SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 11, No. 2, (2025), pp. 540-556
Open Access. Online & Print

DOI: 10.5281/zenodo. 18231445

DIGITAL COMMUNICATION INSIGHTS FROM MUSEUM VISITOR DATA: ASSOCIATION RULE MINING FOR TARGETED ENGAGEMENT

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Received: 24/07/2025
Accepted: 28/10/2025

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ABSTRACT

To increase engagement, cultural product sales, and personalization, digital museology must understand visitor behavior. Museums must use data to optimize visitor interaction and cultural merchandising to balance educational mission and operational sustainability. It predicts museum "superstar visitors" product purchases using association rule mining. This research used transactional data from a large metropolitan museum with digital tracking infrastructure to create a behavior-based cultural product recommendation model. From over 50,000 visitor sessions, RFID (Radio Frequency Identification) path tracking, point-of-sale transactions, mobile app usage, exhibit interaction logs, and demographic tags were collected. Data preprocessing included formatting raw behavior into binary transaction records, discretizing continuous variables like time spent and purchase value, and segmenting visitors by frequency and engagement. The study used Apriori and FP-Growth algorithms to find strong association rules linking actions like visiting Exhibit A, interacting with AR features, or attending paid events to book, replica, and digital media purchases. Superstar visitors made more frequent, consistent, and high-lift rules than general visitors, indicating predictive behavior. Events, weekends, and peak seasons improved rule performance, demonstrating how temporal dynamics affect visitor engagement. Behavior-aware personalization may boost museum visitor loyalty and spending. The study shows how behavioral analytics and recommendation systems can make static exhibitions visitor-centered. It highlights superstar visitors' impact on education and economic outcomes and provides a scalable way for museums to innovate in culture, technology, and audience insight.

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

1. INTRODUCTION

Technological advances, visitor expectations, and financial stability are changing museums worldwide. Visitor-centered, interactive museums are replacing static artifact and academic collections. It's disappeared from preserving and displaying collections to giving diverse audiences immersive, meaningful, and personalized experiences. Mobile apps, interactive displays, augmented reality installations, and RFID-based tracking systems enhance museum visitor experiences and collect behavioral data (Mantra, 2024). A new generation of museum analytics uses behavioral data to show how visitors move, interact, stay, and buy (Yang, Sannusi, & Rizal, 2025). Along with these changes, museums must market cultural products to increase revenue. Gift shops, digital souvenir platforms, and themed merchandise enhance exhibition narratives and visitor engagement. Most museums still use static marketing and curation strategies despite technological advances and increased interaction data. These methods don't personalize recommendations, improve merchandising, or optimise engagement pathways using visitor data (D'Souza, 2021; Gregory, 2021; Santiago, 2022).

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. Identifying and analyzing "superstar museum 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). Megastar 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).

Therefore, studying how superstar visitors interact with museums, how their behaviors affect product purchases, and how this knowledge can improve recommendation systems is crucial. Data-driven personalization is rare in museums that digitize and track behavior. Significant research gaps exist in rule-based analysis of rich behavioral data to reveal actionable patterns, especially those linking visitor interaction to cultural product interest (Murphy et al., 2024). Association rule mining, a market basket analysis data-mining technique, can reveal meaningful museum visitor behavioral patterns, focusing on superstars, to fill this research gap. Association rule mining "if-then" rules include "if a visitor spends over 120 minutes and visits Exhibit A, then they are likely to purchase a book." Through support, confidence, and lift metrics, these rules clarify complex visitor-product relationships.

A strategic partnership with a large metropolitan museum with digital tracking infrastructure provided this analysis's dataset. Over 50,000 visitor sessions, digital entry logs, RFID-enabled path tracking, exhibit interaction records, mobile guide usage, and purchase transactions are included. Preprocessing included transaction formatting, variable discretization, and visitor segmentation before analysis. Star visitors engage more frequently, longer, and spend more than general visitors. Segmentation tailored rule mining to audience behaviors and expectations. Star visitors generated more rules and were more consistent, proving predictive power (Çakir, 2023). This study also examined how contextual moderators like event day, weekend, and peak season affect these associations. Museum engagement and purchases depend on timing. Rules from event days and peak seasons had higher confidence and lift. Museums maximize engagement during high-traffic periods by aligning marketing and product placements with the calendar (Asprino et al., 2024; Hughes-Noehrer, 2023; Schröter Freitas, 2023).

The study has 2 objectives. The research starts with superstar visitor behavior: frequency, time spent, exhibit interaction, and product preference. Second, association rule mining interprets and acts on these behaviors to recommend personalized cultural products. The goal is to personalize museum content, technology, and merchandise based on visitor behavior, not generic visitor segmentation or thematic tagging. This study develops and validates a scalable, data-driven museum visitor experience and operations recommendation model. The findings show how cultural institutions can ethically and effectively integrate computational methods, advancing museology and digital humanities. This model uses real data to tailor storytelling and merchandising to visitors' needs, supplementing curatorial judgment. This research offers timely, evidence-based advice on how museums can digitize and adapt to a new cultural consumption era to give audiences more intelligent, responsive, and meaningful experiences.

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 disconnect 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).

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).

Association rule mining helps culture. No long-term user profiles or item similarity metrics are needed, unlike collaborative filtering. Patterns in transactional or binary data reveal common behaviors. Example: {Visited Exhibit A, Long Duration} ⇒ {Purchased Book}, based on support, confidence, and lift metrics. Metrics inform product recommendation, exhibit redesign, and targeted messaging. E-commerce and retail use association rule mining, but cultural applications are new. Early studies used rule mining to optimize exhibit layouts by identifying common movement patterns or improve educational experiences by linking content interaction to learning outcomes (Çakir, 2023). Small applications target general visitor behavior rather than high-impact groups. Although successful in other fields, rule-based insights are rarely used in museum merchandising or personalization (Massari et al., 2024; L. Meng & Liu, 2021; Maria-Teresa et al., 2023; Wang, 2023).

The association rule mining study of high-value superstar museum visitors builds on this. Rule-based modeling works well with these high-frequency, long-duration, high-value buyers' consistent and rich interaction data. The study personalizes cultural institution behavior by targeting this group. A data-efficient and contextually appropriate approach for non-commercial settings like museums addresses recommender system limitations. Importantly, the study incorporates contextual moderators like event days, weekdays vs. weekends, and peak vs. off-season timing into rule mining. Temporal or programmatic conditions affecting behavior-to-purchase patterns can be understood more dynamically. Event-day rules reveal stronger or different associations than weekday rules for time-sensitive or event-specific personalization. These insights improve recommendation relevance, visitor satisfaction, and institutional efficiency (Chen, 2023; Grammatikopoulou & Grammalidis, 2023; Bahia, 2023; Lieto et al., 2024).

2.3. Star Visitor Behavior Model

This study examines the “superstar museum visitor”—a small but influential group that visits museums more often, deeply, and economically than the average visitor. These visitors qualify with four monthly visits, 120 minutes each, and $100 in cultural product purchases. Beyond quantitative measures, superstar visitors use digital tools, attend paid events, and repeatedly interact with narrative-rich exhibits. The study encodes behavioral metrics as transactions to analyze them. 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. Star 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 "superstar visitors" and their behavioral patterns using scalable, interpretable models to support cultural institutions' real-time personalization and strategic product alignment.

3. RESEARCH METHODOLOGY

3.1. Research Design

Superstr museum 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 superstar visitors and their effects on cultural product interactions.

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 "superstar 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. Transaction formatting organised the dataset into binary or categorical visitor actions and purchases for rule mining. The formatted dataset rows showed visitor sessions with presence/absence indicators like "Visited Exhibit A", "Interacted with Digital Guide", and "Purchased Replica X". Variable discretization was used to bin continuous variables like "Time Spent per Visit" and "Total Amount Spent" into low, medium, and high bins to interpret association rules and ensure mining algorithm compatibility. Visitors who stayed over 90 minutes were "high duration," indicating high engagement.

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:

Superstar 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 superstar visitor rules, which showed high-engagement, high-value consumer behaviour.

Comparisons of segment-specific rules identified superstar visitor 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.

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 (superstar 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.

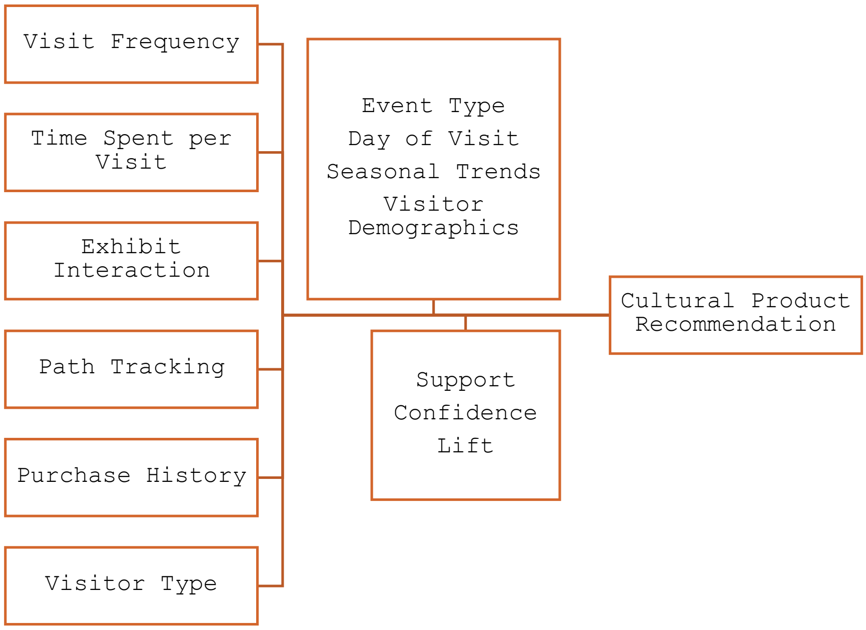

Figure 1: Data Analysis Flow and Research Framework.

4. DATA ANALYSIS

This study found meaningful patterns between museum visitor behaviour and cultural product preferences using structured and multi-phase association rule mining. Rule mined and visualised the preprocessed raw logs, purchase records, and interaction data using Python and R. Pandas, Scikit-learn, and mlxtend cleaned and transformed the data into transactional format, while Apriori and FP-Growth extracted association rules with support, confidence, and lift thresholds. Transaction-based visitor sessions contain behavioural indicators like visit duration, exhibit interaction, and product purchase type, enabling algorithms to generate rules like {Visitor Behaviour Set} ⇒ {Cultural Product}. The results were validated and cross-checked using R's arules package for platform consistency. Association rules were filtered using minimum support of 0.01, confidence above 0.6, and lift above 1.2 for relevance and statistical significance. The analysis was done separately to compare superstar and general visitor behaviour and purchasing habits. To determine how visitor actions affected product preferences, rule metrics were summarised and network graphs showed frequent behavior-product combinations. Additional analysis showed that daily visit, event occurrence, and season moderated rule performance. A robust data analysis methodology identified behavior-driven product preferences, segment-specific trends, and recommendation opportunities, helping museums understand cultural consumption patterns and develop product strategies for high-engagement visitor segments.

Table 1: Data Pre-processing 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

Table 1 lists seven critical transformation steps needed to clean, standardise, and analyse the raw dataset for association rule mining. For efficient rule generation and comparison across visitor types, continuous numeric visit duration values like 87.45 minutes and 130 minutes were discretised into Short, Medium, and Long categories in step 1. Step 2 grouped purchase amounts from $5.75 to $50 into three ordinal bins, Low, Medium, and High, to simplify segmentation and pattern analysis in later mining stages. In Step 3, missing entries, especially null values in the 'Exhibit Visited' column, were removed or replaced with None to preserve 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
Superstar	≥ 4 visits/month, > 120 min, > $100 purchase	850	17%
General	< 4 visits/month, ≤ 120 min, ≤ $100 purchase	4150	83%

Museum visitors are divided into superstar and general visitors in Table 2, which were segmented by visit frequency, average time spent, and purchase amount. Four or more times a month, star visitors spend over 120 minutes and $100 at the museum. Highly engaged museum visitors are more likely to return and donate. 850 superstars 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	Superstar	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	Superstar	Medium	1	1	1	1	0	1	0	0	1
1005	Superstar	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 Superstar and General visitor engagement. Star 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. Optional activities like paid events and cultural product purchases like books, replicas, and digital media vary by session. This transactional structure enables personalised recommendations and visitor type-specific behaviour analysis, preparing museum marketing and product placement strategies.

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
{Superstar, 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 ranks the ten most important rule mining-discovered association rules by lift values, which indicate pattern strength and usefulness beyond random chance. These rules show how visitor behaviour affects cultural product purchases. The rule with the highest lift (2.10) shows that long-term museum visitors who visit Exhibit A are more likely to buy a book, suggesting a strong thematic or content-based link. QR code scanning increases digital media purchases (lift = 2.00), reflecting tech-savvy visitors' digital engagement. Augmented reality and digital guides are also common, indicating that immersive experiences boost purchase intent. Superstar visitors who attend paid events are more likely to buy books, indicating a greater interest in knowledge or collectibles. General visitors with short visits show patterns, especially in buying quick-access digital media, suggesting time-spent profiles can customise product recommendations. The rules show that behavioural and contextual cues can predict purchasing outcomes, allowing museums to create intelligent, behavior-driven recommendation systems and marketing strategies that reflect visitor interests and interaction pathways. These associations are statistically significant and actionable for cultural product promotion and visitor personalisation due to their high lift values across rules.

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
Superstar	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 association rule performance across two key visitor segments—Superstar and General—based on multiple metrics that measure cultural product purchase behavioural patterns' strength, consistency, and predictive power. Superstar visitors generated 145 rules, compared to 98 for General visitors, indicating a richer and more consistent set of behaviours in this highly engaged group. Superstar visitors have an average support of 0.13, suggesting more session-wide behavior-product patterns than general visitors. The average confidence of superstar visitors is 0.72, indicating that certain behaviours lead to product purchases. Superstar rules have 2.05 average lift, twice as likely behavior-product relationships as random co-occurrences, while general visitors have 1.74. Star 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 superstar rules outperform the general group. Superstars' 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 behavior-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. Weekend visitors may buy more due to leisurely exploration or group visits. Seasonal trends provide similar insights. Rules are more frequent and stronger during holidays and major exhibitions, with average confidence of 0.73 and lift of 2.08, than off seasons (confidence: 0.67, lift: 1.81). These differences show that timing and context strongly influence visitor-product relationships. For museums trying to optimize product recommendation strategies, personalize visitor experiences, and align merchandising with calendar-driven visitor behaviors, contextual moderators can strengthen or weaken behavioral patterns' predictive power.

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 (Superstar); 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% Superstar (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; Superstar segment support generally higher than General
Confidence	Derived	Max: 0.91; Avg: 0.72 (Superstar); Max: 0.82; Avg: 0.61 (General)
Lift	Derived	Max: 2.56; Avg: 2.05 (Superstar); 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

Table 7 lists this study's key variables and their data analysis results, showing how they affected pattern discovery and product recommendation. Time spent per visit and visit frequency were key behavioral differences. There were 850 Superstar (≥4/month) and 4150 General visitors. A strong behavioral split occurred, with 40% of sessions lasting over 120 minutes (Long), which correlated positively with product interest and interaction depth. Interactive data showed that Exhibit A had the highest engagement (68%), followed by Exhibit B (54%), and that 61% of sessions used digital guides, indicating strong multimedia engagement. Path Tracking revealed that 30% of visitors followed the common route A → B → C, while 24% followed A → D → E, informing rule mining sequence analysis. 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 superstar 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.

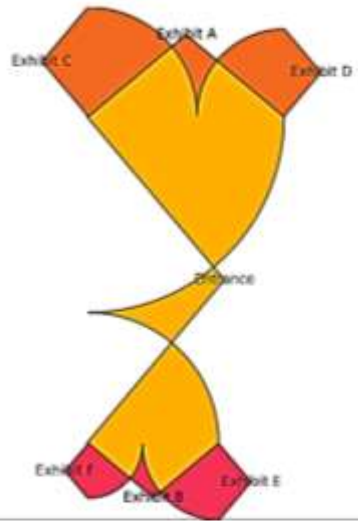

Figure 2: Visitor Journey Flow through Museum Exhibits.

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. Rule generation and segmentation logic benefit from consistent visitor behavior during high-traffic transitions. The data suggests visitors follow structured exhibit sequences, which helps the museum position interactive features, gather engagement data, and recommend products based on journey-specific behaviors.

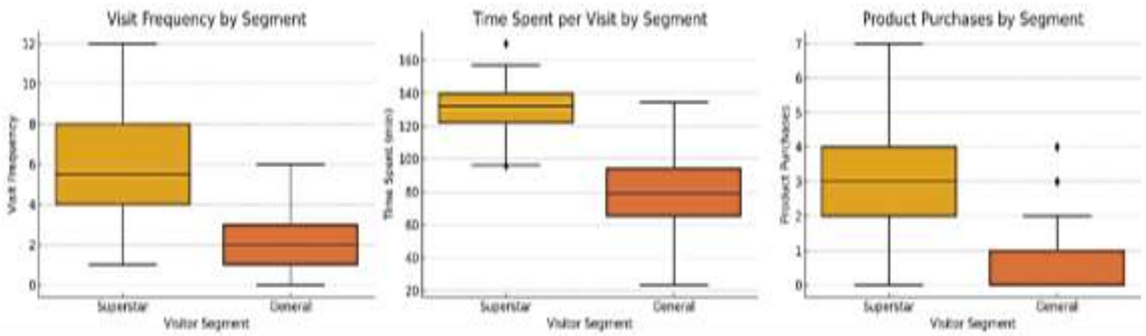

Figure 3: Distribution of Visitor Engagement Metrics by Segment.

In Figure 3, Distribution of Visitor Engagement Metrics by Segment, boxplots show significant differences in engagement intensity between superstar and general museum visitors in three critical behavioral dimensions—visit frequency, time spent per visit, and product purchases. The first plot shows that superstar visitors are more engaged, with an IQR of 4 to 9 visits and some up to 12. Most general visitors visit once or twice, indicating occasional attendance. Second, superstar visitors spend 120–150 minutes in the museum, while the middle 50% stay 120–150 minutes. A major outlier exceeds this range. The IQR ranges from 60 to 100 minutes, and some visits are as short as 20–30 minutes, reflecting more superficial or goal-specific engagement. The third plot shows that superstar visitors buy more often and in larger quantities, 2 to 5 products per session, up to 7. The flat lower whisker and outliers in the 2–3 range suggest that general visitors rarely buy more than one item and many sessions end without a purchase. These visualizations show that superstar visitors are more frequent, stay longer, and spend more, making them a key segment for museum ecosystem targeted engagement, personalized recommendations, and premium marketing.

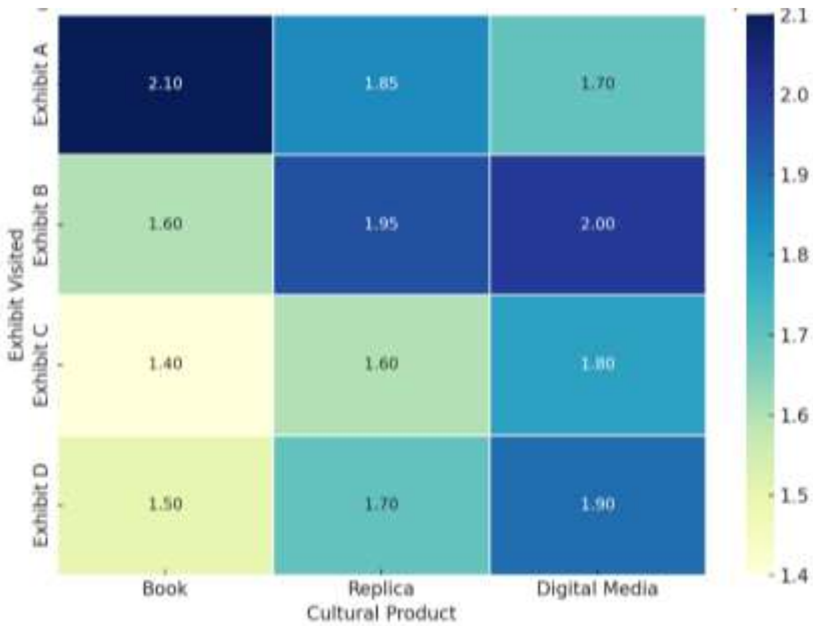

Figure 4: Exhibit Interaction vs. Product Purchase Heatmap.

Figure 4, a heatmap of exhibit interaction versus cultural product purchases, provides nuanced and actionable insights into museum visitors' behavior, particularly how exhibit engagement affects cultural product purchases. The darkest and most prominent cell—which shows the lift value of 2.10 between Exhibit A and book purchases—indicates that visitors who engage with this exhibit are more than twice as likely to buy books than random chance, indicating a highly content-rich, educational, or emotionally resonant exhibit that motivates visitors to buy literature, catalogues, or narrative-based merchandise. Interactive displays like augmented reality or digital storytelling increase the likelihood of visitors buying downloadable or interactive content, as shown by a 2.00 lift in Exhibit B. Exhibits A and B likely display visually iconic, emotionally evocative, or culturally significant objects that visitors want to own in a collectible format, as shown by the consistent but slightly lower associations between replica purchases and these exhibits (lifts of 1.85 and 1.95, respectively). This supports the idea that product appeal is tightly bound to exhibit content and presentation Due to less immersive content or weaker product theme alignment, exhibits C and D, which have moderate lift values across all product categories, may serve as transitional or supporting experiences in the museum journey. They could be redesign or repositioned to increase engagement. The heatmap shows how strategically aligned exhibit content can strongly influence consumer purchasing behavior, giving museums a data-driven foundation for exhibit layouts, visitor pathways, and behavior-based cultural product recommendation systems.

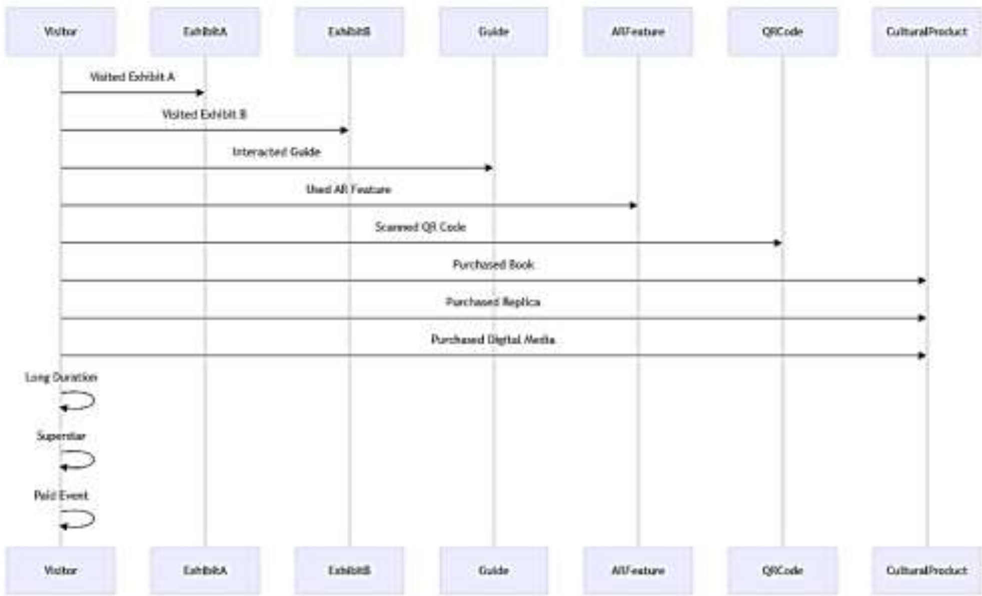

Figure 5: Association Rule Network Graph.

Figure 5 emphasizes lift-based strength, Graph, a force-directed network visualization, maps the strongest association rules between visitor behaviors and cultural product purchases in a clean, well-spaced layout The graph shows how certain behavior combinations consistently lead to certain purchases, revealing museum visitor engagement and consumption patterns. Visited Exhibit A, Scanned QR Code, Long Duration are visitor behaviors, while Purchased Book, Purchased Replica, and Purchased Digital Media are product purchases. Each edge represents a directional association rule with a thickness and label corresponding to its lift value, a statistical measure of its likelihood. 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 Superstar 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.

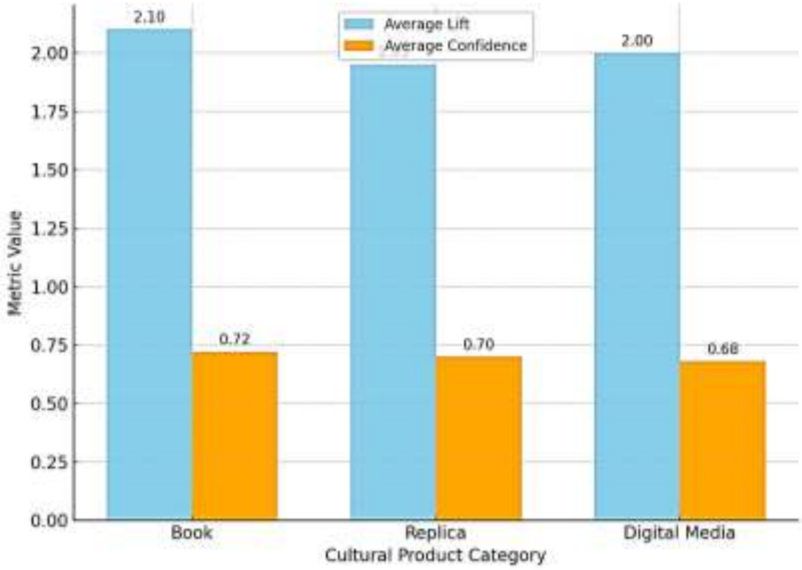

Figure 6: Product Category-wise Rule Strength.

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 has a high lift value (2.00) and a moderately strong confidence score (0.68), confirming that scanning QR codes or interacting with digital features indicate interest in downloads, AR content, or virtual souvenirs. Tech-enabled engagement predicts digital consumption, especially among younger or tech-savvy visitors. Replicas score slightly lower but still have a lift of 1.95 and confidence of 0.70, suggesting that tactile or visually appealing exhibits can boost interest in physical souvenirs. The predictive power is strong, but lower than for books, which may reflect more diverse or spontaneous replica purchases. Books are the most behaviorally predictable, followed by digital media and replicas (Figure 6), which helps design product recommendation systems that match visitor engagement patterns.

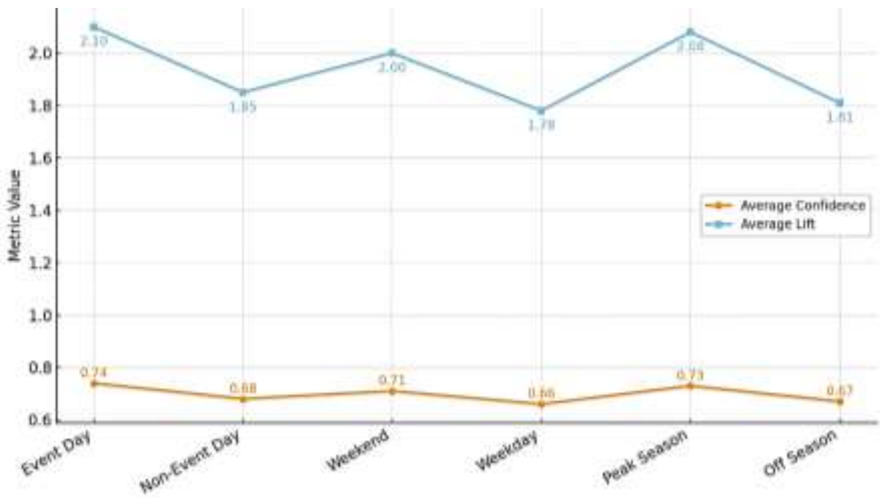

Figure 7: Moderator Impact Visualization.

Events, days of the week, and seasons affect behavioral association rule effectiveness, measured by average confidence and lift, as shown in Figure 7. This figure supports Table 6's moderation effects and shows that museum visits predict visitor behavior and product purchases differently. Event Days have the highest average lift (2.10) and confidence (0.74), indicating that special exhibitions, programs, and themed events structure, intention, and product-oriented visitor behavior. Visiting an exhibit or using a digital feature is statistically significant and behaviorally reliable for product purchases. Events boost visitor engagement and product alignment, making rule-based recommendation systems ideal. Strong rule performance (lift = 2.08, confidence = 0.73) during peak seasons, usually holidays or blockbuster exhibits, suggests museum atmosphere and attendance increase consumer consistency and predictability. Weekend visits outperform weekdays in both metrics, suggesting relaxed, social visits are better for cultural shopping and engagement than quick drop-ins. Non-Event Days, Weekdays, and Off Seasons have lower lift and confidence values, with Weekday behavior having the weakest rule strength (1.78, 0.66). Low-motivated or passive visitors may disrupt behavioral patterns and weaken product association signals. The figure shows that contextual timing moderates museum visitor behavior-product associations and that aligning product recommendations with contextual windows improves marketing precision and visitor experience personalization.

5. DISCUSSION

This study found a complex and data-rich understanding of museum visitor behavior, particularly among “superstar” 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. Star museum 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. Their actions demonstrate their value of product continuity with educational or narrative exhibit themes. This continuity enhances their cognitive and emotional museum experience. Repeat visitors are more likely to buy more culture to extend their museum visit.

This is consistent with experiential consumption, where content interaction drives visitors rather than appearance. This group wants to learn and engage by reading and using digital media for interpretation. General visitors generate foot traffic but have shorter visits, less immersive engagement, and fewer purchases, requiring different engagement strategies. These findings impact marketing and curating. Purchase triggers are found by association rule analysis. Extended stays and Exhibit A visits strongly predict book sales. Exhibitions with more narrative depth or emotional resonance can be used for education and merchandising. 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 superstar and general categories. Event-based recommendations, high-value collectibles, and exclusive items tied to exhibits superstar 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 superstar 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 tracks behavior using museum RFID, mobile app, and POS data. Quantifies, reproduces, and acts on association rules. E-commerce and collaborative filtering are common in museum recommender systems. Although effective in online retail, these methods lack interpretability and institutional alignment. This finding's rule-based approach is transparent and easy to integrate into museum operations, giving curators and marketing teams more control over recommendations and values (Huang et al., 2022). This research views museum visitors as learners and consumers, expanding audience engagement knowledge. Commercial and educational goals must be balanced in cultural product consumption, which reflects curiosity, memory-making, and cultural identity. Evidence suggests that data mining can improve learning pathways and economic outcomes, supporting a hybrid museum model with public and institutional roles. This research's critical visitor behavior analysis lays the groundwork for museum research innovation and theory. Superstar visitor insights, evidence-based recommendation logic, and contextual engagement patterns make museums smarter, more personalized, and more effective. These findings can improve curatorial goals, marketing, and digital infrastructure to make museums more welcoming, culturally relevant, and sustainable. This behavioral analytics method improves museum planning and delivery.

6. CONCLUSION

This study examined museum visitors, particularly "superstar visitors," and developed a cultural product recommendation framework using association rule mining algorithms. A structured approach that included RFID tracking, digital guide interactions, point-of-sale systems, and mobile app usage captured a multidimensional view of visitor engagement. Many data analysis findings help museums match audience behavior and optimize cultural product recommendation systems. A study found that superstar visitors behave differently and more influentially than regular visitors. These visitors come more often, stay longer, interact with more exhibits and interactive features, and buy more cultural products—especially books, replicas, and digital media. Strong association rules with high confidence and lift values behave consistently and predictably. Rules such as {Visited Exhibit A, Long Duration} ⇒ {Purchased Book} and {Scanned QR Code} ⇒ {Purchased Digital Media} show a strong link between exhibit engagement and purchase behavior, particularly among high -engagement periods.

Contextual factors moderate visitor behavior and rule strength, the study found. Event days, weekends, and peak seasons increase association rules. These findings suggest temporal and environmental factors significantly impact visitor engagement and purchase likelihood. Event-day rules had higher average confidence and lift, indicating that themed programming and special events increase interaction and consumption. This helps museums schedule product promotions, digital engagement, and recommendation systems for high-engagement periods. This novel study analyzes museum superstar visitor behavior using association rule mining. In retail, e-commerce, and customer segmentation, rule mining is common, but museology is not. This study shows how association rule mining can explain how cultural institution visitors affect product preferences. Using binary and transactional data—exhibit visits, time spent, AR feature use, and product purchases—Apriori and FP-Growth algorithms generated meaningful and interpretable rules. These rules match statistical associations and museum visitor behaviors like how educational content influences book purchases or technology drives digital media interest.

This method improves cultural analytics and visitor experience design. Data mining in museum research links cultural theory and computational analysis. Museums can use real-time behavioral data for strategic exhibit design, merchandising, and personalized experiences. Beyond visitor surveys and observational studies, visitor segmentation, contextual moderators, and behavioral rules offer a holistic approach. It structures and scales behavior measurements for more accurate insights and dynamic interventions. The research continues the digital humanities and museology trend toward evidence-based personalization. Cultural institutions must personalize visitor experiences to stay relevant and profitable. This research shows that visitors' data can segment audiences and power cultural product recommendation systems based on prior engagement. The study suggests targeting superstars—those most likely to return, engage deeply, and buy—with high-impact personalization for educational and economic returns.

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. Future research should apply the analytical framework to multiple museums or exhibition types for generalizability and robustness. Comparative studies across cultures, museum sizes, and exhibit themes may reveal universal visitor engagement and product interaction patterns, making the cultural sector model more scalable and adaptable. Future research can improve data science and visitor-centered museology for inclusive and innovative museum experiences.

8. IMPLICATIONS

This study affects museum operations, cultural product strategy, academic research, and digital innovation. Museum management can develop long-term loyalty and revenue growth strategies by identifying and analyzing high-engagement visitor behavior. Actionable behavioral insights can help management customize offerings instead of generalized programming. By offering tiered membership models, exclusive experiences, or loyalty-based rewards to highly engaged visitors, institutions can retain and incentivize their most valuable audiences. This change enhances museum-patron relations and resource allocation. The findings suggest cultural product development should shift from intuition-driven merchandising to data-driven visitor interactions. Product teams can create or curate thematic books, limited-edition replicas of high-traffic installations, or digital media for tech-interactive experiences based on visitor engagement. Museums can reduce inventory risk, increase gift shop and online store conversion rates, and create cultural extensions by using behavioral trends to develop products.

Researchers can replicate and scale cultural behavior-driven analysis with this study. Association rule mining, segmentation, and contextual moderation provide a template for other institutions and audience datasets. It explains how to structure, process, and interpret transactional and engagement data for deeper insights. Interdisciplinary projects can involve data scientists, curators, digital humanists, and experience designers. Building technically sound predictive systems that meet cultural institutions' interpretive goals begins with this. This suggests that data-driven decision-making can boost visitor satisfaction, curatorial relevance, and institutional sustainability in personalized cultural landscapes.

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