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Redefining Library Spaces: The Role of Smart Libraries in Enhancing User Experience

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***Abstract* - Purpose: Research aims to transform traditional libraries into intelligent, data-driven smart libraries capable of adapting to user needs in real time. It addresses the limitations of existing feature selection methods in handling high-dimensional data and evaluating user experiences accurately and at scale. Methodology: A novel framework combining Enhanced Binary Particle Swarm Optimization (EBPS) with Adaptive Extreme Gradient Boosting (Adaptive-XGBoost) was proposed. Data were collected through sensor-based interactions, smart application usage logs, and structured user surveys. Preprocessing steps included normalization, missing value imputation, and one-hot encoding to ensure feature quality. EBPS was employed to optimize feature selection, improving the Adaptive-XGBoost model's predictive performance. All phases of data processing, model construction, and evaluation were carried out using Python. Results: The EBPS-Adaptive-XG Boost model achieved superior user interaction rates compared to XGBoost and Adaptive-XGBoost individually with touchscreen interaction increasing to 89.3%, recommendation usage to 91.0%, study area utilization to 93.7%, and book check-in/out frequency to 96.4%. Navigation assistance requests also improved to 87.5%. Sensor-based evaluations showed notable accuracy gains across RFID (89.2%), BLE beacons (90.1%), touchscreen sensors (91.6%), PIR motion sensors (90.7%), and Temp, Humidity, Light Sensors (88.8%), with multi-sensor fusion achieving 94.4% accuracy. Conclusions: The proposed model effectively supports continuous evaluation and improvement of smart library services. It offers a scalable, intelligent solution for real-time user experience assessment and data-driven decision-making in next-generation library environments.**

***Keywords:* Enhanced Binary Particle Swarm with Extreme Gradient Boosting (EBPS-Adaptive-XG Boost), Smart Libraries Services, User Experience, User Satisfaction Levels, Engagement**

I. INTRODUCTION

The rapid growth of digital technology has fundamentally altered libraries' role in society from static collections of information to a dynamic and more engaged space where patrons can interact within a culture of inquiry (Kumar, 2025). Smart libraries that incorporate intelligent technology and live data analytics seek a more customized experience for customers by providing personalized services, adjusted interactions, and improved accessibility (Yaseen & Gul, 2025; Yang & Singh, 2024). However, there are several challenges in developing such environments, particularly in managing high-dimensional user data and accurately gauging product satisfaction in complex, sensor-rich surroundings (Kotis et al., 2025). Traditional feature selection techniques often lead to inefficiencies that affect model performance when applied to large and varied datasets (Aslam et al., 2025). The conventional ways of measuring user experience, relying primarily on static surveys and subjective, manual feedback, do not have the accuracy, scalability, or responsiveness of future-oriented smart library systems, which reflect interconnections through responsive types of dialogue (Ayyaswamy, 2025). The methods that can appropriately select features and measure satisfaction in real time need to break the limitations of these conventional methods. With intelligent environments of multiple data sources (conversations with sensors, usage logs of smart applications, structured surveys), there is increasing pressure for systems to interact with processing data and providing reliable and meaningful outputs (Meena et al., 2025). Additionally, modern library systems increasingly operate in a world where the ability to adapt dynamically based on predictive models of user behaviour and satisfaction is becoming central to quality of service (Reji, 2025; Baggyalakshmi et al., 2023). Recent developments in machine learning in particular, the use of ensemble methods and optimization of algorithms afford exciting avenues to address these challenges. An efficient feature selection process and sound predictive modeling approach is important to guarantee the continued enhancement of service offerings and improvement of user experiences within smart library frameworks (Kaba et al., 2025). Various smarter services have been suggested. These include automated check-in/check-out platforms, adaptable user interfaces, and real-time suggestions/links to actual courses, which are all viewed as offering significant potential for enhancing consumer engagement, satisfaction, and operational efficiency (Wang et al, 2025; Agina-Obu & Oyinkepreye Evelyn, 2023). This research intends to create a generalized approach using Enhanced Binary Particle Swarm Optimization and Adaptive-XGBoost (EBPS-Adaptive-XGBoost Model) to effectively optimize the feature selection and predict user satisfaction, hence facilitating user experience assessment in smart library contexts (Komisarek et al., 2022; Mahmoudi & Lailypour, 2015).

A. Key Contributions

- Min-Max Normalization standardizes the data environment and user-related data through consistent scaling across features to improve the prediction power of smart library algorithms and improve teaching effect.
- Missing Value Imputation repairs incomplete user engagement records, preserving valid information and important processes that are necessary to assess and improve customers' experiences in digital libraries.
- One-Hot encoding converts categorical service attributes into binary vectors, allowing for accurate and comprehensible customer preference modeling to provide customized services in intelligent library settings.
- EBPS-Adaptive-XGBoost Model combines enhanced EBPS-Adaptive-XGBoost to optimize feature selection and advance satisfaction estimate, enabling real-time, smart redefinition of library spaces.

The remainder of this research is organized as follows: Section II reviews related work relevant to smart libraries and feature selection techniques. Section III describes the proposed methodology, including data preprocessing, EBPS-based feature selection, and model development. Section IV presents the experimental results. Section V presented the discussion. Section VI concludes the research and suggests directions for future work.

II. Related Work

Meesad & Mingkhwan, 2024 examined how User Experience (UX) has changed in libraries, emphasizing the value of data analysis, accessibility, engagement in design, and tailored services. It showcased effective user engagement strategies, such as augmented reality and community-driven projects. Future developments in library UX, including data-driven customization, AI, and mobile-first design, were also covered in this chapter. Libraries are being transformed into intellectual hubs by Machine Learning (ML) and Artificial Intelligence (AI). These technologies streamline processes, improve library operations, and customize user experiences. However, issues like resource allocation and moral dilemmas continue to exist for (Naikar & Paul, 2025). Future connections, such as IoT, analytics of large amounts of data, and augmented reality, were projected to significantly improve library capabilities. (Wogu et al., 2024) presented that smart libraries were revolutionizing library operations through the integration of cloud-based computing, big data analytics, Internet of Things (IoT), and AI. These cutting-edge locations offer easy access to electronic materials, encouraging diversity and distance learning. Additionally, they provide interactive experiences via AR and VR, encouraging digital literacy, innovation, and intellectual curiosity. (Adewojo et al., 2025) look at how AI was used in Nigerian libraries and emphasize how it might help with knowledge organization. It suggested strategic methods for integrating AI successfully, such as gradual adoption, cooperative alliances, and ability building. The results demonstrate how AI has a chance to revolutionize library services. (Ramesh, 2024) suggested that educational library services are being revolutionized by intelligent collection applications, which offer improved accessibility, individualized experiences, and effective resource management. By combining technologies like ML, AI, the IoT, and data analytics, these apps let users access resources, work together, and get individualized learning help.

(Wei & Lee, 2025) noted that intelligent library systems were adapting to local needs by integrating technology like maker spaces, self-checkout services, and sophisticated video and audio editing. Many libraries assist a variety of populations, promote digital competence and continuing education, and were essential to the thriving neighborhoods found in many smart cities. (Meesad & Mingkhwan, 2024) examined and emphasized how universities were using AI, VR, and Mixed Reality (MR) methods for better user engagement, accessibility, and services. These technologies facilitate data-driven tailoring, enhance collection management, and produce immersive classrooms. Innovation and fundamental library ideals must be balanced. Lu & An (2025) suggested that the fast development of smart libraries can be attributed to technical progress. These libraries were altering their service models, technology frameworks, and management strategies. 5G technological swift growth has created problems with the safety of data, network infrastructure development, funding, and governmental support (Muralidharan, 2024). The research examined how 5G technology would affect university libraries and makes recommendations for further research (Kulkarni & Dhanamjaya, 2017).

Visnudharshana & Kishore, 2024 investigated AI-powered language improvement techniques for libraries with an emphasis on English. Its goal was to improve information access and user experience by creating intelligent computational language systems, language processing applications, and user-centered techniques. Additionally, the project investigated adaptable interfaces, tailored content recommendations, and artificial intelligence-powered systems for recommending material. (Mammadov & Kucukkulahli, 2025) propose an IoT-based smart library system that integrates real-time sensor data, occupancy tracking, and user feedback to optimize research environments. By combining ML with both subjective and objective inputs, the system enhances resource allocation and user experience. The model also offers potential adaptability to other smart workspaces beyond libraries.

III. METHODOLOGY OVERVIEW

To enhance user experience evaluation in smart libraries, the proposed methodology employs data preprocessing techniques, including normalization, missing value imputation, and one-hot encoding. EBPS is applied for optimized feature selection. The refined features are utilized to train a predictive model, enhancing user experience evaluation and service optimization within smart library environments. Fig. 1 presents the methodology flow of the research.

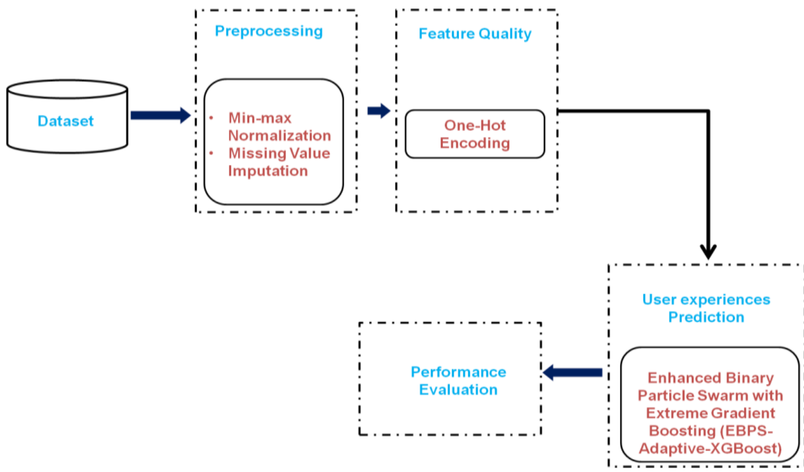

Fig.1 Methodology Flow

A. *Data collection*

The Smart Library User Interaction Dataset collected from Kaggle source (https://www.kaggle.com/datasets/ziya07/smartlibraryux-dataset/data) records real-time user interaction of 1000 users in a next-generation library space. The data includes RFID transactions, motion tracking, touch interactions, app interactions, and satisfaction ratings. The data captures user characteristics such as duration of visit, physical books borrowed, use of digital resources, sensor interactions, app logins, real-time most used recommendations, and user satisfaction between 1 and 10. The datasets can be used to support Machine Learning tasks, such as user analysis that encourages library services and understands satisfaction levels, implements smarter personalized library experiences, and increases library management with data-driven evidence.

B. *Data Preprocessing*

The data preparation effort process included the normalization of variables and imputation of missing data to deal with inconsistencies and missing data in the observations from the sensor-based interactions, the smart application records, and the structured surveys to create high-quality, trustworthy data inputs for analysis.

1. *Missing Value Imputation*

To improve the dataset's completeness and quality, missing value imputation was performed. Missing values in the dataset occurred due to sensor failures or user inactivity in cases of sensor-based data collection, and limited or incomplete responses in instances of structured, user journal-based data collection. An examination was performed initially to assess patterns in the missing data and to apply an appropriate level of handling to mitigate bias. For numerical features, the missing values were filled with the mean of the available data for that feature to maintain an overall distribution. For categorical features, the most frequently occurring category was used to replace the missing values to ensure that the categorical distribution was preserved. This two-faceted imputation strategy was chosen for its relative ease of use and effectiveness in maintaining the structural integrity of the dataset. The imputation handling of the information retained was balanced to provide the analysis and modelling phase to withstand further degradation of the underlying significance of the data.

2. Data Normalization

Data was processed as a necessary step of preprocessing to develop a standardized and comparable dataset. The different sources of data caused a large amount of variation in the scale and unit of the features collected. The sources of data included the interactions provided by sensors, usage logs from smart applications, and structured user surveys. Min-Max normalization enabled the model to avoid dominance effects between features while allowing distance-based and optimization algorithms to function correctly. The data transformation through Min-Max normalization produces values in the range of [0, 1], which maintains original data correlations. The normalization of a feature x is defined by the following Equation (1):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where x signifies the unique feature value, x_{min} and x_{max} denote the smallest and maximum values of feature x within the dataset and x' is the normalized value. Through the scaling process, it is ensured that every input features or attribute contributes equally to the analysis stage that comes next. Normalization provides standardized data ranges that may help reduce bias, create a more efficient model, and support the stability of later machine learning workflow tasks.

3. Feature Quality using the one-hot encoding

To ensure uniformity and quality of feature sets when employing heterogeneous data sources, it used one-hot encoding for categorical variables. It had categorical features from sensor-mediated interaction data, smart application usage data, and structured user survey data, such as device type, service type, and categories of user feedback. One-hot encoding transformed each categorical attribute into a set of binary attributes, separating each category as an attribute by itself. This transformation removed any type of ordering between categories, either implicit or explicit, while simplifying the analysis of the data by machine learning algorithms to a binary scale. It also retained categorical data's non-hierarchical structure, which improved the feature space's integrity. A crucial element in lowering model bias, raising forecasting aggregation precision, and improving feature uniformity was one-hot encoding. This stage was critical to ensuring that the converted features accurately reflected the original data attributes, allowing for strong and trustworthy model creation in subsequent phases.

C. Enhanced Binary Particle Swarm with Extreme Gradient Boosting (EBPS-Adaptive-XGBoost) model to assess and enhance user experiences in smart libraries.

The user experience is evaluated in smart libraries by integrating EBPS -Adaptive-XGBoost. The system intelligently analyzes user interactions, service efficiency, and satisfaction levels by optimizing feature selection and improving model precision. EBPS enhances the search for the most relevant features, while Adaptive-XGBoost ensures robust, real-time predictive performance. Together, they enable smart libraries to make instant, data-driven decisions, offering highly customized, flexible, and engaging services. This framework supports next-generation library environments by continuously adapting to user behavior patterns, ultimately leading to improved user satisfaction and service personalization.

1. Extreme Gradient Boosting (XG Boost)

XG Boost is a scalable, efficient implementation of gradient boosting algorithms that is well-known for its performance, particularly on structured data modeling tasks. The main idea is to sequentially build an ensemble of decision trees, where each new tree is built to correct the residual errors from previous trees. By employing both first-order and second-order gradients for optimizing a distinguishable loss function, the approach improves model accuracy and convergence speed. For improved generality and to avoid overfitting, reinstatement strategies like the first and second penalties are used. Furthermore, XGBoost has additional features such as sparsity-aware learning, proportional quantile sketching, and complemented tree construction, making it ideal for large-scale datasets. Despite its capabilities, regular XGBoost has limits in highly dynamic contexts, particularly in adjusting to real-time modifications to user behavior or fast-changing datasets, necessitating additional model upgrades.

2. Adaptive Extreme Gradient Boosting (XGBoost) Enhances Prediction Accuracy for Dynamic Smart Library Environments

To address the issues of standard XGBoost in dynamic contexts, the approach of Adaptive- XGBoost is proposed. Adaptive XGBoost takes the traditional framework and adds components that assist the model in adjusting to time-based changes in data distribution and user behavior. While traditional XGBoost learns on static training datasets, Adaptive XGBoost uses a continuous learning process to alter the training dataset with every new piece of incoming data. It adjusts hyperparameters on the fly, selectively retrains parts of the model, and implements adaptive weighting strategies to emphasize more recent or more contextually relevant data instances. These adaptations help the model sustain predictive accuracy and robustness in even non-stationary, changing settings. Adaptive-XGBoost improves responsiveness to model changes to data, mitigates prediction drift, and maintains performance over time. Accordingly, Adaptive-XGBoost is particularly appropriate for smart library use cases in which users are constantly reacting and adapting their interactions to the system states. XGBoost is a boosted tree model that combines multiple decision trees into an effective classifier. It enhances the classic Gradient Boosting Decision Tree (GBDT) by optimizing optimization using a second-order Taylor expansion of the loss function. An Adaptive XGBoost model continuously refines itself using real-time user interaction data from smart libraries, enabling more accurate predictions and personalized service recommendation. By modifying feature priority and model parameters, adaptive methods improve responsiveness to changing user actions, decrease overfitting, and increase prediction accuracy. Given s samples and o features, the smart library dataset $C = \{(w_j, z_j)\}(|C| = s, w_j \in Q, z_j \in Q)$is modeled. The final prediction $\hat{z}_j$for each sample is generated by aggregating K regression trees using Equation (2 and 3).

$$\hat{z}_j = \phi(w_j) = \sum_{l=1}^{L} e_l\left(w_j\right) \tag{2}$$

$$Obj = \sum_j k(z_j, \hat{z}_j) + \sum_l \Omega(g_l) \tag{3}$$

Among them, the loss function measuring the difference between actual and predicted user experience scores, $\sum_l \Omega(g_l)$represents the regularization term to control model complexity, z_j is the actual user experience score, and $\hat{z}_j$is the predicted user experience score, as determined using Equations (4-8).

$$\hat{z}_j^{(0)} = 0 \ , \hat{z}_j^{(1)} = e_1(w_j) = \hat{z}_j^{(0)} + e_1(w_j) \ , \hat{z}_j^{(2)} = e_1(w_j) = e_2(w_j) = \hat{z}_j^{(1)} + e_2(w_j) \ , \hat{z}_j^{(s)} = \sum_{l=1}^{s} e_w(w_j) = \hat{z}_j^{(s-1)} + e_s(w_j) \tag{4}$$

$$Obj^{(s)} = \sum_{j=1}^{t} k\left(z_j, \hat{z}_j^{(s-1)} + e_s(w_j)\right) + \Omega(e_l) + constant \tag{5}$$

$$Obj^{(s)} \cong \sum_{j=1}^{t}\left[h_j e_s(w_j) + \frac{1}{2} g_j e_s^2(w_j)\right] + \Omega(e_l) \tag{6}$$

$$= \sum_{j=1}^{t}\left[h_j \theta_{r(w)} + \frac{1}{2} g_j \theta_{r(w)}^2\right] + \gamma S + \frac{1}{2}\lambda\|\omega_i\|^2 \tag{7}$$

$$= \sum_{i=1}^{S}\left[\left(\sum_{j\in J_i} h_j\right)\theta_i + \frac{1}{2}\left(\sum_{j\in J_i} h_j + \lambda\right) f_i^2\right] + \gamma S \tag{8}$$

Especially in (8), $g_j = \partial_{\hat{z}_j^{(s-1)}} k(z_j, \hat{z}_j^{(s-1)}), g_j = \partial^2 \hat{z}_j^{(s-1)} k(z_j, \hat{z}_j^{(s-1)})$. Define $H_j = \sum_{j\in i_i} h_j \, , G_i = \sum_{j\in J_i} g_i$ and substitute into (7), then equation (9) can be simplified as:

$$Obj^{(s)} = \sum_{i=1}^{S}\left[H_j \theta_i + \frac{1}{2}(G_j + \lambda)\theta_i^2\right] + \gamma S \tag{9}$$

In Equations (10 and 11), the leaf node θ_i is an uncertain value. Therefore, the objective function $Obj^{(s)}$seeks the first derivative for θ_i and the optimal value $\theta_i^*$of leaf node i can be solved.

$$\theta_i^* = -\frac{H_j}{G_j + \lambda} \tag{10}$$

$$Obj^{(s)} = -\frac{1}{2}\sum_{i=1}^{S}\frac{H_j}{G_j + \lambda} + \gamma S \tag{11}$$

3. *Feature Selection withEnhanced Binary Particle Swarm Optimization (EBPSO)*

The EBPS algorithm is used to accomplish and optimize feature selection for innovative library datasets. By imitating the social character of particles in a binary search space, EBPS can exploit and explore the feature space for the best attributes. The main goal is to select an ideal feature set to achieve the best predictive performance from the Adaptive-XGBoost classifier while delivering the lowest computational cost. This assures that the model is efficient and accurate, removing redundancy, limiting overfitting, and refining the generalization ability of the system. EBPS-based feature selection framework for innovative library datasets, the position of the jth particle is represented as $w_j = (w_{i1}, w_{i2}, \dots, w_{iC})$, where each dimension corresponds to a specific feature. The velocity of the jth particle is expressed as $u_j = (u_{i1}, u_{i2}, \dots, u_{iC})$. Governing the rate of positional change, positions and velocities are constrained $[W_{min}, W_{max}]^C$ and $[U_{min}, U_{max}]^C$ respectively, to ensure stability during the search process. The best historical position discovered by an individual particle is denoted as $o_j = (o_{i1}, o_{i2}, \dots, o_{iC})$ called $best$, while the best position among all particles is identified as the global best $h = (h_1, h_2, \dots, h_C)$ referred to as $hbest$. The particles iteratively update their velocities and positions based on both $obest$ and $hbest$ to identify optimal feature subsets, and EBPSO performance for smart library user experience analysis (Equations 12-5).

$$u_{id}^{new} = x \times u_{id}^{old} + d_1 \times q_1 \times \left(obest_{id} - w_{id}^{old}\right) + d_2 \times q_2 \times \left(obest_c - w_{id}^{old}\right) \tag{12}$$

$$\text{If } u_{id}^{new} \notin (U_{min}, U_{max}) u_{id}^{new} = \max(\min(U_{max}, u_{id}^{new}), U_{min}) \tag{13}$$

$$T(u_{id}^{new}) = \frac{1}{1 + f^{-u_{id}^{new}}} \tag{14}$$

$$\text{If } \left(q_3 < T(u_{id}^{new})\right) \quad \text{then} \quad w_{id}^{new} = 1 \qquad \text{else} \quad w_{id}^{new} = 0 \tag{15}$$

In EBPS-based feature selection framework for smart library datasets, x denotes the inertia weight, which controls the influence of a particle's previous velocity on its current movement. The variables q_1, q_2, and q_3 are random numbers uniformly distributed between (0, 1), while d_1 and d_2 represent acceleration constants that determine how aggressively a particle explores the search space during each iteration. The velocities u_{id}^{new} and u_{id}^{old} correspond to the updated and previous velocities of the particle, respectively. Similarly, w_{id}^{o} is the current particle position, which is the updated position after velocity adjustment. Particle velocities are confined within $U_{max}$to ensure stability and prevent divergence. The updated position is determined using the transfer function $T(u_{id}^{new})$; if $T(u_{id}^{new})$ exceeds q_3, the position is set to 1, otherwise 0, leading to the identification of the most relevant feature subset using user_*idvisit_durationbooks_borroweddigital_resource_usagesensor_interactionsapp_loginsreal_time_recommendations_useduser_satisfaction".* Pseudo code 1 presented the EBPS -Adaptive-XG Boost.

Pseudo code 1: EBPS -Adaptive-XGBoost

Input: Smart Library Dataset $C = \{(w_j, z_j)\}$, *parameters for EBPS and Adaptive-XGBoost*
Output: Optimized Feature Subset, Trained Adaptive-XGBoost Model
1. Initialize EBPS parameters:
- *Number of particles, inertia weight* (x), *acceleration constants* $(d1, d2)$
- *Velocity bounds* $[U_{min}]$, *Position bounds* $[W_{min}, W_{max}]$

2. Initialize each particle:
- *Random position* w_j *and velocity* u_j
- *Evaluate fitness: Train base XGBoost on selected features, compute prediction accuracy*

3. Repeat until the stopping criterion is met (e.g., max iterations or convergence):
For each particle:
a. Update velocity:
$u_{id}^{new} = x \times u_{id}^{old} + d_1 \times q_1 \times (obest_{id} - w_{id}^{old}) + d_2 \times q_2 \times (obest_c - w_{id}^{old})$ *Clip velocity within* $[U_{min}, U_{max}]$
b. Update position:
Compute transfer function $T(u_{id}^{new}) = \frac{1}{1+f^{-u_{id}^{new}}}$
If $randomq_3 < T(u_{id}^{new})$, *set* $w_{id}^{new} = 1$ *else* $w_{id}^{new} = 0$
c. Evaluate new fitness:
Train base XGBoost on updated selected features
Compute prediction accuracy
d. Update personal best $(obest)$ *and global best* $(hbest)$
4. Output optimal feature subset based on $hbest$.
5. Train Adaptive-XGBoost using the selected features:
- *Initialize Adaptive-XGBoost model parameters*
- *While new user data streams in:*
a. Update the model incrementally with new data
b. Adjust hyperparameters dynamically
c. Reweight recent data instances
d. Selectively retrain trees or model components

6. Monitor performance and adapt continuously to real-time data.
Return: Final optimized feature set and real-time updated Adaptive-XGBoost model.

IV. Results

The experimental setup utilized an Intel Core i7 processor with 16 GB RAM, running on Windows 10. Python 3.9 with Scikit-learn, XGBoost, and custom EBPS implementations were used for model development and evaluation. The smart library datasets that are selected utilize various performance metrics to examine the effectiveness of the feature selection and classification process. Comparative analyses are undertaken to showcase the ability of the process to improve user experience enhancement, efficiency of systems, and overall predictive performance in smart library settings. The relationship matrix among sensor features and user satisfaction in the smart library setting is illustrated in Fig. 2. The low individual correlation values reflect the weak linear relationship between single sensor inputs and satisfaction scores. This reinforces the originally proposed method, integrating multi-sensor fusion and the Adaptive XGBoost model, which effectively captures the non-linear and interdependent nature of features to improve predictive performance.

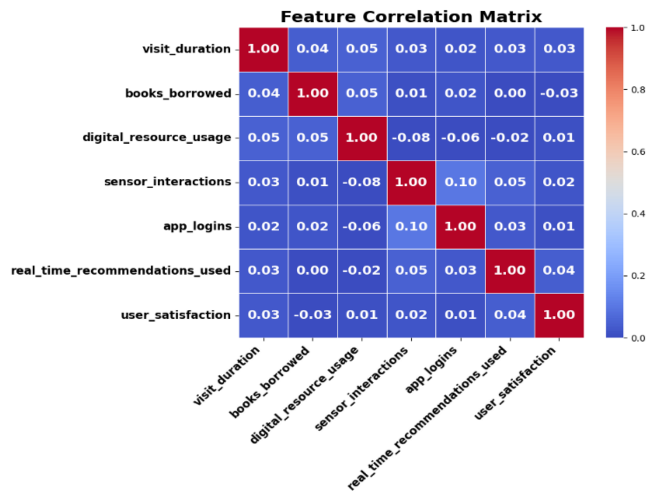

Fig. 2 Correlation Matrix of Smart Library Sensor Features

Fig. 3 presents the confusion matrix for the prediction of usage in the real-time recommendation scenario. The proposed Adaptive XGBoost model made a correct classification of about 90 cases of actual usage. This suggests that it is effective for predictive user engagement in smart library systems. Moreover, the model's ability to mitigate false negatives improves intelligent service delivery consistently to enhance sensor-based user experience.

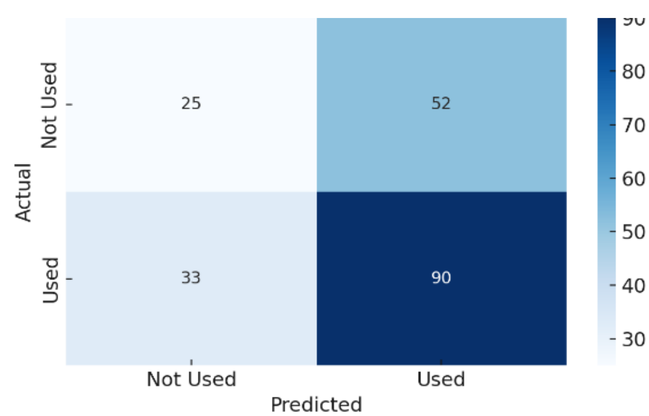

Fig. 3 Confusion Matrix

Fig. 4 demonstrates that users with real-time recommendations reported a more satisfying experience (average score of ~2.60) than users without recommendations (~2.48). This finding supports the research question of whether adaptive recommendation systems can improve user satisfaction in smart libraries with the use of an EBPS-Adaptive XGBoost-driven decision-making system. Fig.4 demonstrates user log activity across 20 sessions, where user engagement varies substantially. A summary of average user scores from the active sessions is included throughout the two weeks, and the highlighted varying scores show user engagement is not consistent. The data are used in this research to introduce a need for adaptive prediction models (EBPS-Adaptive XGBoost) to describe improved user engagement through personalization with intelligent environments in a library context.

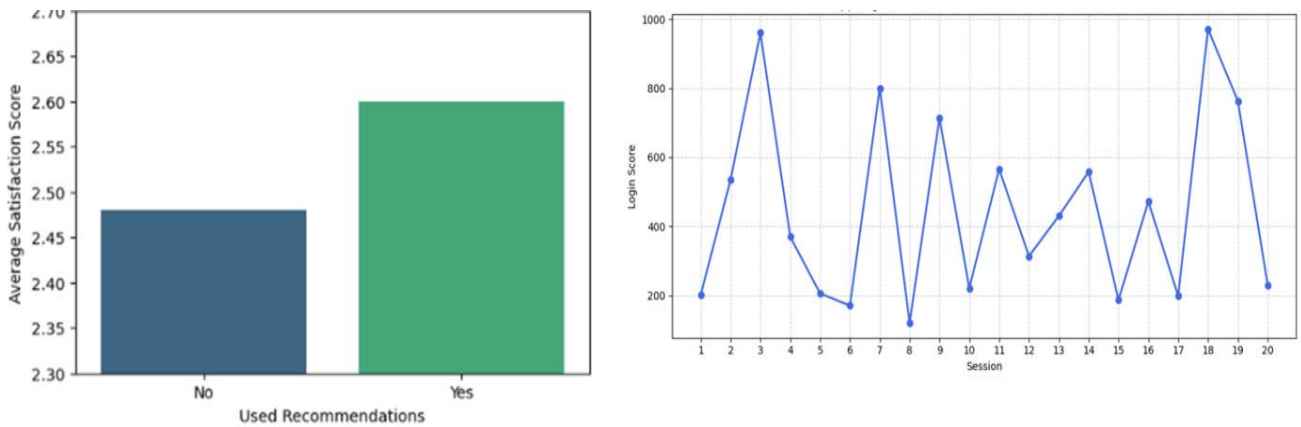

Fig.4 Comparison of User Interaction (a) User Satisfaction, (b) Login Score

Table I presents a comparison of user engagement metrics for the different models. The proposed approach resulted in higher rates of touchscreen interaction, recommendation usage, study area usage, books checked-in and checked-out, and requests for navigation help, indicating a better user experience in smart library settings. The performance trend is illustrated in Fig.5.

TABLE I COMPARISON OF USER INTERACTION METRICS FOR DIFFERENT MODELS IN SMART LIBRARY SYSTEMS

Metric	XGBoost	Adaptive XGBoost	EBPS-Adaptive XGBoost (Proposed)
Touchscreen Interaction Rate (TIR)	81.7%	85.1%	89.3%
Recommendation Usage Rate (RUR)	84.2%	87.3%	91.0%
Study Area Utilization (SAU)	87.1%	90.5%	93.7%
Book Check-in/out Frequency (C-I/O)	91.5%	94.2%	96.4%
Navigation Assistance Requests (NAR)	79.6%	83.3%	87.5%

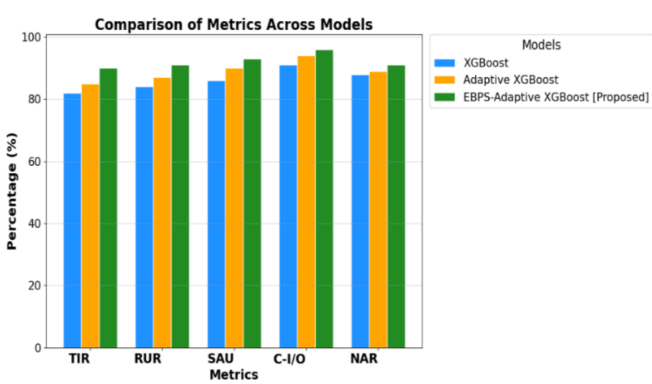

Fig.5 Comparison of matrix across the model

The performance assessment of different sensor features across models is compared in Table II. The results suggest that the proposed feature had better performance in check-in/check-out activity, navigation assistance, touchscreen activity, study area occupancy, and environmental conditions, which demonstrates the usage of sensor data in smart libraries was effective. The relative performance of each sensor is demonstrated in the accompanying Fig. 6.

TABLE II PERFORMANCE EVALUATION OF SENSOR FEATURES ACROSS DIFFERENT MODELS IN SMART LIBRARY SYSTEMS

Sensor Feature	Sensor Type	XGBoost	Adaptive XGBoost	EBPS-Adaptive XGBoost (Proposed)
Check-in/Check-out Activity (C-I/C-O)	RFID Sensors	76.2	84.3	89.2
Navigation Assistance (NA)	BLE Beacons	77.4	85.5	90.1
Touchscreen Interactions (TI)	Touch Sensors	78.1	87.1	91.6
Study Area Occupancy (SAO)	PIR Motion Sensors	77.0	86.2	90.7
Environmental Conditions (EC)	Temp, Humidity, Light Sensors	74.5	84.0	88.8
All Sensor Inputs Combined (ASIP)	Multi-sensor Fusion	82.0	90.5	94.4

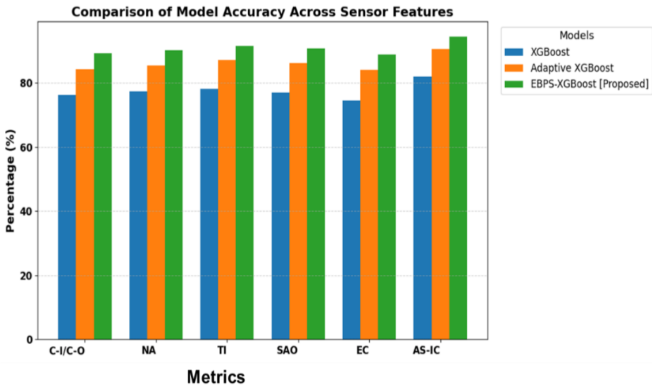

Fig. 6 Comparison of Model Accuracy across Sensor Features

V. DISCUSSION

The superior performance of the EBPS-Adaptive-XGBoost model in enhancing user engagement and predictive accuracy within smart library systems, by integrating multi-sensor fusion, the model effectively captures non-linear and interdependent patterns, outperforming XGBoost and Adaptive XGBoost across all evaluated metrics. Improvements in touchscreen interaction (89.3%), recommendation usage (91.0%), and sensor accuracy (up to 94.4%) demonstrate the model's robustness. The low individual feature correlations and improved confusion matrix classification affirm the value of combining sensor inputs for richer insights. Overall, the proposed approach supports adaptive, personalized service delivery to boost satisfaction and system efficiency.

VI. CONCLUSION

The library spaces are redefined by improving the user experience through smart technologies. The proposed system improves user engagement and interaction in smart library environments using optimized feature selection based on the EBPS algorithm and advanced predictive modeling. The EBPS-Adaptive-XGBoost model outperformed XGBoost and Adaptive-XGBoost, achieving up to 96.4% in user interaction metrics and 94.4% accuracy in multi-sensor fusion. Key improvements were seen in touchscreen (89.3%), recommendations (91.0%), RFID (89.2%), and BLE (90.1%) performance. Experimental results show improved performance in touchscreen interaction, recommendation usage, study area usage, book circulation, and navigation support. Moreover, multi-sensor fusion is adept at capturing user behaviors that are very complex and responsive. Overall, this method provides a means of establishing a clever framework for intelligent user-directed smart libraries. Overall, the proposed method has clear advantages over the previous discussions in creating more adaptive and effective learning spaces.

Limitation and future scope: The main emphasis is related to specific smart library capabilities and a smaller number of sensors. In the meantime, future research should focus on broader environmental contexts, embedding IoTs, and the usage of deep learning models to develop personalization. Real-time adaptive services enhance the user experience in the next generation of the smart library.

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