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ASSOCIATION-RULE MINING FOR TARGETED DIGITAL ENGAGEMENT OF MUSEUM VISITORS: CULTURAL INSIGHTS FROM VISITOR BEHAVIOR

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ABSTRACT

The key to digital museology and the future of cultural communication is the understanding of visitor behavior. With the transformation of museums as a fixed space of exhibition to an experience of a cultural ecosystem, museums should strike a balance between educational missions and operational survivability. The paper examines the impact of data-based insights on improving audience engagement, the sale of cultural products, and customization by targeting the audience of super visitors, high-frequency, and high-engagement visitors whose actions have an unlawful effect on the museum results. With the help of the data provided by the behavioral and transactional activities of one of the largest metropolitan museums, the study incorporates digital tracking and purchase history as well as mobile interactions in order to determine the patterns connecting visitor interests and product preferences. These observations show that the engagement in such events as exhibitions, augmented reality, and special events is correlated with the interest in books, replicas, and digital media. The results prove that periods of high engagement, including weekends and special situations enhance visitor-product associations, which give a chance to implement individualized digital communication and merchandising initiatives. Using the prism of digital cultural communication to apply behavioral data, this study demonstrates how museums can use data in an ethical, creative way in order to create meaningful, personal, and socially valuable visitor experience in the digital age.

KEYWORDS: Museum Visitor Behavior, Association Rule Mining, Cultural Product Recommendation, Digital Museology, Personalized Engagement.

1. INTRODUCTION

The world is transforming museums due to technological development, demands of visitors and financial sustainability. Interactive museums, which are visitor-based, are substituting rigid artifact and scholarly collections. It has long since gone beyond the belief, conservation and presentation of collections to providing a wide range of audiences with lively, purposeful and individual treatment. RFID-based tracking systems, mobile applications and interactive exhibiting displays, augmented reality setups, and interactive displays make the museum visits better and gather the behavioural data (Mantra, 2024).

Emerging museum analytics currently uses behavioral data to demonstrate visitor movement, interaction, residence, and purchase in exhibitions to provide evidence-based insights into the audience (Yang, Sannusi, and Rizal, 2025). Nevertheless, even with advances in technologies, a large number of institutions still depend on the stagnant marketing and cultural curation that does not consider individualization and the opportunity to interact in real-time (D'Souza, 2021). Integrating visitor data in merchandising and narrative design is the key to matching cultural communication to the changing audience expectations, as both Gregory (2021) and Santiago (2022) state.

These transformations also illustrate the broader concept of digital cultural communication, where cultural institutions evolve from passive collection spaces into active media systems that exchange meaning through data and interaction. As Jenkins (2006) explains in his theory of convergence culture, audiences are no longer just consumers but participants in a networked cultural environment that merges media, technology, and storytelling. Similarly, Manovich (2013) describes cultural software as the foundation of how digital tools shape modern communication, identity, and creativity. From this perspective, museum digitization represents not only technlogical progress but a paradigm shift in how culture is communicated, personalized, and co-created in the digital era.

Cultural institutions do not use association rule mining to predict consumer behavior like retail and e-commerce. Unlike businesses, museums face unique challenges. Museum visits are driven by consumer intent, curiosity, emotion, education, and social interaction (Henning, 2020). Thus, creating complex-sensitive analytical models with actionable insights is challenging but necessary. This behavioral analytics gap lets researchers' study how museums can use data science to achieve their missions. While the concept of "Superstar Museums", major cultural institutions that achieve global recognition through iconic architecture and media prominence, has been established in cultural economics (Plaza, Aranburu, & Esteban, 2022), the parallel phenomenon of "super museum visitors" remains a promising yet under-explored area of analytics. Identifying and analyzing "super visitors" is promising analytics. Above-average in many areas. Over four times a month, they spend 120 minutes at the museum, interact with many exhibits and interactive features, and buy books, replicas, and digital media (Duester, 2024). Super visitors generate a lot of museum revenue and have predictable behavior, making them ideal for targeted personalization. Although valuable, academic literature and practical museum strategy rarely study this visitor group, which most models treat as homogenous or focus on aggregate trends (Da Silva Ferreira Gonçalves, 2021; Olgen & Cucuzzella, 2024).

Thus, it is important to examine the interactions of super visitors with museums, the effects of their behaviors on purchasing products and what this information can be useful to enhance the recommendation systems. Digitizing the museums and tracking the behaviors is not common, thus the use of data to personalize individuals is uncommon. There is a considerable research gap in the behavior analysis by rules to expose actionable behavioral patterns (in particular, in how visitor contact is related to cultural product interest) (Murphy et al., 2024). To address this gap in the research, association rule mining, a market basket analysis data mining technique, may provide meaningful patterns of visitor behavior of museum super visitors. Association rule mining rules between groups find rules that are of the form "if a visitor spends more than 120 minutes and visits Exhibit A. These rules elucidate intricate visitor-product relations by means of support, confidence, and lift measures.

Strategic collaboration with a large metropolitan museum that has a digital tracking infrastructure, which includes more than 50,000 visitor sessions of RFID path tracking, exhibit interactions, and purchase transactions. The behavior-based analysis was made possible through preprocessing steps, formatting of transactions, discretization and segmentation. Super visitors are more often, longer involved, and spend more, and their predictive patterns are stronger (as Çakir 2023 shows). Engagement is enhanced by contextual moderators, e.g., the days of event and peak seasons, which have been affirmed by research by Asprino et al. (2024) and Hughes-Noehrer (2023) to suggest that time-related determinants have an extensive impact on visitor behavior and consumption.

This research paper aims at achieving two goals first, the behavior exhibited by super visitors, frequency, duration, exhibit interaction, and product preference and second, compare these behaviors with the data-driven insights to suggest cultural products based on individual preferences. Due to addressing behavioral data as opposed to generic segmentation, the study produces a scaled model, which improves the design of the experience and the operational strategy of a museum. The results as shown reveal the moral way in which museums may put computational procedures into practice to personalize narration and sales to clean up the gap among information sciences, museology, and computerized humanities with the goal of developing smarter, responsive and memorable experiences to the audiences.

2. LITERATURE REVIEW

2.1. *Cultural Product Use and Museum Visitors*

Digitalization changed museum visits. Instead of artifact collections or elite cultural institutions, museums are becoming dynamic, interactive spaces that prioritize visitor engagement, personalization, and accessibility. RFID, mobile apps, and interactive kiosks track museum visitors, exhibits, and time (Asprino et al., 2024; Pisoni et al., 2021). Digital footprints let museums analyze audience behavior, not demographics. Over the past two decades, scholars and practitioners have proposed many museum visitor typologies. Early models labeled audiences learners, explorers, facilitators, or experience seekers. Although useful theoretically, such classifications often fail to capture in-situ visitor behavior's complexity and fluidity. Recent museology advances suggest real-time data-based behavior-based segmentation may help understand visitor interaction with space, content, and technology (Yang & Guo, 2024). Some museumgoers prefer narrative exhibits, others interactive digital features or socializing. These preferences affect movement, attention, and spending (Angelis et al., 2021; Hutson, 2024; Lucchi, 2023). Books and catalogues aid interpretation, while replicas and AR souvenirs are memory anchors or playful re-engagement tools (Yang, Sannusi, & Rizal, 2025). Despite their growing importance, most museums' product placement strategies don't engage visitors. Few museums recommend products by exhibit or digital use (Li et al., 2024; Mihailova, 2021; Winesmith & Anderson, 2020; (Yang & Guo, 2024)).

This disconnects highlights unexplored cultural merchandising and behavior analysis. There are no systematic frameworks for translating behavioral insights into product recommendations despite growing data. High-value visitors who buy and engage are hardest hit. The opportunity is to identify these individuals, understand their behavioral signatures, and create personalized cultural product recommendation systems that match their interests and actions (Ceccarelli et al., 2024).

Theoretically, digitalization of museums is an extension of digital cultural communication more in general, where the active and networked quality of cultural experience is stressed. Jenkins (2006) simply referred to this as the convergence culture where the audience co-creates and circulates meaning on digital platforms instead of just actively consuming the products. This notion has been expanded into digital museology, in which researchers suggest that digital technologies not only change access but also meaning and enable a dialogic as well as a multi-directional relationship between institutions and the public (Parry, 2007; Kidd, 2011; Giaccardi, 2012). Manovich (2013) notes that the experience of culture is redefined by the digital media in terms of the software interfaces of mediation between interaction and authorship. This theorizing underscores the fact that digitization in museums does not occur in a vacuum as a single technological act but rather one that is communicative and participatory and therefore power-shifting whereby the curators are excluded, with the audiences taking their places.

2.2. *Association Rule and Recommender Systems Culture-based Mining*

Personal recommendation systems improve sales and user experience. Using user behavior to predict and recommend products works for online retailers and streaming platforms. These systems filter collaboratively, content-based, or hybrid. Collaboration suggests products that similar users like, while content-based systems suggest products with attributes the user has engaged with. These models are powerful, but they require a lot of explicit user data, such as ratings or preference histories, which museums often lack because user accounts are not persistent and interactions are more subtle and varied (Kamariotou et al., 2021; Massari et al., 2024).

Trends in transactional or binary data may help reveal the pattern of visitor interactions, which can be such as {Visited Exhibit A, Long Duration} ⇒ {Purchased Book} and so on, showing that interaction predicts purchasing behavior. According to Çakir (2023), the initial uses of rule mining in the pliers adapted the layouts of exhibits and improved the results of the educational process based on the interaction mapping. Massari et al. (2024) and L. Meng and Liu (2021) are successful examples; however, as Maria-Teresa et al. (2023) and Wang (2023) point out, museums are unlikely to use them to apply to personalised merchandising and adaptive communication practices.

The study derived from these results, using association rule mining, on high-value super visitors, due to the nature of their frequent and lengthy interactions; behavioral data could be rich enough to make predictions. According to Chen (2023), rule-based systems are the best models of personalizing interaction with limited data cultural environments. The use of contextual moderators, i.e., event days, weekends, and seasonal peaks, is in line with what Grammatikopoulou and Grammalidis (2023) have found that time dynamics influence visitor reactions. On the same note, Bahia (2023) and Lieto et al. (2024) highlight the idea of adaptive and time-sensitive personalization as a means of improving the relevance of recommendations, visitor satisfaction, and efficiency of the institution in the context of the digitally mediated museum space.

In addition to its capabilities of computational use, data-driven personalization in cultural terms also needs to be interpreted in the framework of datafied cultural communication. According to Parry (2010) and Kidd (2014), museum data practices cause the institutions to turn into communicative infrastructures through which cultural meaning and visitor interpretation are mediated by an algorithm. Bonacchi and Krzyzanska (2019) also emphasize that digital heritage analytics show the distribution of power between institutions and publics, in which experience can be perceived and appreciated. Consequently, association rule mining of the museum is a technical optimization approach, as well as a cultural process that demonstrates and organizes visitor engagement with content, information, and identity in the digital realm.

2.3. Super Visitors Behavior Model

This paper analyzes the super visitors, which is a small group that visits museums more frequently, thoroughly and deeply than any other average visitor. These tourists are eligible based on four visits per month, each visit is 120 minutes and a purchase of 100 dollars of cultural products. In addition to quantifiable metrics, digital tools are used by super visitors who visit paid events and engage with narrative-driven exhibits over and over again. The behavioral metrics are coded in the form of transactions to be used in the study. Visit frequency, duration, exhibit interaction (Exhibit A, Exhibit B), interactive features (QR code scans, AR, digital guides), and purchase history to ensure consistency, null values are removed and behaviors are formatted as binary indicators like “Scanned QR Code = 1” or “Purchased Book = 1.” Rule-mining algorithms support discrete time and spending. FP-Growth and Apriori algorithms generate association rules to map behavior to product affinity from frequent itemsets. These algorithms predict product purchases using transactional data trends. Each rule is assessed for support (how often it appears in the dataset), confidence (how likely the product is purchased given the behavior), and lift (how much the behavior increases purchase likelihood compared to random chance). A high-lift rule like {Long Duration, Scanned QR Code ⇒ {Purchased Digital Media} may predict behavior well. The framework generates rules for different groups and situations using visitor segmentation and contextual conditions. Super and general visitor rules may differ in structure and prediction. Peak seasons and events may have different rules than weekdays. Segmentation improves recommendations and operational insights (Pruulmann-Vengerfeldt, 2022; Raimo et al., 2022; Zang et al., 2024).

Intelligent, behavior-driven cultural experiences are created using behavioral data and personalized merchandising. RFID tracking, mobile apps, and interactive exhibits have increased museum behavioral data, but few analytical frameworks turn it into personalized cultural product recommendations. The majority of studies ignore frequent, high-spend visitors and generalize visitor behavior or audience trends. Culture underuses association rule mining, especially for profiling frequent, valuable museum visitors (Bird et al., 2023; Genc et al., 2023; Virto et al., 2024). Businesses use it for consumer insights (Maria-Teresa et al., 2023). This gap warrants research on "super visitors" and their behavioral patterns using scalable, interpretable models to support cultural institutions' real-time personalization and strategic product alignment.

The super visitors concept can be related to general theories regarding cultural involvement and audience interactions. The Contextual Model of Learning, created by Falk and Dierking (2013) focuses on the fact that the interaction of personal, sociocultural, and physical context influences the engagement at the museum on a dynamic level. An example of such integration can be seen in the case of super visitors who visit on a regular basis, which appears to indicate not only continuous motivation, social group belonging and reinforcement of their identity due to cultural involvement (Simon, 2010; Hooper-Greenhill, 2000). In a digital sense, these users can also be considered the prosumer dynamic of Jenkins (2006), which is the co-production of meaning as a result of interaction, feedback and digital consumption. This theoretical prism places the super visitors in the roles of learners and communicators, both of which are significant actors in the dynamic digital museology ecosystem.

3. RESEARCH METHODOLOGY

3.1. Research Design

Super visitors' behaviour is investigated and an intelligent cultural product recommendation system is developed through association rule mining algorithms by using a robust and systematic observational, quantitative, and cross-sectional design methodology. The methodology integrates digital museology, data mining, and cultural institution consumer behaviour to ensure accuracy, reproducibility, and generalizability. Researchers passively observe museum visitors' natural behaviours and interactions in this study. Using quantitative data from visitor logs, purchase records, and engagement systems, statistical analysis and machine learning-based rule extraction find patterns in large datasets. The cross-sectional design shows visitor behaviour across days and events but not time. It identifies museum visitor behaviour, especially super visitors and their effects on cultural product interactions.

In addition to statistical discovery, the research design involves an interpretive layer, which is based on the digital cultural communication theory. The interpretation of association rules was through the prism of visitor communication behavior in which each of the if-then patterns (e.g., {Visited Exhibit A, Long Duration} ⇒ {Purchased Book}) is considered the communicative behavior of the visitors who reveal themselves and their interest in learning and identity by interacting and consuming. Such a method links the findings in computations to culture, linking data mining outputs to the interpretive logic of digital museology. The rules are, therefore, viewed as predictive tools and also indicators of the co-creation of value and meaning by visitors within digitally mediated museum settings.

The combination of quantitative and interpretive reasoning will provide a contextualization of the patterns of algorithms into the communication behavior instead of handling it as an abstract figure. Such a logic of mixed methods empowers the study with its validity because it fills in the gaps between behavioral information gathered and the understanding of the audience and culture, and situates the methodology in the current study on the digital humanities.

3.2. Data Collection

An original dataset was created through a strategic partnership with a large metropolitan museum with digital tracking and sales systems. Structured and semi-structured data from digital entry logs, RFID-enabled exhibit tracking, point-of-sale systems, and interactive mobile application data provide a multidimensional view of visitor behaviour. Includes at least 50,000 visitor records with timestamps, exhibit pathways, interaction logs, purchase history, and demographic tags. Pattern mining uses a core analytical cohort of "super visitors" based on frequency, duration, and cumulative purchases.

The primary data sources for this research cover three museum interaction dimensions: Visitor interaction logs store timestamped data on which exhibits or interactive zones visitors visited and for how long; product purchase data includes transactional information on cultural merchandise like books, replicas, limited edition items, digital downloads, and augmented reality souvenirs; and exhibit engagement metrics measure engagement with specific installations or media. Pattern analysis and visitor privacy are protected by temporarily synchronising and anonymising these datasets. Three data layers explain the visitor journey from museum movement to purchase economic behaviour.

For data quality, structure, and relevance to research goals, rigorous data pre-processing was done before mining. To maintain data integrity, corrupted entries, null values, duplicates, and inconsistent timestamps were removed.

The data set was formatted using transaction formatting, and it was as binary or categorical visitor actions/purchases used in the rule mining. The formatted rows of data presented visitor session where visitors had presence/absence indicators such as Visited Exhibit A, Interacted with Digital Guide and Purchased Replica X. Continuous variables as "Time Spent per Visit" and "Total Amount Spent" were binned with variable discretization into low, medium, and high bins to interpolate association rules and make sure the mining algorithm was compatible. One hundred and thirty-five minutes and above were termed high-duration visitors, which implied high engagement among the visitors. For example, all visitor data used in this study was anonymized before analysis, with no personally identifiable information retained. Data collection and use complied with the museum's data-governance policies and applicable privacy regulations

3.3. Association Rule Mining Algorithm and Visitor Segmentation

Association rule mining, a popular data mining method, uncovers hidden relationships between variables in large datasets. Using Apriori and FP-Growth algorithms, rules like {Visitor Behaviour Set} ⇒ {Cultural Product Purchase} are identified and evaluated using support, confidence, and lift metrics.

- Support is the percentage of the dataset where a rule occurs, indicating how often a behaviour leads to a purchase.
- Confidence measures the conditional probability of buying a cultural product based on behaviour.
- Lift compares rule confidence to expected confidence if behaviour and purchase were independent to assess rule strength.

Statistics and practicality were only considered for rules with support > 0.01, confidence > 0.6, and lift > 1.2. These thresholds were empirically tested and adjusted during iterative validation to balance rule richness and precision.

Analysis with a visitor segmentation model improved recommendation specificity and applicability. Two main visitor groups:

Super visitors, top 5% visit frequency, top 10% longer stay, multiple exhibit interactions, and high-value purchases; Rest of dataset is General Audience.

Segmentation customised rule mining and recommendation strategies. Audience patterns were more relevant than super visitors rules, which showed high-engagement, high-value consumer behaviour. Comparisons of segment-specific rules identified super visitors behaviour markers for targeted marketing and personalised experience.

3.4. Framework and Tools

Academic and industry researchers recommended powerful and reliable open-source data analysis tools for this study. The main data manipulation and algorithm implementation language was Python. Pandas efficiently filtered, grouped, and reshaped large visitor datasets. Scikit-learn discretised continuous variables for association rule mining behaviour metrics like visit duration and frequency. Apriori and FP-Growth algorithms were used in Python mlxtend for fast, scalable pattern extraction. For data validation and exploration, Matplotlib and Seaborn created graphs, heatmaps, and rule maps. Rules were robust across platforms after cross-validation with R's arules package. A GUI-based data mining tool, Weka, was used to visually inspect rule structure and algorithm efficiency during prototype development. These tools enabled repeatable, high-performance analysis of large-scale museum visitor behaviour data.

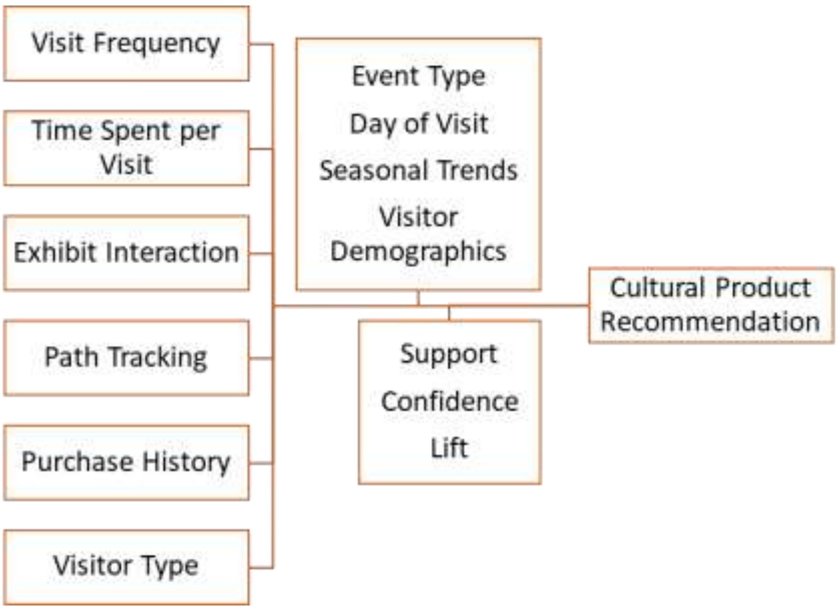

Figure 1: Data Analysis Flow and Research Framework.

This study carefully defined and measured each variable for association rule mining and visitor behaviour analysis. Data from system-logged visitors measured independent variables. Visit frequency was the number of visits per visitor during observation. Visit time was recorded at check-in and check-out and divided into short, medium, and long. Audio guides and QR code scans measured interactive exhibits. Route-organized RFID or app-based navigation logs collected path tracking data. Purchase records listed books, souvenirs, and digital media. Frequency, duration, and spending thresholds determined visitor type (super or general).

Mined association rules inferred cultural product recommendation from behaviour. Recommendation rules were created if a behaviour set consistently led to product purchases. Validated recommendations using rule mining algorithm variables. Support showed visitor session rule frequency. Behavioural confidence measured purchase probability. Lift determined if behaviour increased purchase likelihood. Category moderators like event type, day of visit, seasonal trends, and visitor demographics segmented data before mining. It showed how context affected product interest and visitor behaviour. These measurements confirmed the rules' statistical and behavioural significance. Figure 1 shows the data analysis flow and research framework.

4. DATA ANALYSIS

This paper has identified significant trends in association rule mining on structured and multi-stage visitor behaviour in the museum, as well as preferences of cultural products. Python and R mined and visualized the preprocessed raw logs, purchase records, and interaction data with the aid of Pandas, Scikit-learn and mlxtend, processed and converted the data to transactional format, and Apriori and FP-Growth wrote an association rule with support, confidence and lift. Visitor sessions based on transactions are full of behavioral knowledge such as length of visit, contact with exhibits and product purchase behaviour that allow algorithms to produce such rules as: {Visitor Behaviour Set} ⇒ {Cultural Product). A rules package of R was used to validate and cross-check the results of platform consistency.

The relevance and statistical significance of association rules had a minimum support of 0.01, confidence of above 0.6, and lift of above 1.2. This was done on a separate analysis to compare the behaviour of super and general visitors and purchase habits. Rule metrics summarised and network graphs were presented in order to establish the effects of visitor actions on product preferences. Further discussion revealed that there was a daily visit, event occurrence and moderation of rule performance by season. The parameters of behavior-based product preferences, segment-specific tendency, and recommendation prospects were determined as a result of a sound data analysis strategy that allowed museums to gain insights into cultural consumer behavior and formulate product plans based on high-engagement segmentations among the visitors.

Table 1: Data Preprocessing and Transformation Summary.

Step	Before Preprocessing	After Preprocessing
Raw Visit Duration	87.45 min, 130 min	Short, Medium, Long
Raw Purchase Amount	$12.5, $50, $5.75	Low, Medium, High
Missing Entries	Null values in 'Exhibit Visited'	Nulls removed or replaced with 'None'
Inconsistent Product Names	'Book', 'book', 'BOOK'	Standardized to 'Book'
Formatted Transaction Record	Multiple tables: logs, sales, paths	1 row per session, merged format
Discretized Visit Duration	10 to 180 minutes (continuous)	Short < 60, Medium 60–120, Long > 120
Discretized Purchase Value	$1 to $300 (exact values)	Low < 20, Medium 20–100, High > 100

The raw dataset that will undergo the process of association rule mining requires transformation into a clean, standardised and analysed form, which is achieved through seven key steps, listed in Table 1. To be able to generate and compare all the rules, the short, medium and long categories were used in step 1 with the continuous numeric values of visit duration, such as 87.45 minutes and 130 minutes, discretised into that category. The next process involved binomial sorting of purchase values between 5.75 and 50 in three ordinal categories: Low, Medium and High, in step 2 to map the pattern in stage of subsequent mining. Step 3 involved deleting or replacing missing values, particularly the null values in the column of Exhibit Visited, to maintain the structure and behaviour.

Step 4 standardised product labelling by combining "Book", "book", and "BOOK" into one term, eliminating case-sensitive mismatches and rule redundancy. To include all visitor behaviour in each row, Step 5 reformatted transaction records from visitor logs, sales records, and path trackers into a session-based format. Steps 6 and 7 categorised visit duration and purchase values within rules: durations below 60 minutes were Short, 60–120 minutes Medium, and 120 minutes Long, and purchase values under $20 were Low, $20–100 Medium, and $100+ High, making the mined rules more interpretable, generalisable, and usable for description and analysis

Table 2: Visitor Segmentation Criteria and Distribution.

Segment	Criteria	Visitors	Percentage
Super	≥ 4 visits/month, > 120 min, > $100 purchase	850	17%
General	< 4 visits/month, ≤ 120 min, ≤ $100 purchase	4150	83%

Museum visitors are divided into super and general visitors in Table 2, which were segmented by visit frequency, average time spent, and purchase amount. Four or more times a month, super visitors spend over 120 minutes and $100 at the museum. Highly engaged museum visitors are more likely to return and donate. 850 super visitors comprise 17% of visitors. General visitors spend $100, less than four times a month, and 120 minutes. This group comprises 83% of visitors, 4,150. Sectioning helps analyse behaviour and recommend cultural products. Targeted rule mining lets the study compare how each group engages with exhibits and products.

Table 3: Sample Transactional Data Format for Rule Mining.

Session ID	Visitor Segment	Visit Duration	Exhibit A	Exhibit B	QR Code	AR Feature	Digital Guide	Book	Replica	Digital Media	Paid Event
1001	Super	Long	1	0	1	0	1	0	1	0	1
1002	General	Medium	0	1	0	1	1	1	0	0	0
1003	General	Short	1	0	0	0	0	0	0	1	0
1004	Super	Medium	1	1	1	1	0	1	0	0	1
1005	Super	Long	0	1	1	1	1	0	1	1	0

A structured visitor session representation for association rule mining emphasises behavioural engagement and transactional outcomes (Table 3). Each session row includes visitor segment, visit duration, exhibit interaction, digital engagement, and product purchases. Apriori and FP-Growth can easily find frequent item-sets and generate meaningful binary rules (1 for presence, 0 for absence). The table shows Super and General visitors' engagement. Super visitors (Session 1001, 1004, and 1005) scan QR codes, visit more exhibits, and attend paid events. Advanced features like AR and digital guides are used more. General visitors (Sessions 1002 and 1003) examine one exhibit or product and interact less. Activities such as paid activities and buying of cultural products that are optional, such as books, replicas, and digital media, differ per session. It is a transactional system that allows individual suggestions and visitor-type behavioural analysis to pre-plan museum marketing campaigns and product placement activities.

Table 4. Top 10 Association Rules (Ranked by Lift).

Rule	Support	Confidence	Lift
{Visited Exhibit A, Long Duration} ⇒ {Purchased Book}	0.12	0.72	2.10
{Scanned QR Code} ⇒ {Purchased Digital Media}	0.15	0.68	2.00
{Visited Exhibit B, AR Feature} ⇒ {Purchased Replica}	0.09	0.65	1.95
{Super, Paid Event} ⇒ {Purchased Book}	0.08	0.75	1.92
{General, Short Duration} ⇒ {Purchased Digital Media}	0.14	0.63	1.87
{Visited Exhibit A, Interacted Guide} ⇒ {Purchased Replica}	0.11	0.70	1.85
{AR Feature, Long Duration} ⇒ {Purchased Digital Media}	0.10	0.66	1.80
{Visited Exhibit B} ⇒ {Purchased Replica}	0.13	0.60	1.78
{Interacted Guide} ⇒ {Purchased Book}	0.16	0.67	1.75
{Paid Event} ⇒ {Purchased Digital Media}	0.07	0.58	1.70

Table 4 shows the ten most influential association rules based on the lift values, which display the effect of visitor behaviors on the purchasing of cultural products over and above a random relationship. The highest (lift = 2.10) rule indicates that the long-term visitors of Exhibit A are more likely to purchase books showing a thematic interest. On the same note, the scanning of QR codes (lift = 2.00) also forecasts the purchasing of digital media, and the interaction is technology-driven. Digital guide, augmented reality, and purchase intent are also boosted by these things, and super visitors attending paid events show their preferences for collectable items and books. General audiences that have short visitations prefer to consume quick-access digital media, meaning time elasticity. Together, these behavioral and situational patterns guide predictive, individualized museum merchandising and marketing programs which boost involvement and revenue.

Table 5: Rule Metrics by Visitor Segment.

Visitor Segment	Number of Rules	Avg. Support	Avg. Confidence	Avg. Lift	Max Confidence	Max Lift	Min Confidence	Min Lift
Super	145	0.13	0.72	2.05	0.91	2.56	0.60	1.60
General	98	0.09	0.61	1.74	0.82	2.10	0.50	1.30

Table 5 compares the performance of the association rule between two main visitor groups of Super and General visitor segments on several metrics that help to determine the strength, consistency and predictive power of the cultural product purchase behavioral patterns. There were 145 rules for super visitors, as opposed to 98 for General visitors, and therefore, a more solid and well-developed repertoire of behaviors among such an engaged group. The average support of super visitors is 0.13, meaning that there is a higher degree of session-wide behaviour-product patterns than general visitors do. The average confidence of super visitors is 0.72, indicating that certain behaviours lead to product purchases. Super visitors rules have 2.05 average lift, twice as likely behavior-product relationships as random co-occurrences, while general visitors have 1.74. Super visitors have a maximum confidence value of 0.91 and a lift of 2.56, indicating reliable and influential patterns. However, the general segment has 0.82 maximum confidence and 2.10 lift. Both groups' minimum confidence and lift values show that even weak super visitors rules outperform the general group. Super visitors' stability, predictability, and actionability make them better targets for personalised recommendation systems and strategic product placement. General visitors are informative but have more variability and less certainty in behavior-to-purchase associations.

Table 6: Moderation Effects on Rule Strength.

Moderator Condition	Number of Rules	Average Confidence	Average Lift	Max Confidence	Max Lift	Min Confidence	Min Lift
Event Day	65	0.74	2.10	0.89	2.45	0.62	1.70
Non-Event Day	50	0.68	1.85	0.81	2.10	0.55	1.45
Weekend	60	0.71	2.00	0.88	2.38	0.60	1.60
Weekday	55	0.66	1.78	0.79	2.05	0.52	1.35
Peak Season	58	0.73	2.08	0.87	2.42	0.60	1.68
Off Season	52	0.67	1.81	0.80	2.15	0.54	1.40

Guest behavior-cultural product purchase association rules are affected by contextual moderators like event type, day of the week, and seasonal timing in Table 6. Special event days have the highest average confidence (0.74) and lift (2.10), suggesting that visitor engagement strengthens and predicts behaviour-to-purchase patterns. The maximum confidence (0.89) and lift (2.45) under event conditions show that promotional or themed programming increases visitor responsiveness. Weekend rule strength is higher than weekdays, with confidence at 0.71 and lift at 2.00 versus 0.66 and 1.78. Visitors on weekends can purchase more because of explorations or visits in groups. The same can be seen in seasonal patterns. The rules are more prevalent and more intense in the case of holidays and big expos, with a confidence average of 0.73 and a lift of 2.08 in comparison with off-seasons (confidence: 0.67, lift: 1.81). These variations demonstrate that visitor-product relations heavily depend upon time and situation. In museums experimenting with product recommendation strategies in order to focus on visitor experiences, aligning merchandising with visitor behaviour based on calendar cycle, the predictive power of behavioral patterns can be increased or decreased by contextual moderators.

Table 7 contains the list of the key variables of this study and their results of the data analysis according to their impact on the discovery of patterns and product recommendation. The most important behavioral differences were time per visit and frequency of visit. The number of Super (≥4/month) and 4150 General visitors was 850 and 4150, respectively. There was a high behavioral dichotomy, as 40% of the sessions took over 120 minutes (Long), positively predicting product interest and the depth of interaction. Interactive statistics were that Exhibit A had the most engagement (68%), the next was Exhibit B (54%), and the number of sessions using digital guides was 61% this suggests a high level of multimedia participation. Path Tracking exposed the rule mining sequence analysis by showing that 30% of visitors used the normal route A → B → C, and 24% used the normal route A → D → E. 42% of visitors bought books, 38% replicas, and 27% digital media products, with some sessions involving multiple purchases, supporting engaged visitors' multi-interest profiles. Event days, weekends, and peak seasons had higher average rule strength, with Event Days lifting 2.10 vs. 1.85 on Non-Event Days. Weekend rules outperformed weekday rules, and peak season rules rose 2.08 versus 1.81 in the off-season. Support, Confidence, and Lift were higher for super visitors, with confidence 0.91 and lift 2.56. Finally, Cultural Product Recommendation had the strongest effect on book, replica, and digital media purchases, with rule lift values of 2.10, 1.95, and 2.00. This proves behavioral and contextual factors predict museum cultural product recommendations.

Table 7: Variable Classification and Analytical Role.

Variable Name	Variable Type	Summary of Observed Results from Analysis
Visit Frequency	Independent	850 visitors had ≥4 visits/month (Super); remaining 4150 had <4 visits/month (General)
Time Spent per Visit	Independent	40% Long (>120 min), 35% Medium (60–120 min), 25% Short (<60 min)
Exhibit Interaction	Independent	Exhibit A: 68% visits; Exhibit B: 54%; Digital Guide usage: 61% overall
Path Tracking	Independent	Most common: A → B → C (30%); A → D → E (24%)
Purchase History	Independent	Books (42%), Replicas (38%), Digital Media (27%) — some visitors purchased multiple categories
Visitor Segment	Independent	17% Super (850); 83% General (4150)
Event Type	Moderator	Rules from Event Days had 2.10 lift vs. 1.85 on Non-Event Days
Day of Visit	Moderator	Weekend visits produced 60 rules, with 0.71 avg. confidence vs. 0.66 on weekdays
Seasonal Timing	Moderator	Peak season lift: 2.08; Off season lift: 1.81
Visitor Demographics	Moderator	Group visitors showed higher AR use; solo visitors had more frequent book purchases
Support	Derived	Max: 0.16; Average: 0.12; Super segment support generally higher than General
Confidence	Derived	Max: 0.91; Avg: 0.72 (Super); Max: 0.82; Avg: 0.61 (General)
Lift	Derived	Max: 2.56; Avg: 2.05 (Super); Max: 2.10; Avg: 1.74 (General)
Cultural Product Recommendation	Dependent	Most predicted products: Book (rule lift 2.10), Replica (1.95), Digital Media (2.00), based on behavior sets

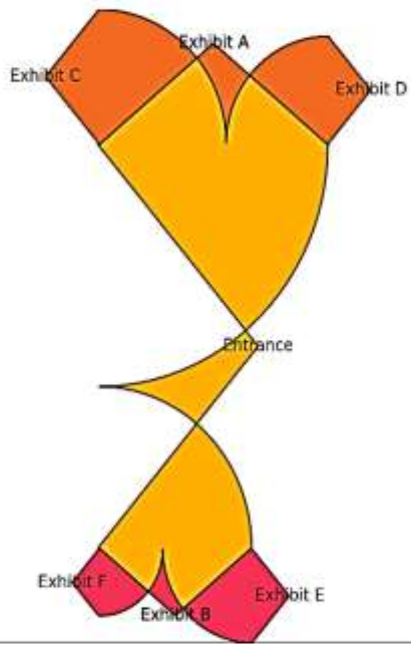

Figure 2: Visitor Journey Flow through Museum Exhibits.

Sankey diagrams of museum visitors' most common routes are shown in Figure 2. At the entrance, 180 visitors visited Exhibit A and 120 visited Exhibit B. A is a transition hub because most goes to Exhibits C (100) and D (80). Visitors to Exhibit B also visit Exhibits E (70) and F (50), suggesting a different engagement pattern. The logic of rule generation and segmentation has the advantage of consistent visitor behavior when there is high-traffic transitioning. The data indicates that visitors use guided exhibit scans, and this enables the museum to locate interactive capabilities, acquire engagement statistics, and prescribe products in accordance with journey-specific actions.

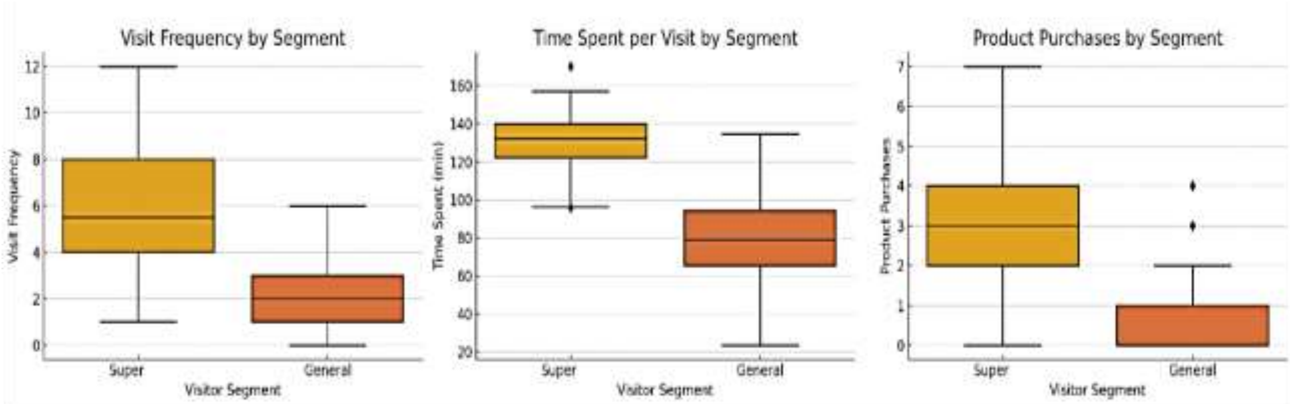

Figure 3: Distribution of Visitor Engagement Metrics by Segment.

Figure 3 shows the difference in the visitor engagement measures according to the three major dimensions, including visit frequency, two-step visit time, and purchasing of products between the super and general visitor groups. Boxplots indicate that super visitors are more active, coming every 4-9 times on average (up to 12), and the main visitors, in general, came once or twice. Super visitors have an average duration of 120-150 minutes on average in a single visit, and in some instances, even higher duration, compared to the average response of a general visitor of 60-100 minutes, which is goal-focused behaviour. Purchase trends are similar to those- super visitors will purchase 2-5 items per session (a maximum of 7), and general visitors will hardly purchase more than 1. All in all, these allocations attest that the visions of super visitors play a central role in the purposeful interaction, individualized recommendations, and high-quality museum marketing solutions.

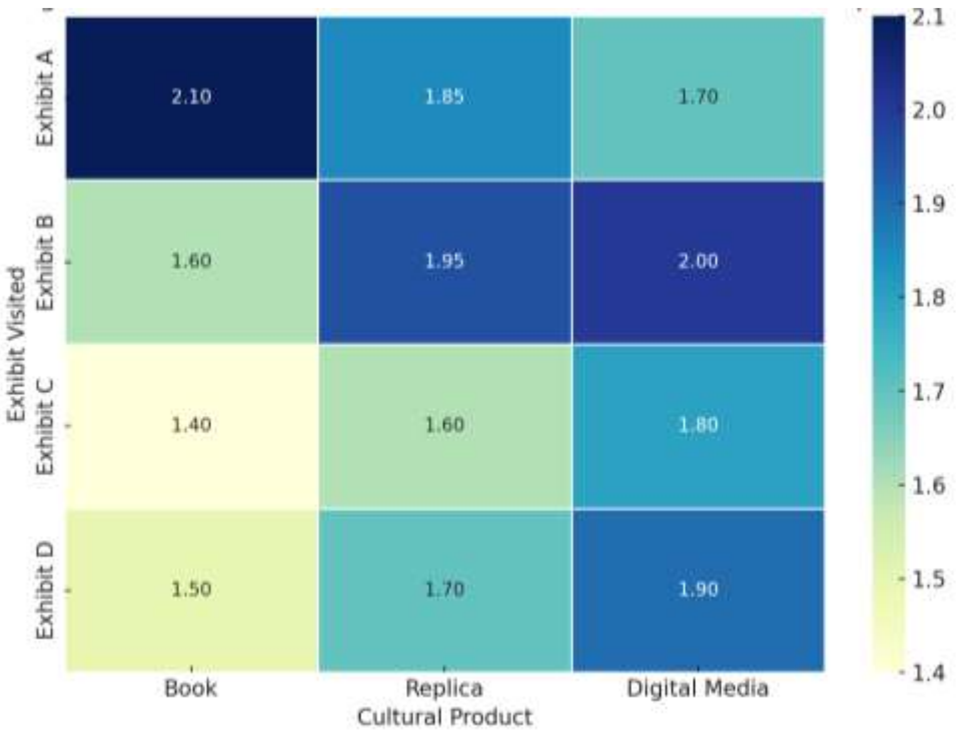

Figure 4: Exhibit Interaction vs. Product Purchase Heatmap.

The heatmap of exhibit interaction versus cultural product purchase (in Figure 4) offers subtle and practical information about the behavior of the museum visitors, specifically how exhibit interaction influences cultural product purchases. The most powerful and darkest cell, the cell that shows the lift value of 2.10 between purchases of Exhibit A and purchases of books, indicates that the visitors who visit this exhibit are more than twice as likely to make purchases than are random excitement, which would mean that the exhibit has a high level of content, is educational, or that it touches the soul and heart of the visitors causing them to purchase literature, catalogues and other items based on stories.

Augmented reality and digital storytelling have an even stronger increase in users of downloadable content, as demonstrated by a 2.00 lift in the Exhibit B, and other exhibit elements allowing a visual or emotional connection with the artifact (Exhibit A and Exhibit B), also correlated with purchasing the replicas (lifts = 1.851.95), proving that the appeal of the products is highly consistent with the exhibits design and content. Conversely, the lift in Exhibits C and D is moderate implying little immersion or thematic interest. The heat map suggests that the exhibits could have a strategic approach, based on which buying activity and data-informed choices of museum organization and individual products could be managed.

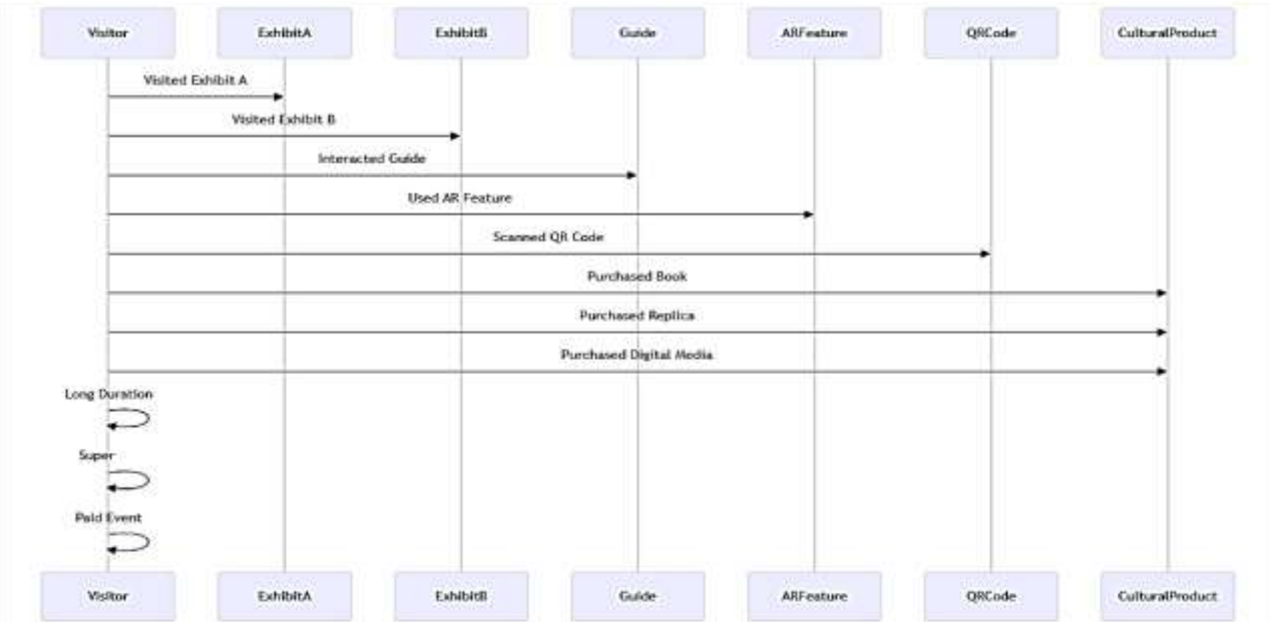

Figure 5: Association Rule Network Graph.

In Figure 5, the focus is on lift-based strength, Graph, which is a force-oriented network depiction, and displays the strongest association policies among visitor patterns and cultural product purchases displayed in a neat and spaced-out format. The graph indicates the overall approach taken by visitors to the museum, as certain behaviour patterns invariably result in certain purchases. The other visitor behaviors are Visited Exhibit A, Scanned QR Code, Long Duration, whereas product purchases are purchased Book, purchased Replica, and purchased Digital Media. The edges indicate the directional association rules, each with the thickness and label equal to its lift value, a measure of its probability. With a lift of 2.10, Visited Exhibit A and Long Duration leading to Purchased Book is the strongest rule in the graph.

Visitors who spend more time at that exhibit are twice as likely to buy a book than random behavior. Scanned QR Code is strongly associated with Purchased Digital Media (lift = 2.00), linking tech interaction to digital product interest. The node AR Feature affects Purchased Replica and Purchased Digital Media, especially when combined with Visited Exhibit B or Long Duration, showing how immersive, interactive content increases product engagement. Book purchases by high-engagement Super visitors at Paid Events (lift = 1.92) show their purchasing power and intellectual interests. Specific recommendation systems and museum merchandising benefit from this graph's concise but powerful overview of behavior-driven purchasing patterns.

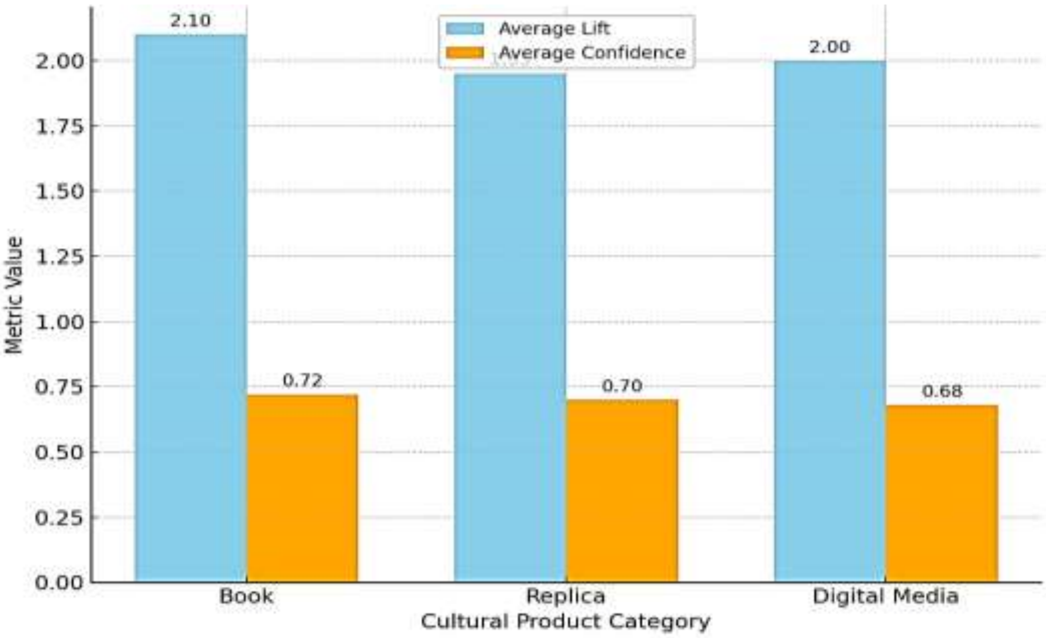

Figure 6: Product Category-wise Rule Strength.

Association rule mining of museum visitor behavior yields in Figure 6. The rule strength bar chart compares the average lift and confidence scores for Books, Replicas, and Digital Media, the three main cultural product categories. The chart shows that books are the most strongly predicted product type in terms of lift (2.10) and confidence (0.72), indicating that visitors who visit certain exhibits or spend more time will buy books. This suggests that engaged museum visitors are interested in books and that their purchase behavior is directly influenced by their actions during the visit, making them a prime target for rule-based recommendation systems.

Digital media records a lift value (2.00) and medium confidence (0.68), meaning the scan of the QR code and online interaction, meaning high interest in downloads, AR experiences and virtual souvenirs, and this is more likely among technology-minded visitors. Replicas, with a lift of 1.95 and confidence of 0.70, show that visually appealing exhibitions are more likely to lead to physical purchases of a souvenir, but with less consistency. Books still continue to be the most predictable type of product, followed by digital media and replicas (Figure 6), which offer a behavioral basis of product recommendations to target the needs of a museum.

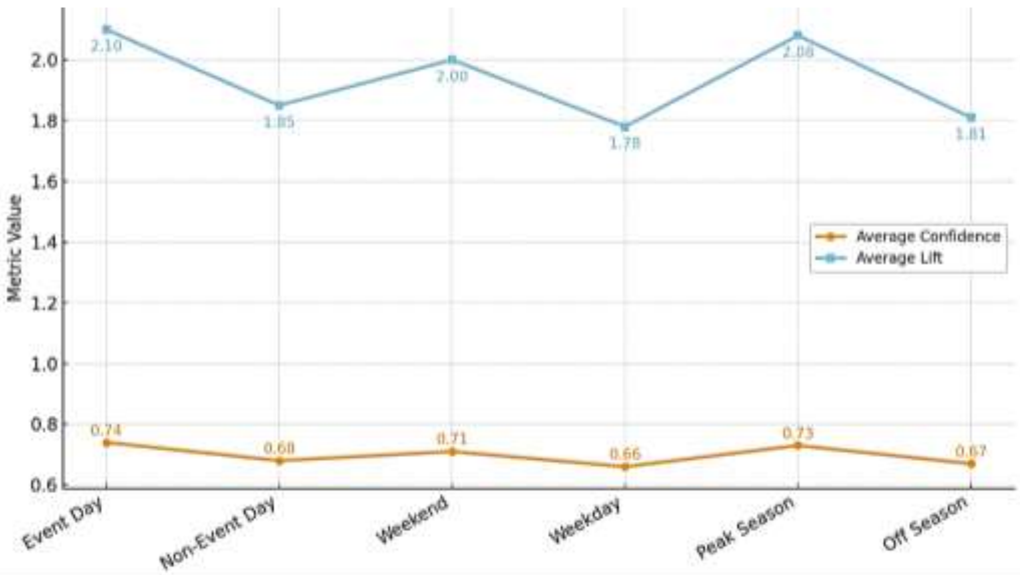

Figure 7: Moderator Impact Visualization.

Figure 7 shows the impact of the phenomenon of events, weekdays, and seasons on the effectiveness of behavioral association rules, which are manifested in the differences in the average lift and confidence. The highest performance is obtained on the event days (lift = 2.10, confidence = 0.74), which shows that special programs and product-themed exhibitions are what encourage intentional and product-focused activity. On the same note, the predictability is high in peak seasons; in this case, holidays or big exhibitions (lift = 2.08, confidence= 0.73) since the high attendance in peak seasons promote stability in behavior and buying. The weekends beat the weekdays since there are more visits during weekends that are social and leisure-oriented to do cultural shopping. On the other hand, weekdays and off-season indicate lower association (lift = 1.78, confidence = 0.66). On the whole, contextual timing plays a significant role as a moderation factor in behavior purchase relationships, which helps museums to maximize recommendations and marketing in order to target high-engagement times.

5. DISCUSSION

This study found a complex and data-rich understanding of museum visitor behavior, particularly among “super visitors” who visit frequently, spend long periods, engage deeply with exhibits, and buy large cultural products. This group's behavior reveals visitors' priorities and influences museum marketing, curation, and personalized experience design.

Behavioural habits demonstrate specific digital interaction processes that determine how museums can inform diverse viewers. In the case of the super visitors, the frequent application of the AR features, digital guidelines, and QR scanning to visit can be regarded as instances of participatory communication behavior, as the visitors are not involved in the consumption part of the process but the active co-creation of meaning by means of the interaction. Their participatory approach aligns with Jenkins's (2006) convergence culture, in which audiences flow freely across media platforms, with learning, socialisation, and consumption converging. In these regards, digital characteristics are communicative interfaces by expanding the narrative of the exhibition and creating two-way communication between the institution and the visitor (Parry, 2007; Kidd, 2016). As an overall visitor whose interaction would be less experiential and interactive, an effective digital communication would have to be more guided by simple navigation, simplified storytelling, and instant sensory gratification, reinforced by accessibility and inclusion over interpretative perceptiveness.

Audience segmentation further exposes these observations by explaining how communication approaches could be varied on the basis of behavioral profiles. High levels of cognitive and emotional investment and reaction to interpretive richness, personal notifications, invitations to exclusive events, and sophisticated material like expert lectures or behind-the-scenes online tours can keep guests going. Visitors who do not need to be general, however, take advantage of communication strategies that enable exploration, gamified elements, wayfinding indicators, or speedy online communications raise retention and adhesion to next engagement levels. The museum is therefore a multi-layered communication ecosystem, with each audience group getting a unique balance of information, experience and interactivity. The frameworks of interpreting association rules based on this communication paradigm enable museums to convert behavioural information to narrative-based engagement design and immediate cultural conversations (Giaccardi, 2012; Falk, and Dierking, 2016).

Super visitors want engaging, immersive, and interactive experiences. They use AR features, digital guides, and multiple exhibits to gain intellectual and emotional depth as cultural participants. This group likes books, replicas, digital media, and paid events. Super visitors show an inclination towards the products with the expansion of educational or narrative exhibition motives and the deepening of cognitive and emotional impressions. Experiential consumption with value being generated through meaningful interaction in regards to repeat engagement and predictable spending patterns is evident. The above behaviors directly contribute to the museum revenue and museum sustainability, similar to other cultural economics research findings of the Guggenheim Bilbao, which has been successful in achieving tourism and economic growth by data-driven, behavior-sensitive marketing techniques (Plaza, 2006).

This is in line with the concept of experiential consumption, where visitors are motivated not by their appearance but by their content interaction. This group desires to study and participate through the interpretation of reading and working with digital media. General visitors create foot traffic and do not require much immersion as they have brief visits, are less likely to make a purchase and therefore need alternative ways of engaging with them. The implications of these results include a marketing perspective and curation. Association rule brings purchase triggers. The book sales are highly anticipated by long substantiations and visits made by exhibit A. Education and merchandising can be done via exhibitions, which have a greater narrative or emotional appeal. Museums can seamlessly transition from interpretation to transaction when exhibit design matches themed merchandising. The exhibit narrative includes cultural products, not just commercial ones (Liddell, 2021; Y. Meng et al., 2023).

Curation can incorporate products and exhibits while educating. Interactive and layered storytelling exhibits, especially those enhanced by technology, are more likely to lead to purchases, as shown by digital media and AR lift values. Layered media and multi-sensory interpretation may help curators boost engagement, product interest, and visitor loyalty. Marketing is behavior-sensitive and targeted with insights. Personalization goes beyond demographics by segmenting visitors into super and general categories. Event-based recommendations, high-value collectibles, and exclusive items tied to exhibits super visitors are most likely to visit can be featured in mobile apps, digital kiosks, and newsletters Introductions, cross-sells, and simplified interactive elements may help general visitors explore and stay longer.

This finding suggests using real-time behavioral data in digital kiosks and mobile recommendations. Intelligent systems make dynamic product recommendations using visitor paths, interaction logs, and purchase history. After scanning an AR exhibit QR code and spending more than 90 minutes in the museum, the system can suggest a digital souvenir or themed book at the exit kiosk. Paid lectures and tours may include exclusive content or curated product bundles, increasing satisfaction and purchase likelihood. When cultural space users want personalization, these apps are crucial. Museums can create dynamic, context-aware experiences that adapt to individual and group behavior using visitor behavior patterns. Strong confidence and lift values in the super segment make the association rules evidence-based and likely to succeed (Huo et al., 2024; Jingwen & Lin, 2023).

The research advances digital humanities and museology theory. The finding advances museum scholars' and practitioners' methods by mining visitor behavior data using association rule mining. This predictive and scalable method goes beyond descriptive statistics and qualitative observations to understand exhibit use and purchase. Computational rigor and a replicable model for audience research across institutions and exhibit formats are gained. Contextual moderators and segmentation improve theory. The finding examines how visitor type, event timing, day of the week, and seasonal trends affect behavior because visitor dynamics are complex. Cultural analytics and digital humanities emphasize situational and temporal engagement. It implies that museum programming, marketing, crowding, and ambiance influence visitor preference. The comparison of moderator rule performance suggests museums should be flexible and calendar-aware with merchandising and visitor engagement. Peak seasons and event days are most predictive. Museums can schedule campaigns and product rotations around high-engagement times. Promotions, bundled offers, and interactive touchpoints may keep customers spending off-seasons and weekdays (Orea-Giner et al., 2021; Podara et al., 2021).

Beyond literature models, this research advances the conversation. Traditional audience models personify visitors with surveys, interviews, and observations. Though useful, these methods are subjective and small-scale. This finding track behavior using museum RFID, mobile app, and POS data.

This paper measures and implements association rules to improve museum recommender systems with a transparent, understandable method that does not undermine institutional values (Huang et al., 2022). Seeing the visitors as learners and consumers, it fulfills the educational and commercial goals, exploiting the data-led insights to enhance the engagement, learning, and revenue. With the inclusion of behavioral analytics, museums will be able to maintain smarter personalization, improve evidence-based planning and make visitor experience more culturally appropriate and sustainably mindful.

5.1. Implications

The paper has important applications in museum practice, the strategy of cultural products, and digital innovation. The identification of high-engagement visitor behavior by the museum management will enable it to create lifestyle programs along with revenue development programs that are sensitive to behavior but not programmatic. Data-driven loyalty programs, differentiated memberships and experiences would be effective in enhancing retention and resource allocation. Likewise, cultural product teams are able to transition intuitive merchandising into data-intensive development and make themed books, limited-edition reproduces, or digital media that respond to visitor behaviour.

These strategies minimize inventory risk, grow the rate of conversion, and well as visitor satisfaction.

Digital strategy and cultural policy are informed by the results as well, with responsible and participatory digital transformation being the key idea. The behavioral analytics should be included in the digital communication approach of the museums to expand visitor experiences through the use of various platforms like apps, AR and online exhibits. Ethical data policies need to be put in place to guarantee privacy, transparency, inclusivity by policymakers.

By incorporating personalization, based on analytics, within institutional and national cultures and approaches, the museums will become more participatory, sustainable, and technologically responsive areas, which will allow to reconcile innovation with both the educational and cultural objectives.

6. CONCLUSION

This paper analyzed museum visitors, especially the super visitors, to build a data-driven cultural product recommendation rule based on association rule mining. The research takes RFID tracking, mobile app data, and purchase records, which revealed the consistent patterns of behavior as related to exhibit engagement and product preference, such as {Visited Exhibit A, Long Duration} ⇒ {Purchased Book}. These results indicate that the predictable positive engagement, constant visitors, long stays, and pricey audiences can generate super visitors, regular, long-duration, and high-spending visitors, which can be used to shape the personalization of the museum.

In addition to analytics, the research allows for identifying both practice-focused and policy implications. Behavioral data can be used to create specific digital communication profiles, custom recommendations, dynamic storytelling, and promotions based on events to enhance engagement and remain profitable, waste. On an institutional level, the acknowledgment of super visitors as strategic cultural stakeholders confirms those policies that focus on ethics of data, participatory design, and access to digital heritage inclusively. Association rule mining is, therefore, a communication and management tool, and this allows museums to match digital interaction to mission-driven objectives. The framework offers a gradable model of making evidence-based decisions that enhance stellar visitor experience and the sustainability of an institution during the digital cultural age.

7. LIMITATIONS AND FUTURE RESEARCH

This association rule mining study examines museum visitor behavior and cultural product recommendation, but several limitations must be acknowledged to contextualize and guide future research. Track system structure and scope limit data first. RFID paths, digital logs, and POS collected visitor session profiles but not museum complexity. Untracked emotions, social interactions, and non-digital engagement may obscure product interest-influencing behavior. A single metropolitan museum may have limited visitor age, culture, and motivation for the large dataset. This may limit the results' applicability to other museums or international audiences. Another cross-sectional study examined visitor behavior over time. This design analyzes patterns and correlations without tracking visitors. Repeat visits, changing preferences, and digital engagement or product exposure effects can be studied longitudinally. Understand visitor lifecycle patterns and improve recommendation system predictiveness.

Third, association rule mining was insightful but struggled with complex, nonlinear behavior data relationships. In future studies, deep learning and hybrid recommendation systems may improve accuracy and personalization through collaborative filtering, content-based methods, and rule mining. They process multimedia and respond to user feedback live. Study concluded with one institution. The analytical framework ought to be used in future studies on many museums or types of exhibitions so that the findings can be generalized and considered a strong tool. Universal engagement and interaction patterns of the visitor and the products may be found in comparative investigations across cultures, museum size, and subject of the exhibition; hence, the cultural sector may be even more scalable and flexible. The future study will enhance data science and visitor-centred museumology to design the inclusive and innovative museum experiences.

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