the benefits received, whereas understanding the context of preferences for content type turns out to be less influential on price value perception.

Third, based on previous hypothesis testing results, the Trust in AI variable on the

Performance Expectancy variable has a p-value less than 0.05, namely < 0.001, and its t-statistic value is greater than 1.96, namely 16.960. Based on these two values, it is stated that the Trust in AI variable has a significant influence on the Performance Expectancy variable. The findings are supported by Wongras (2023) and Choung (2023), who state that Trust in AI affects perceived usefulness and Performance Expectancy.

Additionally, found that trust in AI systems is a key driver of user expectations and performance outcomes; in a similar vein, Berente (2021) highlighted that AI transparency directly influences the functional benefit assessments made by users. Based on the factor loading results shown in Table 1, indicator AI3 has a high value of 0.822. This aligns with the statement that users trust the transparency of the personalization algorithm.In contrast, the lowest factor loading result of 0.801 is found at AI1, which corresponds to the statement that users trust the reliability of the AI system. These results indicate that the Trust in AI variable has a significant effect on the Performance Expectancy variable, suggesting that algorithm transparency plays an important role in users' expectations of platform performance, while system reliability is less influential for user performance expectancy.

Fourth, based on previous hypothesis testing results, the Trust in AI variable on the Effort Expectancy variable has a p-value less than 0.05, namely < 0.001, and its t-statistic value is greater than 1.96, namely 15.269. Based on these two values, it is stated that the Trust in AI variable has a significant influence on the Effort Expectancy variable. This finding aligns with research conducted by Wongras (2023), which states that Trust in AI significantly influences Effort Expectancy.

Based on the factor loading results in Table 1, indicator AI4 has a high value of 0.821. This aligns with the statement that users trust the fairness of the AI system in providing recommendations. Conversely, the factor loading result for indicator AI1 has the lowest value of 0.801, with the statement that users trust the reliability of the AI system. These results indicate that the Trust in AI variable significantly influences the Effort Expectancy variable, showing that trust in the fairness of the AI system makes users feel it is easier to use personalization features, whereas trust in system reliability is less influential in increasing the perception of ease of use.

Fifth, based on previous hypothesis testing results, the Price Value variable on the Intention to Subscribe variable has a p-value less than 0.05, namely < 0.001, and its t-statistic value is greater than 1.96, namely 5.985. Based on these two values, it is stated that the Price Value variable has a significant influence on the Intention to Subscribe variable. This finding is consistent with findings of Barata (2021), Saufi (2023), and Mäntymäki (2020), which state that Price Value affects the intention to subscribe.

Chang (2021) found that in music streaming, the strongest driver of premium subscription conversion is value perception Venkatesh (2003), and Seifert (2024) confirmed that the benefit-cost ratio is the biggest driver of freemium-to-premium conversion. Then, based on the factor loading results in Table 1, indicator PV3 has a high value of 0.847. This aligns with the statement that the benefits obtained from AI personalization are comparable to the subscription cost. Conversely, the factor loading result for indicator PV4 has the lowest value of 0.828, with the statement that the subscription price provides good economic value. These results indicate that the Price Value variable significantly influences the Intention to Subscribe variable, emphasizing the importance of the perceived balance between the benefits of AI personalization and the subscription cost in driving subscription intention, whereas the economic value offered by the subscription price is less influential in increasing users' subscription intention.

Sixth, based on previous hypothesis testing results, the Performance Expectancy variable on the Intention to Subscribe variable has a p-value less than 0.05, namely < 0.001, and its t-statistic value is greater than 1.96, namely 4.272. Based on these two values, it is stated that the Performance Expectancy variable has a significant influence on the Intention to Subscribe variable. This finding aligns with research conducted by Risanti (2022), Barata (2021), and Elsafty (2022), which state that Performance Expectancy influences subscription intention.

Based on the factor loading results in Table 1, indicator PE2 has a high value of 0.863. This aligns with the statement that the AI system will enhance the overall music listening experience. Conversely, the factor loading result for indicator PE3 has the lowest value of 0.795, with the statement that the AI system will help discover new music that suits preferences. These results indicate that the Performance Expectancy variable significantly influences Intention to Subscribe, showing that users' expectation of an overall enhancement of the music listening experience through AI is the main driver of subscription intention, whereas the ability to discover new music is less influential in driving subscription intention.

Seventh, based on previous hypothesis testing results, the Effort Expectancy variable on the Intention to Subscribe variable has a p-value less than 0.05, namely 0.006, and its t-statistic value is greater than 1.96, namely 2.741. Based on these two values, it is stated that the Effort Expectancy variable has a significant influence on the Intention to Subscribe variable. This finding aligns with research conducted by Barata (2021) and Elsafty (2022), which state that Effort Expectancy influences subscription intention. Then, based on the factor loading results in Table 1, indicator EE2 has a high value of 0.849. This aligns with the statement that the AI personalization features are easy to understand and use. Conversely, the factor loading result for indicator EE1 has the lowest value of 0.807, with the statement that interaction with the AI system does not require much mental effort. These results indicate that the Effort Expectancy variable significantly influences Intention to Subscribe, showing that ease of understanding and using AI personalization features can drive subscription intention, whereas the level of mental effort required to interact with the system is less influential in increasing subscription intention.

Eighth, based on previous hypothesis testing results, the Habit variable on the Intention to Subscribe variable has a p-value less than 0.05, namely < 0.001, and its t-statistic value is greater than 1.96, namely 3.982. Based on these two values, it is stated that the Habit variable has a significant influence on the Intention to Subscribe variable. These findings are consistent with those of Risanti (2022), Saufi (2023), and Barata (2021), which indicate that Habit affects subscription intention. Indeed, Lim et al. found that in the context of streaming services, habitual use has been shown to be a major driver of continuance intention, while Ávila Torres (2025) found that integration into daily routines with algorithmic systems forms long-term commitment to individual platforms.

Based on the factor loading results in Table 1, indicator HB1 has a high loading value, which aligns with the statement that the use of the music streaming platform has become a daily habit. Conversely, the factor loading result for indicator HB4 has the lowest value of 0.808, with the statement that users believe they have to use the platform regularly. These results indicate that the Habit variable significantly influences Intention to Subscribe, showing that the habit of using the music streaming platform throughout daily routines naturally promotes subscription intention, whereas feeling obligated to use the platform is less influential in increasing subscription intention.

Ninth, the mediation effect test results indicate that the Price Value variable mediates the relationship between Personalization and Intention to Subscribe (indirect effect value = 0.194; t-statistics = 5.164; p-value < 0.001). This finding suggests that AI personalization directly influences subscription intention while also having an indirect effect on perceived price value. The results reveal that when users appreciate AI personalization and the music recommendations provided by the system cater to their interests, it gives them an impression of getting value for money, which in turn influences their intention to subscribe.

Lastly, regarding the mediation effect test results, the Performance Expectancy variable serves as a mediating variable between Trust in AI and Intention to Subscribe, represented by an indirect effect value of 0.151, t-statistics = 3.959, p-value < 0.001. It indicates that higher user trust in the AI system in terms of reliability, consistency, transparency, and fairness causes users to have greater expectations of music streaming platform performance, which influences their intention to subscribe. Therefore, Trust in AI influences subscription intention not only directly but also indirectly through higher performance expectations.

Results of the mediation effect test, as shown in Table 6, indicate that the Effort Expectancy variable serves as a mediating variable between Trust in AI and Intention to Subscribe, with an indirect effect value of 0.100, t-statistics = 2.549, p-value = 0.011 (Hypothesis 11). This result shows that trust in the AI system makes users feel that the personalization features provided by the platform are easier to use, which in turn increases their intention to subscribe. While this path represents the weakest mediation effect out of the three mediated hypotheses, it still serves as a significant contributor to the model.

CONCLUSION

From the analysis and discussion results, this study indicates that personalization through artificial intelligence has a significant influence on the behavior of music streaming service users in Indonesia. Conclusion: AI Personalization has proven able to encourage user trust and strengthen the perception of price value in a positive way. This finding aligns with the notion that users assess service quality not only based on accurate music recommendations but also on how well the system fits user preferences, provides control to users, and delivers a relevant and flexible experience. Hence, AI personalization becomes an underpinning strategy that is crucial to creating a user value-inducing experience. Trust in AI was also a significant influence on users' perceived expectations of the platform's performance and ease of use. When the level of user trust toward the reliability, transparency, consistency, and fairness of the AI system is high, users believe more in its functional benefits and usability in daily activities. Thus, this shows that the technical and ethical characteristics of AI no longer represent complementary factors, but rather critical components impacting technology acceptance in personalization-oriented digital services. In addition, the results showed that users' subscription intention is determined mainly by perceived price value and, secondly, by performance expectancy and usage habit. Among music streaming users in Indonesia, the determination to subscribe to premium services is generally based on an understanding of the alignment between the costs incurred and benefits obtained. Finally, when usage develops into a daily habit and real value becomes apparent, subscription becomes much more likely. This underlines that, while economic factors are always prominent in the findings, they cannot be divorced from providing a consistent and high-quality experience over time.

The results of this study also illustrate that the relationship between AI personalization, trust in AI, and subscription intention is realized through a mediation mechanism. Price Value, Performance Expectancy, and Effort Expectancy are key mediators that clarify how personalization features and trust in AI indirectly affect subscription intention. In simple terms, users do not choose to subscribe just because the AI technology is smart — but because it enhances expectations of benefits, ease of use, and the perception of the value of the service received. In general, this study confirms that the UTAUT2 model can be extended by adding Personalization and Trust in AI constructs with significant relevance to explain the behavior of music streaming users in Indonesia. This model demonstrates that in the digital era, not only price and habit, but also the quality of personalization and trust in the AI system are factors that impact subscription decisions. This research theoretically contributes to the literature on the adoption of AI in music streaming by: (1) extending the UTAUT2 framework with Personalization and Trust in AI constructs validated empirically; (2) elucidating for the first time how personalization via AI is linked to increased subscription intention through trust and value pathways, as indicated by a five-path mediation analysis conducted in Indonesia; and (3) validating a replicable research model applicable to other AI-driven subscription services. These findings have specific strategic implications for music streaming service providers in designing AI systems that are more transparent, adaptable, and user-centric.

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AUTHOR CONTRIBUTION STATEMENT

Frando Adolian Pella contributed to the study's conceptualization, research design, data collection, data analysis using PLS-SEM and writing of the manuscript. Tuga Mauritsius assisted with study supervision, analytical model validation, result interpretation, and manuscript critical revision. All authors have read and approved the final manuscript and agree to be personally accountable for all aspects of the work.

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