Journal of Humanities and Applied Social Sciences

451

Received 27 November 2024
Revised 25 December 2024
27 March 2025
28 April 2025
Accepted 25 May 2025

Transforming music listeners to subscribers: music recommendation system's impact on customer subscription intention with the mediating role of customer experience

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Abstract

Purpose – Exploring the critical role of recommendation system characteristics (Accuracy, Novelty, and Diversity) in shaping customer experience and their subsequent impact on customers' intention to subscribe to online music streaming services, by addressing the gap in existing literature and focusing on their nontechnical implications.

Design/methodology/approach – A conceptual framework was developed to investigate the proposed direct and indirect relationships. Data were collected using an online questionnaire from 400 respondents who have used music streaming platforms. Structural equation modeling was employed to test the hypotheses and examine the fit of the conceptual model.

Findings – The findings highlight the substantial direct and indirect effects of recommendation system accuracy on customer subscription intention and experience. In contrast, novelty and diversity have less direct impacts on subscription intention. However, they influence it indirectly through the mediating role of customer experience.

Originality/value – The originality of this research lies in its focus on the intersection of consumer behavior and technology adoption within the music streaming sector. Unlike traditional studies that emphasize algorithmic or technical aspects of recommendation systems, this paper shifts the focus to psychological and behavioral outcomes, such as customer experience and subscription intention. This perspective is underexplored and offers a novel contribution to both academia and industry.

Keywords Artificial intelligence, Recommendation system characteristics, Music recommender, Customer experience, Customer subscription intention, Subscription-based online services, Music streaming platform/services, Technology adoption model

Paper type Research paper

1. Introduction

In recent years, there has been a growing preference among customers for more personalized product/service recommendations, reflected in the rapid growth of the services industry, which generated an estimated 7.6 billion USD in revenue in 2021 and is projected to grow by over 65%, reaching 11.6 billion USD by 2026 (Statista, 2024a, b). The concept of "recommendation," according to the Oxford English Dictionary (2024), refers to a suggestion or proposal that provides the best choice and course of action. As stated by Liu *et al.* (2017), recommendations can be delivered through various channels, including word of mouth provided by a trusted person, advertisements showing certain products/services, or recommendation systems (RS). Along with the rapid technological advancement that has been

Journal of Humanities and Applied Social Sciences
Vol. 7 No. 5, 2025
pp. 451-472
Emerald Publishing Limited
2632-279X
DOI 10.1108/JHASS-11-2024-0212

conquering the world in diverse industries, it's noticeable that the RS is emerging as a key driver influencing customers' behaviors and interactions toward personalized recommendations (Kumar *et al.*, 2021). RS is considered to be an Artificial intelligence-based application that helps in the thriving of e-commerce, digital marketing, online shopping and other personalized marketing methods (Chinchanachokchai *et al.*, 2021; Verma and Sharma, 2020). According to Shen (2014) and Huseynov *et al.* (2016), RS is defined as intelligent software used by businesses to match and suggest personalized recommendations of products/services to customers based on their previous preferences and usage patterns. The RS's significance appears in narrowing down the overload of information and item varieties that the customers are exposed to, allowing the system to provide customers with relevant, individualized, and customized offerings (Dadoun *et al.*, 2023; Nurdin and Abidin, 2023). Thus, this research aims to shed light on the pivotal role of RS. Where questions persist regarding how these systems impact customer experience (CX) and the subsequent influence on subscription intention. The CX, another construct handled in this research, is the outcome of the interaction between the customers, brand, product, and company (Pappas *et al.*, 2014). Correspondingly, the customer's subscription intention of online service is the tendency of customers to subscribe to any e-business that provides access to content in exchange for a regular fee, usually on a monthly/annual basis (Spurgeon and Niehm, 2020; Ramkumar and Woo, 2018; Kim and Kim, 2020).

The music industry as a research area is elevating and has recently gained substantial attention from academia and industry (Schedl *et al.*, 2018). The music industry has experienced significant changes with the emergence of online platforms and streaming services, which helped undergo a paradigm shift, transitioning from traditional formats to online streaming platforms that provide customers with extraordinary access to a vast array of musical options with just a few clicks (Bonini and Magaudda, 2023; Schedl *et al.*, 2017). An example of a streaming platform is Spotify, which is counted to be the world's most popular audio streaming subscription service, boasting over 574 million users, with 226 million subscribers across 180 markets (Spotify, 2023). Thus, Spotify has around 30% market share of music streaming platforms, while Apple has 25% and Amazon Music has around 12% (Khalil and Zayani, 2022). Thus, understanding the intricate relationship between music recommendation systems and customer behaviors presents a pressing research problem that emerged to the author's interest. As per Pu *et al.* (2012), RS is primarily assessed within the context of technological innovation and algorithms, yet it lacks a significant correlation with consumer behavior. Hence, this research will address this gap by concentrating on aspects beyond technical issues.

The rest of this paper is organized as follows: the literature review is discussed and explained regarding the research constructs, which are the recommendation system, customer experience, and customer subscription intention. Followed by results from exploratory research to provide insights and an understanding of the current market dynamics in the music industry. Then, a conceptual model was illustrated and explained. Followed by the research methodology, including the data collection tool, population and sampling techniques, and data collection process. Furthermore, the findings of the data analysis and a discussion of the results. Finally, the implications, limitations and suggestions for future research are presented.

2. Literature review

Over the last 6 decades and beyond, artificial intelligence has evolved into one of the broadest sectors within contemporary technology development (Song *et al.*, 2019; Bawack *et al.*, 2022; Rane *et al.*, 2024). In today's world, it's common to observe the consumption of such technology in every aspect of life. Subsequently, the integration of AI affected consumers, organizations, and business institutions (Lee, 2020; Soni, 2020). As identified by Grand View Research (2023), the global artificial intelligence market was valued at 196.63 billion USD in 2023 and is expected to grow from 2023 to 2030 with a compound annual growth rate (CAGR) of 37.3%. Later on, it was introduced to the field of marketing as stated by Huang and Rust (2021). The ongoing changes in the marketing sector occurring due to artificial intelligence are tremendous. Driven by the accessibility of big data, heightened computational capabilities, advancements in machine learning algorithms, and reduced computing expenses have led to unlocking personalized features that will enhance the customer experience and streamline purchases besides overall effectiveness (Stone *et al.*, 2020; Nair and Gupta, 2021). This research will tackle one of the most important technologies that arose from AI, which is the recommendation system.

2.1 Recommendation system (RS)

For companies to stay competitive in today's rapidly evolving business landscape, it is crucial to view personalization as an essential integrated tool, which is particularly relevant when considering the issue of information overload customers face in a world flooded with a vast amount of data and content, personalized technologies like recommendation systems offer tailored solutions (Rust and Huang, 2014). A recommendation system or as often referred to RS is an information filtering system designed to provide users with personalized content or item suggestions based on their preferences, historical interactions, or explicit feedback (Valentine *et al.*, 2023; Chen *et at.*, 2022). According to Dadoun *et al.* (2023), RS can also be considered as an algorithm that calculates the extent to which customers can like and interact with a certain product/service based on historical data collected through AI (Hajarian and Hemmati, 2020). RS operationalization depends on several characteristics as the accuracy, novelty, and diversity of the system that enhance the power of recommendation. According to (Roudposhti *et al.*, 2018; Shani and Gunawardana, 2011; Pu *et al.*, 2011; Shen, 2014; Nilashi *et al.*, 2016; Silveira *et al.*, 2019), recommendation system accuracy (RSA) refers to the extent to which users believe that the recommended products/services align with their preferences. Thus, it determines the ability of the recommendation system to effectively assess and fulfill customers' preferences and desires. As for recommendation system novelty (RSN), it is defined as the ability of the RS to assist customers in discovering new and undiscovered music. Moreover, as mentioned by Adomavicius and Kwon (2011) and Avazpour *et al.* (2014), recommendation system diversity (RSD) stands for the dissimilarity between products/services recommended. Diversity classifies the extent of difference within the recommended list.

2.2 Customer's subscription intention (CSI)

Customer purchase intention is a critical concept in the field of marketing and consumer behavior as it helps businesses understand, predict, and influence consumers' buying decisions (Younus *et al.*, 2015). Initially, purchase intention is a stage in the decision-making process that examines why customers purchase a certain product from a certain brand (Agarwal and Gupta, 2017). Thus, purchase intention can be defined as an individual's conscious plan to try to purchase a certain product from a brand (Bhakar *et al.*, 2015). As technology developed, customers encountered a huge paradigm shift that shaped their behavior and purchase/subscription intention in particular. Digitalization has significantly transformed customers' purchase intention by applying the subscription-based online services (SOS) model, which involves any e-business that provides access to content, features or tools in exchange for recurring payments. Instead of a one-time purchase or pay-per-use model, users pay a regular fee at predefined intervals, typically on a monthly or annual basis, to maintain access to the service (Kim and Kim, 2020; Ramkumar and Woo, 2018; Spurgeon and Niehm, 2020). The main focus of Music as a Service is not selling the music but rather making the music available as a service, continuously highlighting access to the music over ownership. For instance, in the past, consumers purchased cassette tapes featuring Amr Diab or vinyl records of Om Kalthoum, famous singers in the Middle East. However, now they can access an extensive library of songs anytime and anywhere. Convincing customers to pay for such a service and subscribe to it is not as easy as it seems, especially with the available substitutes being fee-free, which creates a background in the customer's head that this content must be free (Papies *et al.*, 2011; Fernandes and Guerra, 2019). The growing importance of such streaming services is being acknowledged as of 2022. The global count of music streaming subscribers reached 616.2 million. Paid subscriptions for music streaming have become the standard choice for numerous music enthusiasts and the industry has witnessed consistent and remarkable growth in subscriber numbers in recent years (Statista, 2022). In this context, we can say that a customer's subscription intention can be measured through the customer's tendency and willingness to subscribe, continue subscribing, and recommend the streaming service to others (Leowarin and Thanasuta, 2021; Barata and Coelho, 2021).

2.3 Customer experience (CX)

To thrive in this customer-centric era, organizations must commit to delivering exceptional experiences supported by data-driven insights, effective communication, seamless interactions, and a dedication to continuous improvement (Verhoef *et al.*, 2009). Thus, the concept of customer experience arose to fill the gap between product/service providers and customers (Hollebeek and Macky, 2019). Customer experience emerged with foremost significance as it focuses on crafting an exclusive, enjoyable, and lasting interaction (Jain *et al.*, 2017). According to Lemon and Verhoef (2016), the customer experience is the fundamental base for all marketing management activities. Also, Becker and Jaakkola (2020) and Palmer (2010) mentioned that business owners and leaders perceive customer experience as the core competitive advantage of any firm. Moreover, it's essential in creating customer satisfaction, customer loyalty, brand image, differentiation, and positive word of mouth. As mentioned by Koetz (2019), customer experience emerged as the number one ranking priority among executives of various companies such as Google, IKEA, Tesco, Amazon, and KPMG, who hired chief customer experience officers and similar job titles to oversee and shape the overall customer experience. Furthermore, Schmitt (1999) and Lemon and Verhoef (2016) clarified that experiences emerge from engaging, undergoing, or living through events. It is operationalized as cognitive, emotional, sensorial, behavioral and relational.

2.4 Recommendation system and customer's subscription intention

According to (Roudposhti *et al.*, 2018; Shani and Gunawardana, 2011; Pu *et al.*, 2011; Shen, 2014; Nilashi *et al.*, 2016; Silveira *et al.*, 2019), recommendation system accuracy (RSA) refers to the extent to which users believe that the recommended products/services align with their preferences. Thus, it determines the ability of the recommendation system to effectively assess and fulfill customers' preferences and desires. As for recommendation system novelty (RSN), it is defined as the ability of the RS to assist customers in discovering new and undiscovered music. Moreover, as mentioned by Adomavicius and Kwon (2011) and Avazpour *et al.* (2014), recommendation system diversity (RSD) stands for the dissimilarity between products/services recommended. Diversity classifies the extent of difference within the recommended list.

A recommendation system is vital in influencing a customer's subscription intention by providing personalized content/product suggestions. Moreover, Behera *et al.* (2020) and Nguyen and Nguyen (2024) found that accurate recommendations enhance subscription intentions by reflecting an understanding of customer preferences. Similarly, Dabholkar and Sheng (2012) argued that accuracy indirectly influences subscriptions through satisfaction and trust, rather than exerting a direct impact. Even though Wu *et al.* (2024) noted that novelty alone does not directly drive subscriptions but can engage customers in the short term, Hurley and Zhang (2011) disagreed, suggesting that novel recommendations can directly enhance subscription intentions, whereas they asserted that diversity in recommendations can influence CSI directly and indirectly. Furthermore, Gomez-Uribe and Hunt (2015) highlighted that diverse recommendations aid in product exploration but may dilute accuracy. Correspondingly, Roudposhti *et al.* (2018) discussed how recommendation novelty, diversity and accuracy affect the recommendation system quality, which enhances purchase intention. Therefore, the subsequent hypotheses were developed.

H1. The recommendation system's accuracy enhances the customers' subscription intention.

H2. The recommendation system's novelty enhances the customers' subscription intention.

H3. The recommendation system's diversity enhances customers' subscription intention.

2.5 Recommendation system and customer experience

The recommendation system plays a crucial role in shaping the experiences of the customers. In the research conducted by Liu *et al.* (2017), it was clarified that there's a strong relationship between the performance of the RS and the customer experience. Moreover, Behera *et al.* (2020) mentioned that personalized recommendations give consumers the impression that their thoughts have been read and have a profound effect on the overall e-shopping experience across all digital channels. According to Kim *et al.* (2021), recommendation accuracy and diversity increase the likelihood of users finding new products/services of interest, but also foster a sense of trust and confidence in the recommendation system. Furthermore, novelty in recommendations introduces users to new and unexpected content, enhancing their overall experience by providing fresh and diverse options (Raajpoot and Ghilni-Wage, 2019). Hence, the author formulated the following hypotheses.

H4. The recommendation system's accuracy enhances the overall customer experience.

H5. The recommendation system's novelty enhances the overall customer experience.

H6. The recommendation system's diversity enhances the overall customer experience.

2.6 Customer experience and customer's subscription intention

Initially, Nasermoadeli *et al.* (2013), illustrated that the level of experience the customers are exposed to emphasizes and reshapes their purchase intention to acquire a certain product. According to Yeo *et al.* (2017), Pappas *et al.* (2014) and Hamouda (2021), in the context of an online shopping environment, the customer's experiences significantly affect the customer's purchase intention. Additionally, these research findings revealed that the factors influencing customer online purchase intention, including customer experience, are applicable in countries with low uncertainty avoidance and those with high uncertainty avoidance, like Egypt (Hofstede-insights, 2024). From the above, there's likely a relationship between customer experience and purchase intention in the online setting. However, the focus on streaming services and subscription intention in previous literature is rarely handled. Thus, the researcher delves deeper into this relationship and proposes the following hypotheses.

H7. The customer experience impacts the customer's subscription intention.

H8. Customer experience mediates the relationship between the recommendation system's accuracy and the customer's subscription intention.

H9. Customer experience mediates the relationship between the recommendation system's novelty and the customer's subscription intention.

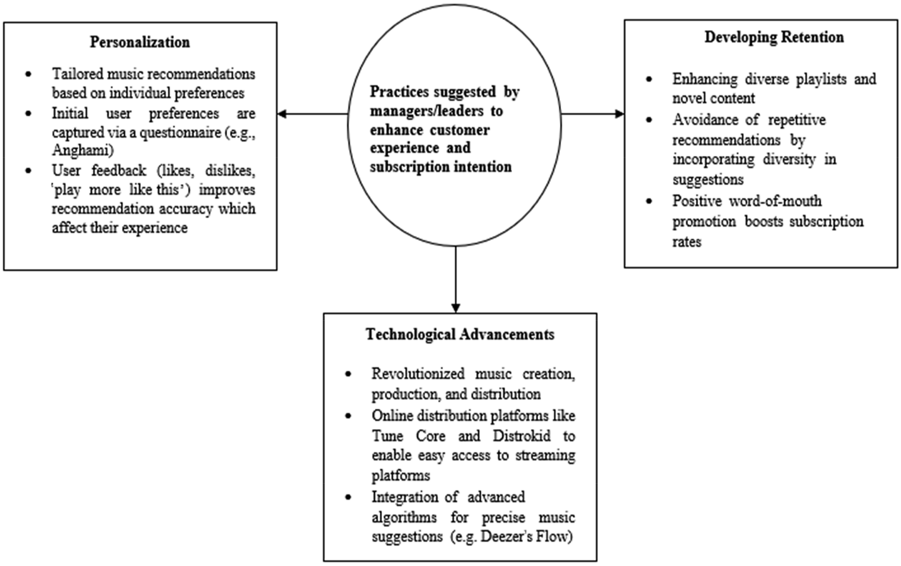
H10. Customer experience mediates the relationship between the recommendation system's diversity and the customer's subscription intention.

3. Insights from an exploratory study

Following the literature review, an initial exploratory study was employed as a qualitative investigation that attempts to unleash new and interesting concepts by waking up to the research topic (Swedberg, 2020). The researcher conducted one-to-one in-depth interviews with four managers/leaders (as shown in Table A2/A3) in the music streaming industry to gather practical insights from industry experts, engaging this subset of experts as a representation of the larger population to allow for sufficient variability in insights while maintaining focus on relevant themes. Theoretical saturation was justified by the point at which no new insights, themes or perspectives emerged from the interviews with experts (Saunders *et al.*, 2018). These experts are directly involved in implementing new technologies as recommendation systems to ensure a good customer experience and eventually enhance them to subscribe to the platforms. This allows a comprehensive understanding and accurate categorization of constructs in this research (Eppich *et al.*, 2019). A thematic analysis was used, which is useful for uncovering insights gathered from industry professionals (Guest *et al.*, 2012). The results highlighted the significant transformation in music production and distribution due to technological advancements and the shift from physical to digital platforms. Traditionally, music distribution was handled by companies like Mazzika Production. However, modern distribution has shifted to online platforms like TuneCore and DistroKid, where artists can add descriptive "tags" for their music's genre and type. These platforms then automatically distribute the music to streaming services such as Anghami, Deezer, iTunes, Apple Music, etc. Recommendation systems, such as Deezer's "Flow" and Anghami's algorithm, are centered on being accurate and personalized to the extent that they go deeper by picking up on the beat of the music you listen to, not just the general genre. While errors in recommendations occur, platforms such as Spotify and Anghami have addressed them by incorporating feedback mechanisms, ensuring a seamless customer experience. An insightful perspective was introduced, emphasizing that most customers are unlikely to cancel their subscriptions unless they encounter recurring issues and their continuous feedback is ignored. As for novelty and diversity, effective algorithms prioritize diverse content to prevent monotony while introducing fresh tracks. For example, instead of repeatedly suggesting songs by the same singer within a genre, recommendations span various artists, addressing customer preferences without redundancy. Platforms like YouTube Music often fail in this regard, leading to customer boredom and a diminished experience. To counter this, many platforms curate diverse playlists and weekly tapes. These playlists may be professionally crafted by music experts to align with customer tastes and moods. In conclusion, recommendation systems play a pivotal role in shaping customer experiences and driving subscription growth. The results of this stage are presented in Figure 1.

3.1 Conceptual model

Accordingly, the proposed model, as shown in Figure 2 consists of five main constructs which are the recommendation system's accuracy, novelty, diversity, customer experience, and customer's subscription intention. The recommendation system's accuracy, novelty, and diversity can be termed as the characteristics of the RS, which are exogenous constructs. The RS's characteristics are hypothesized to directly influence CX and CSI, which are the endogenous constructs. Also, it's proposed that it has an indirect impact on CSI through the mediating role of CX. Furthermore, the author integrated elements from the technology acceptance model (TAM) and the unified theory of acceptance and use of technology model (UTAUT) while building this model (Davis, 1989; Venkatesh *et al.*, 2003). As per Sim *et al.* (2014), the technology adoption in the music streaming industry is still in its formative stage, which further supports the inspiration from these models. In this research context, the recommendation system serves as the principal technology that is tested to be adopted and accepted by the customers. Under the umbrella of the TAM model, Roudposhti *et al.* (2018) stated that accuracy enhances perceived usefulness by ensuring reliable and effective



Source: Created by the author

Figure 1. Practices by managers/leaders.

recommendations, while novelty and diversity add value by providing new music and a wider range of options. This contributes to delivering valuable recommendations, which makes it align more closely with the perceived usefulness of the TAM model. As for the perceived ease of use, it is mainly related to the customer experience through which a well-designed user interface, clear instructions, and responsive design ensure customers perceive the interactions with the music platform as easy. Furthermore, customer experience can be closely linked with customers' attitudes toward using a particular technology. Therefore, in the TAM model, customer experience plays a critical role in shaping users' attitudes, which in turn influences their intention to use technology (Anshu *et al.*, 2022; Yoon and Yu, 2022). As for the UTAUT model, the performance expectance is a mirror of the perceived usefulness of TAM. This can correlate to the fact that accuracy boosts performance by delivering relevant recommendations to customers. Likewise, novelty and diversity enhance performance by expanding available music choices. Furthermore, the Effort expectancy corresponds to customer experience (CX), as an intuitive and user-friendly interface reduces effort and enhances the overall perception of ease of use. Additionally, customer experience in the model mirrors the mediating role often highlighted in UTAUT, where experience influences behavioral intention and eventual technology adoption. In this context, customer experience bridges the relationship between RS characteristics and customer subscription intention. This reflects UTAUT's view that user experience shapes adoption decisions (Cabrera-Sánchez *et al.*, 2020; Wang *et al.*, 2012). The originality regarding choosing these variables lies in grouping them uniquely from different literature that had not been categorized in this specific manner before. Each variable was selected as it represented the most critical aspect in its respective context. While the research draws inspiration from the TAM and UTAUT, the variables are not directly derived from or based on them. Instead, they served as a conceptual guide for exploring the relationship between recommendation system characteristics, customer experience and subscription intention, which provides a significant addition to the body of literature and social science.

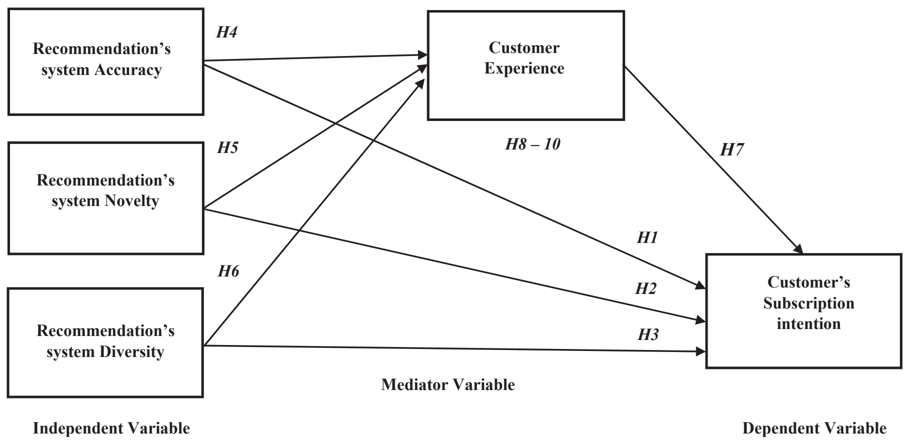


Figure 2. Research Model. Source: Created by the author

4. Research methodology

The researcher started with a thorough literature review to identify, adopt and verify the main research constructs, as well as to investigate the relationships among the studied constructs (Teng *et al.*, 2020). This was followed by exploratory research that acted as a preliminary method for identifying the main problem and gaining further knowledge regarding the topic. The main research depended on a quantitative approach using the questionnaire, which serves as the most valuable data collection method addressing the conceptual model constructs (Halcomb and Hickman, 2015). The qualitative part gave the researcher valuable insights, yet the need for a quantitative survey in this research is justified by its ability to provide measurable and generalizable insights into the relationships between recommendation system characteristics, customer experience and customer subscription intention. Given that the paper focuses on assessing how recommendation systems influence customer behavior, a quantitative approach allows for the collection of standardized data from a large sample, ensuring statistical validity and reliability (Kumar, 2018).

4.1 Data collection tool (questionnaire)

All constructs are measured using a 5-point Likert scale, ranging from “strongly agree” to “strongly disagree” as its efficient in collecting structured data on the perceptions and attitudes of participants (Gómez and Mouselli, 2018). Furthermore, the nominal scale was used to categorize participants based on specific characteristics such as demographics (Bryman, 2016). To ensure the validity of the data collection tool, the researcher adapted the questionnaire statements from previous literature to fit the context of music streaming services (as displayed in Table A1). Statements assessing recommendation system accuracy, novelty, and diversity were tailored and adapted from Roudposhti *et al.* (2018), Pu *et al.* (2011), Abumalloh *et al.* (2020) and Nilashi *et al.* (2016). Similarly, customer experience items were drawn from Schmitt (1999) and Rather (2020). Lastly, customer subscription intention statements were adapted from Kim and Kim (2020), Shafiq *et al.* (2011), Barata and Coelho (2021) and Kumar *et al.* (2009). The questionnaire was translated into Arabic and back-translated to English to ensure accuracy. It was also pilot-tested to check for any unclear or unfamiliar expressions to ensure respondents understood all statements. Leading to adjustments in statement phrasing based on their feedback. This refinement enhanced the questionnaire’s user-friendliness and ensured the validity of the research findings.

4.2 Research population and sampling technique

The research population includes individuals who have previously used a music streaming platform and have a basic understanding of recommendation systems. As for the sampling technique, the nonprobability sample is adopted, given that the sample frame is not available and there are no dependable sources that provide a complete list of music streaming platform users. Additionally, the sample was not pre-determined, and the respondents were unknown beforehand. Thus, the method incorporates an element of partial randomness, adding credibility to the results. In this research context, convenience sampling followed by snowballing was employed to reach a diverse sample. Convenience sampling, as noted by Farrokhi and Mahmoudi-Hamidabad (2012), provides quick, cost-effective access to participants, leveraging existing networks to efficiently reach the target sample. To extend the reach, the snowball method will be followed, enabling participants to refer others, particularly those less accessible through direct approaches (Noy, 2008). The sample size was 400 individuals using filtering questions regarding respondents' familiarity with the platform and whether they had used it before or not, which will ensure the representativeness of the population. The large sample size exceeded the recommended 384, enhancing the reliability and generalizability of the research findings (Del Águila and González-Ramírez, 2014; Singh and Masuku, 2014).

4.3 Data collection process

The data collection period spanned three months using online Google Forms, which were distributed through various online platforms and messaging applications. Thus, there was no control over the country or where the sample was collected. To ensure ethical concerns, the process was conducted anonymously, without offering any financial compensation to respondents, making it a practical approach given the time constraints.

5. Quantitative data analysis and findings

As for the main research, it started with providing a brief analysis of the sample respondents' background. Afterward, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. According to Hair *et al.* (2021), Sarstedt *et al.* (2021), and Hair *et al.* (2011), it is suitable for predicting and extending models, such as the adapted TAM model. PLS-SEM is ideal for testing complex relationships, including direct and indirect effects, particularly when mediators like customer experience are involved. It handles latent and observed constructs simultaneously and does not require normally distributed data, making it flexible for social science applications. Furthermore, according to Hubona *et al.* (2021), Hair *et al.* (2020) and Hair *et al.* (2019), the PLS-SEM is applied using the two-stage approach, by which the first stage includes the composite factor analysis (CCA) to establish the measurement model, whereas the second stage aims to examine the structural model, including both the direct and indirect relationships.

5.1 Respondent background

As shown in Table 1, the data revealed that respondents' backgrounds concerning gender involve males (53.8%) compared to females (46.2%), indicating that both genders are well represented. Furthermore, the majority of the respondents fall within the age range of 20 to less than 25 years (75.2%). This indicates that they're likely in the early stages of adulthood, called Generation Z. This generation is considered a digitally savvy one that treats innovation, authenticity, and personalization as the norm. They had to grow up in an era where technology and the Internet were universal. Thus, the demographic profile of the respondents is perfectly justified as the nature of this research is correlated with their relevance in understanding trends within digital entertainment and media consumption. This is also reflected in their educational level (72.4%) of respondents are currently university students. A smaller proportion has

Table 1. Respondents background

Background	Categories	No. of respondents	Percentage of respondents (%)
Gender	Male	226	53.8%
	Female	194	46.2%
Age	Less than 20 years	27	6.4%
	From 20 to less than 25	316	75.2%
	From 25 to less than 30	34	8.1%
	From 30 to less than 35	18	4.3%
	Above 35	25	6%
Education Level	High School student	7	1.7%
	University student	304	72.4%
	Bachelor's degree	76	18.1%
	Postgraduate degree	33	7.8%
Occupation	Student	296	70.4%
	Unemployed	24	5.6%
	Public sector employee	9	2.1%
	Private sector employee	71	16.9%
	Business owner	18	4.4%
	Professional	2	0.6%

Source(s): Created by the author

completed their education, with 18.1% holding a Bachelor's degree and 7.8% obtaining a Postgraduate degree. According to Kwong and Park (2008), college students are the most active in the music industry concerning subscription behavior. As for the occupation, the majority (70.4%) are students, which aligns with the high percentage of individuals in the 20 to less than 25 years age group and their educational status. A smaller portion of the population is employed, primarily in the private sector (16.9%), while a few are business owners (4.4%), unemployed (5.6%) or professionals (0.6%). The data overall suggests that the respondents are mostly young adults focused on their education, with a minority already engaged in the workforce or self-employment.

5.2 Measurement model assessment

Regarding composite factor analysis, the validity and reliability of all constructs and items were evaluated and confirmed, as shown in Table 2. According to Sarstedt *et al.* (2021), Hair *et al.* (2017) and Hair *et al.* (2020), item loading is a concept in factor analysis, a statistical method used to measure the degree to which items, referred to as factors, are related and represent the underlying constructs being analyzed. Initially, the recommendation system novelty item (RSN1) had a low loading (i.e., below 0.60), negatively impacting overall reliability. Consequently, it was removed, and the updated item loading results were presented. All measurement items exceed the cut-off point of 0.60, confirming their reliability. Moreover, Sürücü and Maslakci (2020) and Ahmad *et al.* (2016) stated that the reliability analysis assesses the consistency and stability of measurements, including Cronbach's alpha (CA) and Composite reliability (CR). Both of them measure internal consistency, evaluating how well a set of items represents a construct. Metrics requiring values of 0.70 or higher to indicate good reliability, all constructs (as shown in Table 3) are reliably measured by their items with more than 70%, and the items are consistently related to each other and measure the same underlying construct. This is further confirmed through validity analysis; it serves as an indicator of how effectively the instrument (questionnaire) performs its function, and it includes convergent and discriminant validity. Convergent validity was measured using the average variance extracted (AVE), where a value of 0.5 or higher indicates a strong correlation and accurate representation of the construct. Discriminant validity was evaluated using the Fornell–Larcker test, which

Table 2. Measurement model assessment

Item reliability Measurement items	RSA	RSN	RSD	CSI	CX
RSA1	0.792				
RSA2	0.788				
RSA3	0.799				
RSA4	0.671				
RSA5	0.817				
RSN2		0.754			
RSN3		0.735			
RSN4		0.793			
RSN5		0.697			
RSD1			0.784		
RSD2			0.688		
RSD3			0.656		
RSD4			0.632		
RSD5			0.766		
CSI1				0.802	
CSI2				0.819	
CSI3				0.825	
CSI4				0.783	
CSI5				0.673	
CX1					0.696
CX2					0.744
CX3					0.733
CX4					0.712
CX5					0.704
CX6					0.697
CX7					0.786
CX8					0.797
CX8					0.731
CX10					0.722
Construct Reliability					
Cronbach's Alpha (CA)	0.832	0.733	0.748	0.841	0.904
Composite Reliability (CR)	0.882	0.833	0.833	0.887	0.921
Construct Validity					
Convergent validity (AVE)	0.601	0.556	0.501	0.613	0.537
Discriminant validity					

Fornell-Larcker criterion	CX	CSI	RSA	RSD	RSN
CX	*0.733*				
CSI	0.650	*0.783*			
RSA	0.673	0.550	*0.775*		
RSD	0.646	0.501	0.612	*0.708*	
RSN	0.581	0.467	0.555	0.616	*0.745*

Source(s): Created by the author

ensures a construct is distinct if the square root of its AVE is greater than its correlation with other constructs. Both analyses confirm the validity of the constructs. The AVE for all constructs exceeds 0.50, confirming that over 50% of the items effectively measure their respective constructs, satisfying convergent validity. For discriminant validity, the bolded diagonal values (square roots of AVE) are higher than the off-diagonal correlation values, indicating each variable is distinct and more strongly related to its items than to others. Therefore, both AVE and Fornell-Larcker tests are accepted, with no adjustments needed.

5.3 Structural model assessment

In concern to the structural model, the multicollinearity is conducted to ensure the absence of difficulties regarding the estimation of the relationships between the independents and the dependent constructs, and all constructs are not linearly combined (Daoud, 2017). The researcher used the Variance Inflation Factor (VIF) to assess multicollinearity, as it is commonly used in practice. According to Hair *et al.* (2020), a VIF between 1 and 5 is generally considered acceptable. However, Shrestha (2020) suggests that this threshold may be too high and recommends that a VIF of 3 or lower indicates no multicollinearity issues. In both case scenarios, this is not considered a problem as the VIF for all constructs is between 1.740 and 2.271, as displayed in Table 3. Afterward, the direct and indirect relationships were analyzed through the *p*-value and the beta. According to Andrade (2019), the *P*-value is used in hypothesis testing to measure the significance of the results. The smaller the number, the stronger the relation. In light of this, the hypothesis would be accepted if the *p*-value is below 0.05 (5%). This means the results are accurate with a percentage over 95% confidence level. As per Geissinger *et al.* (2022), the beta is the coefficient representing the change of the independent in the dependent variable while indicating the size, magnitude and direction of the effect. As shown in Table 4, the analysis reveals that recommendation system accuracy significantly and positively influences both customer subscription intention ($p = 0.004$, $\beta = 0.165$) and customer experience ($p = 0.000$, $\beta = 0.393$), thus supporting hypotheses H1 and H4. In contrast, recommendation system novelty and diversity do not directly affect customer subscription intention ($p = 0.131$ and $p = 0.325$, respectively), leading to the rejection of hypotheses H2 and H3. However, novelty and diversity positively impact customer experience ($p = 0.000$, $\beta = 0.183$ and $p = 0.000$, $\beta = 0.293$), supporting hypotheses H5 and H6. Furthermore, customer experience strongly influences subscription intention ($p = 0.000$, $\beta = 0.459$), validating hypothesis H7. As for the indirect effect, the accuracy of the recommendation system has both direct and indirect effects on subscription intention via customer experience, indicating partial mediation. In contrast, novelty and diversity have full mediation effects, as their influence on subscription intention operates entirely through customer experience. Notably, diversity has a slightly stronger effect than novelty in translating into subscription intentions. Lastly, According to Shmueli *et al.* (2019), Cameron and Windmeijer (1997) and Miles (2005), using PLS-SEM, it is essential to assess both the explanatory and predictive power of the model. The R-squared (R^2) is a common metric that measures how well the independent construct explains the variance in the dependent constructs within the sample. However, R^2 may increase even with irrelevant constructs, so the adjusted R-squared (R^2 Adjusted) is used to account for this and ensure the added constructs improve the model. While R^2 measures explanatory power, it does not assess predictive accuracy for new, unseen data. To address this, the Q-squared (Q^2) metric is used to evaluate the model's ability to predict missing or omitted data points. Both matrices range from 0 to 1, with higher values indicating better performance in explanation and prediction. The analysis reveals in Table 5 that the model explains 56% of the variability in customer experience, indicating a strong level of explanatory power, with the adjusted R-squared value of 55.7% confirming that the model is well-fitted and free of unnecessary constructs. For customer subscription intention, the model explains 50% of the variability, with the adjusted R-squared equal to the R-squared, suggesting that all independent constructs contribute meaningfully. The predictive relevance, measured by the Q^2predict, shows moderate effectiveness for customer experience (0.547), meaning the model can predict 54.7% of future observations. However, for customer subscription intention, the Q^2predict value of 0.346 suggests lower predictive power, with only 34.6% of the future variance being explained. As a result, the theoretical model specification and identification are shown in Figure 3.

Table 3. Multicollinearity assessment

Independent variable	Dependent variable RSA	RSN	RSD	CSI	CX
RSA				2.090	1.740
RSN				1.831	1.755
RSD				2.135	1.940
CSI					
CX				2.271	

Source(s): Created by the author

Table 4. Direct and indirect relationships

Hypothesis	Path	*P*-value	β-value	Decision
H1	RSA → CSI	0.004	0.165	Supported
H2	RSN → CSI	0.131	0.072	Not Supported
H3	RSD → CSI	0.325	0.060	Not Supported
H4	RSA → CX	0.000	0.393	Supported
H5	RSN → CX	0.000	0.183	Supported
H6	RSD → CX	0.000	0.293	Supported
H7	CX → CSI	0.000	0.459	Supported
H8	RSA → CX → CSI	0.000	0.180	Supported (Partial Mediation)
H9	RSN → CX → CSI	0.002	0.084	Supported (Full Mediation)
H10	RSD → CX → CSI	0.000	0.134	Supported (Full Mediation)

Note(s): One-tailed positive direction hypotheses testing is used
Source(s): Created by the author

Table 5. Model assessment

Dependent constructs	R-square	R-square adjusted	Q^2 predict
CX	0.560	0.557	0.547
CSI	0.50	0.50	0.346

Source(s): Created by the author

6. Research discussion

The research highlights that results regarding RSA align with Behera *et al.* (2020) and Nguyen and Nguyen (2024), who found that accurate recommendations positively impact subscription intentions as customers trust and have confidence in the system's ability to understand their needs and preferences. However, Dabholkar and Sheng (2012) argued that accuracy impacts subscription intentions indirectly through mediators like satisfaction and trust rather than directly. As for novelty and diversity, the research shows they do not significantly influence subscription intentions directly, consistent with Wu *et al.* (2024) and Dabholkar and Sheng (2012). Novelty and diversity are appreciated for short-term engagement but lack long-term subscription commitment. This could contribute by keeping consumers engaged through varied and new content. However, the influence may not be strong enough to drive subscription intention directly. Also, Excessive novelty or diversity can overwhelm customers, reducing personalization and relevance (Gomez-Uribe and Hunt, 2015). In contrast, Hurley

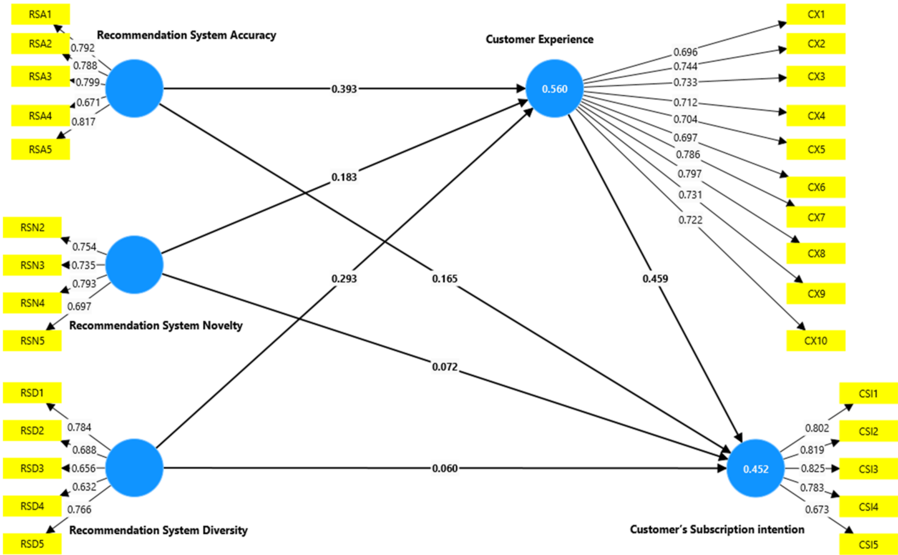


Figure 3. Structural Equation Model Results. Source: Created by the author

and Zhang (2011) argued that novel and diverse recommendations can directly enhance subscriptions by maintaining customers' interest and catering to varying preferences. This correlates with the fact that recommendation system characteristics positively impact customer experience. Accurate recommendations enhance positive experiences by delivering precise and relevant suggestions (Liu *et al.*, 2017; Behera *et al.*, 2020), while novelty refreshes customer interactions and enriches experiences (Raajpoot and Ghilni-Wage, 2019; Hurley and Zhang, 2011). Diversity promotes exploration and prevents monotony, fostering engaging experiences (Kim *et al.*, 2021). However, excessive novelty or diversity might confuse customers, reducing their perceived value (Dabholkar and Sheng, 2012; Gomez-Uribe and Hunt, 2015). Lastly, customer experience mediates the relationship between recommendation characteristics and subscription intentions. Accurate systems enhance reliability, novelty stimulates curiosity and diversity offers comprehensive options, collectively improving satisfaction and loyalty (Pu *et al.*, 2012; Roudposhti *et al.*, 2018). However, other constructs like perceived ease of use and trust may also influence these relationships. For example, overemphasis on one characteristic may hinder relevance and subscription intentions despite a positive experience (Konstan and Riedl, 2012).

7. Theoretical/practical implications

7.1 Theoretical implications

This research advances theoretical understanding by highlighting the mediating role of customer experience in the relationship between recommendation systems characteristics and the intention to subscribe. Proposing a new version of the technology acceptance model (TAM) by incorporating experiential factors to provide a deeper insight into technology use and adoption in the music industry. Furthermore, the research can contribute to understanding how digital experience in nontraditional settings. This expands the current theoretical framework of customer experience in digital media, which is particularly relevant as music consumption shifts online. Additionally, the research provides a foundation for exploring how technology-enabled services shift consumer behavior patterns in digital media industries, contributing to the context of the subscription economy.

This research contributes significantly to providing insights regarding the shift from viewing recommendation systems purely as AI-driven algorithms to recognizing their broader impact on consumer behavior. While past research primarily focused on technical aspects of recommendation systems, this research emphasizes their role in influencing customer experiences and intentions, thus contributing to a more holistic understanding of how recommendation systems can shape consumer behavior. Lastly, customer subscription intention is a new and multifaceted variable that wasn't discussed thoroughly in the literature before. Thus, understanding the interplay between customer experience, recommendation system characteristics and subscription intention can provide valuable insights into how customers decide to subscribe to a service.

7.2 Practical implication

For streaming service managers broadly, recommendation systems accuracy is pivotal in potentially boosting subscription rates. Thus, managers should focus on continually refining algorithmic precision to ensure recommendations align closely with individual customer preferences. Furthermore, they should allocate a budget to upgrade advanced data analytics and machine learning to adapt to customers' listening behaviors dynamically, which will eventually generate monetary revenues for the platform. Furthermore, managers must understand that, beyond offering personalized content, the systems must create positive, seamless and emotionally rewarding customer experiences. By focusing on accuracy, novelty and diversity as all of which combined create a holistic experience, which in turn will translate to a money stream from the continuous subscriptions of the customers toward the brand.

Zooming into music streaming services specifically, personalized recommendations have become a major determinant of customer experience and subscription intention. According to Statista, global recorded music revenues reached $29.6bn in 2024, with streaming accounting for $20.4bn, nearly 70% of the total industry revenue (Statista, 2025). This marks the tenth consecutive year of growth for the global music industry. To maintain growth, Managers should consider periodic customer feedback mechanisms to identify any gaps in the recommendation process and tailor the system to cater to evolving tastes. By doing so, they can create a more engaging, personalized experience that not only attracts new customers but also encourages existing ones to subscribe and remain loyal to the platform. This industry expansion has been facilitated by broader digital transformations.

The World Bank reports that global Internet penetration rates reached over 66% in 2023, providing the foundation for the booming digital entertainment markets (World Bank, 2024). Thus, managers can enhance the recommendation system's perceived attractiveness by partnering with popular artists, festivals or influencers. These partnerships can create exclusive content and experiences for customers, reinforcing customer experience and making subscriptions more attractive. As most respondents are from Gen Z, which has ever-changing preferences, recommendation systems must be adaptive, continuously learning from their interactions to refine and update suggestions in real time. This could include tracking what they listen to and how they engage with the platform, such as skipping songs, replaying tracks or saving them to playlists. By doing so, they can create a more engaging and satisfying platform that aligns with the values and behaviors of this digitally savvy generation.

8. Research limitations and research suggestions for future research

The online anonymous data-collection tool resulted in having a sample primarily from Generation Z, who also happen to engage more often with music streaming platforms. This concentration on demographics and the streaming industry could limit the generalizability of the findings to other age groups or more diverse consumer populations from various sectors. Future research could include a comparative study among various age groups, income levels and genders. Exploring the behaviors and preferences of older consumers or those from underrepresented demographics can provide a broader understanding of how different customer segments interact with music recommendation systems and their impact on subscription intention. Furthermore, future research could incorporate a comparative analysis across different industries, such as music streaming, video streaming and e-learning, to provide deeper insights into how recommendation systems influence customer behavior across various digital platforms.

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Supplementary material
The supplementary material for this article can be found online.

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