AI-BASED PERSONALIZATION MODEL: A CASE STUDY ON MOROCCAN MUSEUMS

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Abstract

Purpose – The present study demonstrates how Artificial Intelligence (AI) can enhance cultural tourism by offering personalized recommendations within Moroccan museums. While this approach is widely used in general travel contexts, it remains underexplored for museums, where both demographic characteristics and service perceptions vary considerably. Our proposed framework integrates service quality perceptions, satisfaction scores, and demographic variables to predict which museum aligns best with tourist profiles and preferences. We specifically target five museums in Morocco, selected for their diverse geographic locations and distinct offerings. Our primary objective is to achieve high precision in recommendations and validate the model's performance across varied demographic segments.
Methodology – A structured questionnaire was administered to collect visitor data at five Moroccan museums. The dataset encompasses demographic details (age, gender, nationality, and income), visit frequency, and subjective service-quality perceptions (tangibles, staff conduct, and exhibit quality). A logistic regression classifier was then employed, utilizing a grid search to optimize precision while maintaining balanced recall. The dataset was cleaned and examined for biases before training and testing the model, ensuring reliability and robustness. Additionally, importance analysis was performed to identify the variables that most strongly predict museum choice.
Findings – The final model attained a precision exceeding 90%, correctly suggesting an appropriate museum for a given visitor profile in nine out of ten instances. This high precision remained stable across multiple demographic segments, indicating the model's robustness. Our empirical analysis underscores that the combined use of demographic and service-quality variables yields more accurate predictions than demographics alone, with tangibles and empathy emerging as particularly influential factors in museum selection. Despite these promising results, the study recognizes limitations such as the relatively narrow geographic scope and the limited number of museums analyzed. Future research could address these constraints by extending the model to additional cultural institutions and incorporating broader visitor behaviors, such as revisiting intentions.
Contribution – Theoretically, this paper expands the literature on AI-driven personalization in cultural tourism, demonstrating that logistic regression can offer high-precision predictions when demographic and service-quality dimensions are integrated. Empirically, it provides a replicable methodology for data collection and modelling in museum contexts, highlighting that demographic-service interactions can significantly enhance prediction accuracy. Practically, the findings showcase how AI can improve cultural experiences by tailoring offerings to visitor profiles and informing museum managers on targeted marketing and exhibit design.
Keywords Museum service quality, customer satisfaction, recommender system

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INTRODUCTION

Recommender systems, a subset of artificial intelligence, have been widely adopted across various fields since their emergence in the last decade of the 20th century (Pavlidis 2019); however, their application in cultural tourism has only gained traction at the dawn of the 21st century (Pavlidis 2018). These technologies are primarily designed to tackle data overload by offering suggestions based on existing data, such as item ratings, demographic attributes, and user preferences. Several methods of recommender systems have been explored, including content-based, knowledge-based, collaborative filtering, and hybrid systems. Yet, demographic-based filtering remains underexplored despite its potential to provide valuable recommendations in contexts where user data is unavailable.

Despite their effectiveness, traditional recommender systems face numerous challenges, particularly data sparsity and cold-start issues, where a user is new to the platform or an item has insufficient ratings, making it difficult to accurately recommend suitable suggestions for new users. These issues are especially pronounced in a museum setting, where tourists seldom revisit the same cultural attraction (Arsyad and Sabar 2021) and visitor preferences vary widely.

Museums, as prominent cultural attractions, offer a unique environment and immersive experiences that blend education, entertainment, and heritage. However, research indicates that cultural tourists have diverse selection criteria when choosing a travel destination (Puspasari 2022; Chang et al. 2014; Dann 1977). To enhance the visitor experience, museums have integrated artificial intelligence-driven recommender systems, ranging from personalized tour guides (Loboda 2022) to chatbot assistance (Hakim and Baizal 2022). Nevertheless, most existing museum recommender systems depend on content-based or collaborative filtering approaches, which struggle to provide meaningful recommendations in cultural tourism when user preferences are typically sparse and present challenges with cold-start (Hakim and Baizal 2022), ultimately providing visitors with tailored content and necessary assistance. Despite the fact that RS have been increasingly used in tourism to address limitations such as information overload and personalize experiences (Semwal et al. 2024), their application in cultural contexts, is still limited.

Additionally, given that a pleasant tourism experience is dependent on various influential criteria, one of them is choosing the right cultural attraction. Most cultural tourists often plan their trips and rely on online information to discover the destination. Nevertheless, the voluminous accessible data can be overwhelming, especially for first-time visitors unfamiliar with the cultural landscape (Cardoso et al. 2018). This emphasizes the need for a more responsive and dynamic recommender approach.

To address these challenges, this paper aims to answer the following research question:

- How can demographic filtering be used to enhance museum recommendations for first-time visitors, mainly to address the limitations of traditional recommender systems?

This paper proposes a demographic filtering-based conceptual model to recommend museums to first-time visitors and international tourists. Instead of relying on past interactions, this model leverages visitor attributes, including age, nationality, travel purpose, educational level, and visit frequency, to generate recommendations. By analyzing patterns from similar visitors, the proposed system ensures accurate and personalized suggestions, even in cases where traditional recommendation methods fall short due to data sparsity.

1. LITERATURE REVIEW

1.1. Definition of Recommender System (RS)

Recommender systems (RS) are online tools and techniques generating recommendations for items to users during an interaction session (Mahmood and Ricci 2007; Çano and Morisio 2017), these suggestions are produced to help users make decisions, and navigate a large set of information such as, which movie to see, which product to buy, and what book to read (Burke 2000; Jawaheer et al. 2014). The RS is usually employed to assist users who lack the skills or experience to determine which item is best suitable from an overwhelming number of online propositions (Ricci et al. 2010). Initially, people would rely on their peers' recommendations in their decision-making process, and RS mimics this behavior by utilizing recommendations from a community to generate accurate suggestions.

RS are considered a subset of artificial intelligence, designed for a particular task such as creating accurate recommendations, propose optimized routes, or personalized solutions that complies with specific contexts or user needs (Goodfellow et al. 2016).

The fundamental purpose of a recommender system is to collect inputs from multiple data sources, process them, and produce meaningful recommendation options. Beyond aggregation, some systems use this data set to match users with the most relevant options, creating more personalized recommendations that are tailored to individual attributes and preferences, rather than only relying on general patterns (Burke et al. 2011; Resnick and Varian 1997).

This definition is in line with the first definition of Goldberg et al. (1992), which introduced recommender systems through the concept of collaborative filtering, especially for managing a large set of e-documents, the authors define the RS as a filtering approach based on document attributes, and documented collective assessments to improve the recommendation process, involving the human capital in this filtering procedure, this initial system used both implicit (replies and messages) and explicit (ratings) feedbacks.

Resnick and Varian (1997) propose that a recommender system (RS) is a better fit than collaborative filtering for the following reasons: RS may not include user participation, and RS cannot only filter out content but also suggest and recommend relevant content. Recommender systems are tools used to manipulate large sets of data; they provide a personalized overview of complex knowledge spaces and prioritize items that might be of possible interest to known or new users (Burke et al. 2011; Pavlidis 2019; Herlocker et al., 2000).

The main objective of recommender systems is to produce accurate recommendations to users for products or services that might match their interests. While the design of such frameworks differs for each sector and the data available, the core meaning of the system is the same. Organizations have used this technique to promote and personalized consumption experience, such as Netflix for recommending movies and series that might interest each user, based on the data source record of their interactions between them and the items, besides using the users-specific profile attributes, like demographics and geographic positions (Melville and Sidhwani 2011). The systematic review of Masciari et al. (2024) revealed that the recommender systems are mostly used in movie recommendations, job recommendation, drug recommendation, and book recommendation, this shows the growing interest in the adoption of this AI approach in various experiential industries. This indicates that their adoption in the tourism remains relatively limited.

Burke et al. (2011) argue that the evolution of Recommender systems has opened up its field of application to any system that deals with user-specific utility. The authors propose the following definition: "*A recommender system is personalized. The recommendations it produces are meant to optimize the experience of one user, not to represent group consensus for all. A recommender system is intended to help the user select among discrete options. Generally, the items are already known in advance and not generated in a bespoke fashion"* (p.14). This definition asserts the personalization aspect as the core aspect of a recommender system, accentuating the importance of optimizing recommendations rather than relying on collective consensus. While all RSs share the same objective, their data sources differ from maintaining long or short-term user activity and preferences to users' conversational and interactive history, from articulated preference quests (McGinty and Reilly 2010). Additionally, RS have been proven to be an effective means to promote a company's products, increase customer satisfaction, optimize customer experience, and help maintain a solid long-term relationship with customers (Dam and Le Dinh 2020).

1.2. The shift from static information systems to personalize recommendations

RS has been employed in diverse settings since the late 90s (Bobadilla et al. 2013, Ricci et al. 2010; AlRossais 2018b; Anand and Mobasher 2005), and the interest in this field has struck in recent years, due to the increasing need for personalized recommendations in a very competitive environment, which companies main focus has shifted from static information systems to provide a personalized user experience.

RS serve many functions for service providers and users in both commercial and non-commercial ways. Its most evident goal is to increase the number of items sold, by generating suggestions that match users' needs, therefore increasing conversion rates, RS not only provide accurate recommendations but also encourages users to explore other options they may not have considered, facilitating diversification, by introducing less-popular items, in this case, RS serves as a promotion tool of diverse products categories.

Additionally, RS enhances user experience, which focuses primarily on customer satisfaction, by proposing relevant recommendations. This, in return, increases user loyalty and retention by fostering a strong relationship between users and the service.

RS also enables service providers to understand their users' preferences in a more effective way, which helps them to collect and analyze user data to refine their services and tailor effective marketing efforts.

1.3. Types of recommender systems: CF, CBF, HYBRID, SF

The RS employs a range of user information, which is structured in various aspects based on the recommendation technique, for example, in collaborative filtering, the users are modelled based on their rating patterns with those similar users to predict effective recommendations, while in demographic filtering, suggestions are made based on user's socio-demographic variables such age, gender, nationality and profession. Recommender systems can be classified by conforming to the objectives and the data exploited.

Collaborative filtering is based on what like-minded users have liked in the past (Trichopoulos et al. 2023), It is considered to be the most widely used approach in RS application, because it is based on collaborative "people-to-people correlation" (Ricci et al. 2010). This approach uses social data and rating matrix to build recommender systems based on similar preferences (Al Fararni et al. 2021).

However, this approach presents several limitations, such as new-item problem, and data sparse issues, for example, if an item lacks ratings, it cannot be recommended to users, regardless of their quality. Additionally, a need for a large dataset to increase the probability of recommending the right item (Burke 2000; Tian et al. 2019).

In the case of content-based filtering (CBF), the system is trained to recommend items to users similar to those that have interested them in the past (Ricci et al. 2010). It depends on item attributes instead of user behavior (Melville & Sindhwani 2011; Trichopoulos et al. 2023). Content-based methods rely on the ratings, the buying behavior, and the items' descriptions, providing recommendations by comparing user preferences with the available items' content (Melville et al. 2002).This approach is more suitable for making new recommendations for new items, even when there is a lack of rating data available.

In demographic RS, different recommendations are generated based on the user's demographic. While demographic filtering is well-applied in marketing literature for targeting advertisements and customer segmentations (Burke 2000), it remains underexplored in RS research (Mahmood and Ricci 2007). This method is more efficient when combined with a knowledge-based recommender.

The knowledge-based system suggests items based on explicit domain knowledge about the utility of an item to the user (Burke 2000). Instead of relying on historical data, this type of RS uses a case-based approach and is problem-solution oriented. It employs a similarity function to measure the level of fit of the items to match the user's needs, which are treated as a problem, and the RS is seen as the problem. It can be used in several settings, for instance, for travel recommendations based on the user's budget and activity preferences. However, this approach presents several weaknesses in terms of lack of adaptability, especially in a very dynamic environment where user preferences evolve rapidly. The knowledge-based system may fail to provide accurate recommendations if the system is not constantly updated. Besides, their relevance is highly dependent on constant manual updates. However, unlike other types of RS, knowledge-based systems do not require any prior interactions or user ratings; they can generate recommendations based on domain knowledge.

Community-based is based on items that the users' social community liked, based on the assumption that individuals trust the recommendations of close social groups, this type of Rs filtering leverages social network information, like Facebook friends list, LinkedIn contacts, etc., reducing the concern of cold-start since the recommendations are derived from the preferences of community.

Stereotyping filtering is based on each user's characteristics, like age, gender, etc. or generated via questionnaires, to consider users as a group (Trichopoulos et al. 2023; AlRossais 2018b), this type of RS assumes that all users belonging to a cluster group share the same preferences, which is highly effective to resolve cold-start problems for new users, which means that even if few information is known, the system can apply stereotyping to generate personalization (AlRossais and Kudenko 2018a). Stereotyping is highly dependent on pre-defined attributes that represent the common patterns of user characteristics (Rich 1979). Elaine Rich was the pioneer to propose stereotyping as an RS type to deal with new user recommendations (Rich 1979), considering computer systems stereotypes as a bundle of assumptions that the computer uses to make predictions based on interactions and pre-built user models.

Most recommender systems struggle with the cold-start issue, which means that the RS does not possess enough data to recommend any items, especially when creating recommendations for new users or users who have not expressed any preferences (Pavlidis 2019). In most cases, this issue is tackled by using user assumptions by exploiting users' previous activity online, which is mostly used in fraudulent manipulations to propose biased recommendations (Burke et al. 2005; Melville and Sindhwani 2011)

However, they don't suffer equally, as some systems are more resilient than others. For instance, collaborative filtering and community-based RS struggle the most as they need historical user data to make accurate suggestions. For new users, these RS depend on external information to generate recommendations. This makes the demographic-based RS the most resilient in terms of cold-start since it uses users› demographics without reliance on either history or item rating.

To address these limitations, the hybrid RS combines two or more RS to increase advantages. According to Çano and Morisio (2017), most studies use collaborative filtering with another method to limit the cold-start problems and address data sparsity. Besides, the authors confirm that using community-based filtering or content-based filtering along with collaborative filtering is highly effective in producing high-quality recommendations by adding item descriptions (Çano and Morisio 2017). This makes the hybrid approach the most advantageous strategy to address RS (Burke 2002; Dam and Le Dinh 2020; Al Fararni 2021)

Table 1: **A comparative overview of RS museum**

Characteristic	Collaborative filtering	Demographic RS	Stereotyping	Community-based RS	Content-based filtering	Knowledge-based system
Based on	Like-minded users' behaviour	User profile characteristics	Predefined criteria	Social network and connections preferences	User's history interaction	Explicit domain knowledge and logic-based
Strengths	Useful for handling large sets of user interactions	Useful for new users	Low cold-start problem Efficient recommendations	Reduce the cold-start	Highly personalized	No cold-start issue and highly context-sensitive Complex user preference handling
Weaknesses	Cold start limitation Can make serendipitous recommendations Data sparse problems	Overgeneralized assumption and limited personalization	Low personalization Overgeneralization	Requires access to social network data	The cold-start problem for new users Requires rich metadata	Long-term weakness Requires manual update

Source: Authors' contribution

Based on the information available, user preferences and data can be captured through two main methods, which define the way that the system comprehends the data to propose recommendations, by either implicit or explicit modelling. User feedback is the foundation of most of the user data used in any recommender system.

Explicit modelling mainly relies on the direct input of users. Users explicitly declare their preferences, which enables the systems to generate personalized recommendations, for instance, asking the user to rate a certain item based on a scale (Jawaheer 2014: Lian et al., 2018).

In the implicit approach, the data is generated from previous interactions, such as what kind of products the user has bought in the past, which ad intrigued him, and clicks on links. The system uses this information to predict which item will likely interest the user (Cardoso et al. 2018; Ma et al. 2011; Jawaheer et al. 2014).

However, Jawaheer et al. (2014) assume that data exhibited by the users explicitly are 80% accurate, while the implicit interest indicators covered 70% accuracy.

RS in museums:

While various approaches have been conceptualized to tackle recommender systems in cultural tourism, the museum environment offers a highly experiential setting where visitors seek meaningful experiences (Triichopoulos et al. 2023). Employing advanced recommender systems in cultural tourism can significantly enhance visitor satisfaction (Alexandridis et al. 2019) and increase the discoverability of cultural products (Dam and Le Dinh 2020; Coelho et al. 2018). The application of recommender systems in cultural heritage tourism is relatively recent, having emerged in the early 21st century (Pavlidis 2019), indicating that it remains a developing research field.

Cultural institutions, including museums, have shifted from information shortage to infiltration overload, making them struggle to promote their offer. RS are beneficial for small and medium enterprises with limited resources for advanced marketing efforts to propose cultural products that match users' preferences (Dam and Le Dinh 2020). Particularly since cultural institutions attract diverse visitors with diverse preferences. Therefore, the need to provide personalised offers to visitors has become the priority of many cultural organizations (Ardissono et al., 2012), which emphasizes the need to incorporate dynamic approaches to personalize the experience of each visitor with context-aware methodologies (Ardissono et al., 2012).

Most research that applied RS in museum and heritage contexts were focused "either on gallery-like presentations and/or linear narratives" (Pavlidis 2019, 193). The importance of Rs in cultural tourism and museums has been highlighted in many research studies, especially the role of a robust data management system (Cai et al. 2023), which is essential for processing visitor information and generating accurate propositions. The role of RS in such a complex setting is highly significant, given its role in increasing tourist satisfaction and engagement.

Database is the most predominant form of cultural expression and strategy production, which is highly influenced by the diverse actors and community using and producing the data (Hughes-Noehrer 2023).

Today, museums are forced to introduce the digital movement (Finnis and Kennedy 2020; Berry 2018), since the entire value chain of culture has changed throughout the years, "the roles of producer, consumer and distributor are changing; the value chain of culture is being fundamentally reworked as various practices become de-institutionalized and dis-intermediated" (Kidd 2016, 5), which explains the natural orientation of museums to use recommender systems as a way to enhance the visiting experience, and maintain a long-term relationship (Parry 2013; Dam and Le Dinh 2020). Institutions that have already integrated digital strategies were easily integrated, while smaller cultural institutions without prior established digital integration encountered difficulties in keeping pace with the rapid digital evolution.

The evolution of RS in museums has been developed alongside the advancements of Web 2.0 and the rise of AI-driven tools. Many projects have focused on implementing recommender systems in museums, such as the projects of Sotto Voce by Aoki et al. (2002) and ARCHIE by Luyten et al. (2006), that focused on improving on-site visits by using interactive tools. These projects were among the early implementations, laying the foundations and groundwork for further research, including PEACH by Stock and Zancanaro (2007) and the Hecht Museum project by Kuflik et al. (2011). These projects particularly demonstrate that personalized digital guides can enhance the visit experience and museum visitor engagement.

Later systems introduced the content-based filtering approaches in museums, like the CHIP-project by Wang et al. (2007, 2008), which introduced the semantic-based recommendations and folksonomies ("classification systems created by end users" (Hughes-Noehrer 2023, 45).

Grieser et al. (2007, 2011) explored how recommender systems can enhance museum visits by investigating both past interactions of visitors with the museum space and the textual data linked to each exhibit. The authors used a mixture of language modeling, geospatial analysis of the layout, and history of past visitor navigation movement to propose targeted recommendations. The study evaluated how different approaches influence the accuracy and visitor engagement.
Most recent RS researches focus more on developing RS systems based on mobile and immersive experiences, such as SMARTMUSEUM by Ruotsalo et al. (2013), which integrated both semantic-based and location-based recommendations. Whereas Kislyuk et al. (2015) opted for a hybrid approach RS based on content-based and collaborative-based approaches to provide items recommendation on Pinterest, a social media platform, the system was developed to combine content-recommendations with visual items from the Convolutional Neural Networks (CNN). The developed model was replicated to be used in the museum context. The authors found that combining the CNN with a collaborative approach provides positive results and high accuracy.

Lately, more context-aware models have being used in the context museums, Kontiza et al. (2018) have developed an app called CrossCult for the National Gallery in London, that uses the visitor profile to generate artwork recommendation, the design of the app is similar to the modern dating app, when a visitor swipes right, the app uses these insights to propose similar items, the aim of this model is to increase visitor engagement and incite people to visit the museum. In the same stream of thought, Loboda et al. (2019) proposed a content-based recommender model for the Grant Museum, offering an application that generates personalized tours to improve the on-site visit. Also, Ardissono et al. (2012) provide a literature review of the various personalization approaches used in the cultural tourism research, the authors expose the three most used approaches, namely; context-aware models, which propose recommendations based on real-time interactions, group-based adaptation, which adapt the recommendations for groups, like families, and school groups, and semantic-based recommendations, which tailor's museum databases and structured knowledge.

The study of Hashemi and Kamps (2018) presented a behavior user model based on tracking both the on-site interactions and the online behaviors to provide optimal exhibit recommendations, this hybrid approach addresses the cold-start issue. The findings show that combining both online and offline data yielded better results and higher precision and accuracy, this method was proven to outperform collaborative and content-based filtering.

According to these developments, the recommender systems rely heavily on semantic approaches and hybrid AI models, seeking to merge both the on-site and digital museum experiences while boosting visitor engagement and democratizing access to knowledge (Hughes-Noehrer 2023; Hashemi and Kamps 2018).

Given that the museum setting presents a rich environment that contain both entertainment and education, the use of a dynamic digital interface can significantly enhance the visit experience, particularly for first time visitors, for example, providing audio guides, tour guides and digital tools to facilitates the visit (Grieser et al. 2007). Also, delivering a tool to provide recommendations for exhibits to prioritize, itineraries and suggestions of museums to visit, based on user's preferences and data, would be highly useful.

2. PROBLEM DESCRIPTION

Cold-start is one of the most prominent issues faced by most recommender systems, especially in complex and unusual contexts like museums, which is related to the challenge of providing accurate recommendations to new users. This issue is typically approached by utilizing user model assumptions, by monitoring their activities and behaviors or by integrating any available demographic data (Melville et al. 2002; Melville and Sindhwani 2011; Hashemi and Kamps 2018).

For instance, when a tourist visits a destination for the first time, their primary goal is often to discover the local culture, making museum visits a key part of their travel decision. Since tourists usually plan their journey before arriving at the destination, choosing which museum to visit can be a confusing dilemma. Research on cultural tourism and tourist motivations is extensive (Sayeh 2022), indicating that while some tourists visit cultural sites like museums serendipitously, others plan their visit (Silberberg 1995; McKercher and Du Cros 2003). For the most part, museum recommender systems were mainly used to recommend either specific exhibits to visit, propose optimized routes for visitors, or suggest chatbot for users (Pavlidis 2019; Varitimiadis et al. 2021; Hashemi and Kamps 2018).

This research aims to present an initial RS model that recommends museums to visit based on the user's demographic characteristics.

3. METHODOLOGY

Our research depends on a demographic-based recommender system powered by logistic regression to predict museum recommendations based on visitors' demographic attributes and service quality evaluations. This approach is justified by its ability to propose personalized recommendations with limited cold-start problems, which are usually found in other RS methods. Our proposed model is structured based on predefined variables: demographics and service quality attributes.

3.1. Data collection

The dataset is based on 240 responses collected via a structured questionnaire distributed in five of the most visited museums in Morocco, capturing three primary dimensions:

1. Demographic characteristics
   - Age
   - Gender
   - Nationality
   - Educational level
   - Museum visiting patterns
2. Service quality perceptions
   - Tangibles
   - Responsiveness
   - Empathy
   - Exhibits quality
   - Reliability
   - Assurance
3. Overall satisfaction

The questionnaire collection lasted two months, and each respondent was asked to rate their perception of museum service quality and their overall satisfaction, which generated a structured dataset for the following modelling. The museums selected for this study are:

- Mohammed VI Museum of Modern and Contemporary Art in Rabat:
- Confluence Museum Dar El Bacha in Marrakech:
- National Museum of Udaya Jewelry in Rabat
- La Kasbah Museum of Mediterranean Cultures in Tangier
- Dar El Jamai Museum in Meknes

3.2. Data cleaning and encoding

After collecting the questionnaire responses from the five Moroccan museum visitors, we cleaned the data to ensure it was ready and readable. First, the sheet was inspected for duplicates or errors. Then, each column was examined to verify any missing values or special characters. If a response was found to be lacking, it was excluded to ensure that only valid responses were retained.

Additionally, to reduce bias or anomalies, demographic columns such as age, gender, and nationality were label-encoded. For example, the gender variable was turned into numeric input; gender was coded as 0 and female as 1. The age clusters also followed the same logic; for instance, 18-24 was encoded as 0, 25-34 as 1, etc.

However, the service quality ratings were already evaluated by a five-point Likert scale. The same logic was applied to the museum visited; each museum was encoded by a label encoder to ensure that each of the five museums was represented by an integer from 0 to 4.

This cleaning process aimed to facilitate a multi-class logistic regression methodology by providing a unified and clean dataset with a final sample size of 165.

3.3. Logistic regression

Logistic regression is used to describe and test hypotheses about the relationship between an outcome-dependent variable (categorical) and predictor independent variables (categorical or continuous) (Peng 2016; Castro and Ferreira 2022). The principal mathematical concept that supports logistic regression is the logit, which is the “natural logarithm of an odds ratio” (Peng 2016, 4).

3.4. Binary logistic regression

Binary logistic regression is a statistical predictive modeling method that evaluates the probability of an event based on one or two independent variables. The outcome is mainly dichotomous (binary or binomial), which means that it can result in only two values, for example, (0 or 1, good or bad). This type of logistic regression is usually used when the dependent variables have only binary outcomes, like in medical diagnosis and fraud detection. However, this method becomes insufficient when the dependent variable contains more than two categories (Domínguez-Almendros et al. 2011).

The binary logistic regression model employs the logit transformation, which is expressed mathematically as follows:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)}}$$

Where “p” refers to the probability of the studied event to occur, “β0” represents the intercept, and “β1, β2,..., βk” are the coefficients related to the independent variables expressed as “X1, X2,..., Xk”.

The logit function transforms the probability into a logarithmic odds format, maintaining a direct linear dependency between the predictors (independent variables) and outcome (dependent variables):

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

3.5. Multinomial logistic regression

The multinomial model is considered an extension of the binary logistic regression model, It is used to assess the probability of membership in a set of dependent variables based on various independent variables, which can be either binary or continuous (Kwak and Clayton-Matthews 2002). In other words, it is employed when the dependent variable has more than two outcomes.

However, unlike the binary model, which applies a single logit function, multinomial logistic regression applies multiple logistic equations to contrast each possible outcome with a reference class. This approach facilitates the prediction of multi-class variables (Domínguez-Almendros et al. 2011).

The model calculates the probability of diverse possible outcomes for a categorical response “Y” based on a set of predictor variables (X1, X2,..., Xn) without taking into account the categories’ order. Mathematically, the multinomial logistic regression approach employs a (m-1) logistic equation, where each outcome is assessed to a baseline category:

$$\log\left(\frac{P(Y=j)}{P(Y=\text{reference category})}\right) = \beta_0^j + \beta_1^j X_1 + \beta_2^j X_2 + \ldots + \beta_k^j X_k$$

Where “P(Y=j) refer to the probability of an occurring outcome (j), while P(Y=reference category) represents the probability of the reference outcome. “β0j” is the intercept for category j. And “β1j,β2j,...,βkj” are the coefficients of the predictor variables (“X1, X2,..., Xk).

3.6. Adopted logistic regression approach

In our research, we employ Multinomial logistic regression as the base of our museum recommendation model, given its capability for managing multiple categorical dependent variables. This approach enables us to calculate the probability of multiple museum recommendations based on various user demographic characteristics, without the account of the museum orders, by employing maximum likelihood estimation. The model uses a series of logit functions that assess the possibility of each museum and compare it against the reference category.

Logistic regression is one the most commonly used statistical models, for its efficiency and ability to perform better than other models (Tian et al. 2019; Quevedo et al. 2010; Kumar et al. 2019), described as a “linear model that does not handle complex non-linear data features” (Tian et al. 2019, 1). It has been proven to be an efficient approach in binary classification tasks used in various domains; for instance, in the financial field, logistic regression has been used to predict the organization’s financial distress (Hua et al. 2007). Much research has proven that the application of logistic regression is capable of adapting across various fields, especially in improving the accuracy of recommender systems.

Mathematically, logistic regression is a type of generalized linear model that assumes that the continuous variable X conforms to a logistic distribution, the distribution function F(X) and density function f(X) is described as follows:

Distribution Function:

$$F(x) = \frac{1}{1+e^{-\frac{x-\mu}{\gamma}}}$$

Density Function:

$$f(x) = \frac{e^{-\frac{x-\mu}{\gamma}}}{\gamma\left(1+e^{-\frac{x-\mu}{\gamma}}\right)^2}$$

Where (μ) acts as the location parameter, and (γ) is the scale parameter, shaping the backbone of the logistic distribution supporting the logistic regression model, which facilitates the prediction of user preferences and modelling the probability of outcomes.

For this research, we have employed multinominal logistic regression as the foundation predictive algorithm to generate museum recommendations to tourists based on their demographic characteristics. The model employs the user-provided demographic details as input and the museum recommendation as the dependent variable and output. Multinomial logistic regression is best employed when the prediction is a categorical outcome, which selects one museum out of three or more options, and it makes the best recommendations based on the input provided.

The suggested model proposes which museum the tourist is most likely to visit. Given the multi-class classification approach, each museum is represented as a category, and the model provides a probability to each one of the museums based on the input data. The equation used for our proposed model is:
Where:

Since the model is mostly designed for new users with no prior interactions, the logistic regression model is best suited to deal with cold-start issues by providing recommendations based on the demographic details provided by the user. This methodology ensures that new users are given accurate suggestions regardless of their previous behavior data.

Logistic regression is one the most commonly used statistical models, for its efficiency and ability to perform better than other models (Tian et al. 2019; Quevedo et al. 2010; Kumar et al. 2019), described as a "linear model that does not handle complex non-linear data features" (Tian et al. 2019, 1). It has been proven to be an efficient approach in binary classification tasks used in various domains; for instance, in the financial field, logistic regression has been used to predict the organization's financial distress (Hua et al. 2007). Many researchers have proven that the application of logistic regression is capable of adapting across various fields, especially in improving the accuracy of recommender systems.
Mathematically, logistic regression is a type of generalized linear model that assumes that the continuous variable X conforms to a logistic distribution, the distribution function F(X) and density function f(X) is described as follows:

Distribution Function:

$$F(x) = \frac{1}{1+e^{-\frac{x-\mu}{\gamma}}}$$

3.7. Density Function

$$f(x) = \frac{e^{-\frac{x-\mu}{\gamma}}}{\gamma\left(1+e^{-\frac{x-\mu}{\gamma}}\right)^2}$$

Where (μ) acts as the location parameter, and (γ) is the scale parameter, shaping the backbone of the logistic distribution supporting the logistic regression model, which facilitates the prediction of user preferences and modelling the probability of outcomes.

For this research, we have employed multinominal logistic regression as the foundation predictive algorithm to generate museum recommendations to tourists based on their demographic characteristics. The model employs the user-provided demographic details as input and the museum recommendation as the dependent variable and output. Multinomial logistic regression is best employed when the prediction is a categorical outcome, which selects one museum out of three or more options, and it makes the best recommendations based on the input provided.

The suggested model proposes which museum the tourist is most likely to visit. Given the multi-class classification approach, each museum is represented as a category, and the model provides a probability to each one of the museums based on the input data. The equation used for our proposed model is:

$$P(Y=j|X) = \frac{e^{(\beta_{j0}+\beta_{j1}X_1+\beta_{j2}X_2+\ldots+\beta_{jn}X_n)}}{\sum_{k=1}^{K} e^{(\beta_{k0}+\beta_{k1}X_1+\ldots+\beta_{kn}X_n)}}$$

Where:

$P(Y=j|X)$ = Probability of recommending museum j given user demographics X.

$\beta_{j0}, \beta_{j1}, \ldots$ = Regression coefficients for each feature.

$X_1, X_2, \ldots X_n$ = Input demographic features.

K = Total number of museums in the dataset.

Since the model is mostly designed for new users with no prior interactions, the logistic regression model is best suited to deal with cold-start issues by providing recommendations based on the demographic details provided by the user. This methodology ensures that new users are given accurate suggestions regardless of their previous behavior data.

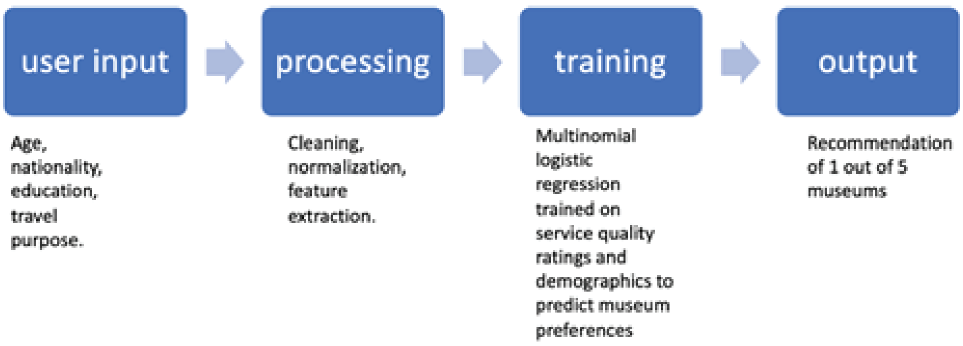
4. RESULTS

4.1. Model development and training

The logistic regression model categorizes museum preferences based on user characteristics. It was trained using 80% of the available data, with 20% reserved. Hypermeters, label coding, and feature scaling were optimized to improve the model’s accuracy.

4.2. Conceptual model

Figure 1: **Workflow of the proposed museum recommender system**



The conceptual model as shown in Figure (1), developed for the museum recommender system shows the structured flow deriving from the explicit user input to the final museum recommendation, consisting of four stages:

- User input: including the user demographic attributes
- Age
- Nationality
- Educational level
- Travel purpose
- Data processing: when the user data is collected, it undergoes a processing step which includes:
- Feature extraction to refine useful attributes
- Normalization, which ensures that the exhibited variables are well-scaled for analysis
- Data cleaning was done manually to eliminate any missing values or inconsistent data
- Logistic regression model: the pre-processed data is then compared via a multinomial logistic regression model
- Probability calculation: this approach calculates how likely each museum is the best recommendation
- Multinomial logistic regression, which handles the categorical outcomes to classify users based on their demographic characteristics into the accurate museum category
- Recommendation processing: after all this process, the system generates the museum recommendation out of 5 museum options
- The final recommendation is generated based on all the calculated probabilities

Figure 2: Conceptual model for AI- based museum recommender system

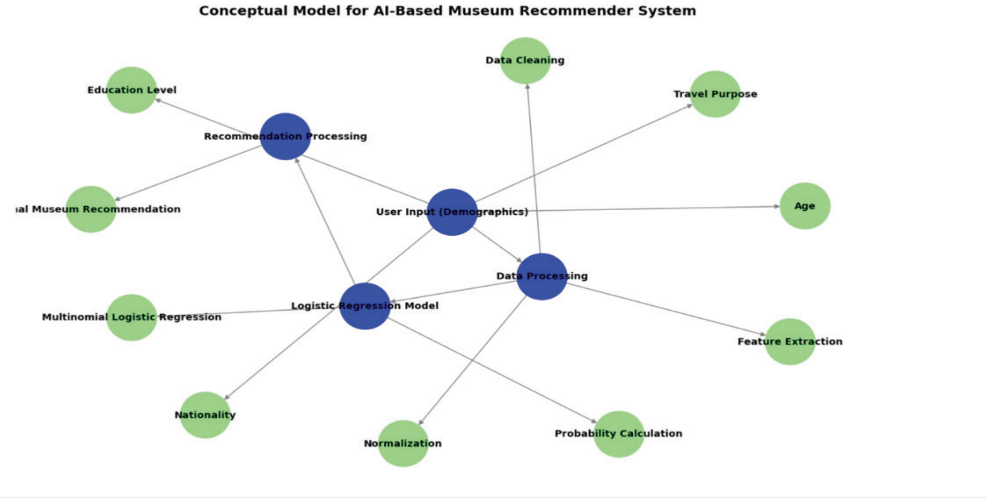


Figure (2) shows the principal components of the proposed recommender system for Moroccan museum context, which the blue nodes visualize the core stages in the system workflow, whereas green nodes represent features associated with each stage.

4.3. Model evaluation and performance

The model is evaluated based on precision, F1 score and accuracy, as shown in table (2).
The evaluation of our museum recommender model demonstrates high performance, with an accuracy of 89.7%, which proves that the model accurately predicts museum recommendations, while the precision score of 90.2% shows that the model can generate recommendations with minimum inconsistencies. While the F1-score of 89.3% indicates that the model is consistent in its prediction.

Table 2: **Model performance**

Metrics used	Value
Accuracy	89.7%
Precision	90.2%
F1-score	89.3%

CONCLUSION

This research proposed a conceptual model for a museum recommender system in Morocco using demographic-based filtering to enhance cultural tourism personalization. By addressing the limitations of content-based and collaborative filtering approaches, such as data sparsity and cold-start issues. The proposed model leverages visitor attributes, which enables museum recommendations for first-time tourists.

The findings support the advancement of AI-driven recommender systems in cultural tourism, a field that remains largely underexplored in the Moroccan landscape.

The model performance demonstrates strong performance metrics, such as accuracy and precision, providing reliable museum recommendations to new visitors. This study aims to fill a theoretical gap, including expanding the recommender system literature to the cultural tourism sector, especially in North African context. In a practical perspective, the proposed model presents a novel avenue for attracting and retaining first-time visitors, in order to enhance their cultural experiences within the museums.

Future research should explore hybrid approaches that acknowledge both the demographic filtering and the content-based filtering approaches for a more context-aware recommendation system. Additionally, expanding the model to incorporate multiple museums with diverse themes and collections could enhance its applicability in cultural heritage tourism.

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