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Development of Digital Twins for Library Information System Simulation

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***Abstract* - The creation of digital twins for Library Information Systems (LIS) simulation models provides new insights into the automation, management, efficiency, and user experience of modern-day libraries. A digital twin captures metrics from its real-world counterpart in real time, enabling analysis, monitoring, and optimization. The research is focused on LIS digital twin designs and implementations within the context of IoT, data analytics, and machine learning. Digital twins can simulate user behavior, resource usage, and subsystem interactions, offering great potential to enhance cataloging, circulation, space management, and personal service delivery, thereby augmenting advanced services. The research presents a schema that corresponds to the tangible assets within the library, including books and users, along with the infrastructure for their virtual representations. This enables predictive maintenance of the assets, automated inventory monitoring, and scenario testing. The development supports changing interface elements and user-operated control recommendation systems based on real-time usage data. Initial simulation results suggest improvements in library service delivery and decision-making capabilities within the library ecosystem. This paper addresses major concerns in data harmonization, vulnerability, privacy, and strategies for achieving effective twin deployment. The findings explain how the application of the digital twin disrupts library systems to provide responsive and user-centered information services.**

***Keywords:* Digital Twins, Library Information System (LIS), Simulation, System Modeling, Data Analytics, IoT Integration, Smart Libraries**

I. INTRODUCTION

A digital twin is defined as a virtual representation of an object, system, or process that is simultaneously being updated in real-time. Since their initial development in the manufacturing and aerospace sectors, digital twins have evolved to utilize data from the physical environments in which they reside. This data is collected through sensors, IoT devices, and software analytics to monitor, simulate, and optimize systems (Tao et al., 2018; Mohammed et al., 2023). It now has a feedback loop between the physical and digital aspects, which feeds information both ways. Simulations and predictions of the model can be sent to a physical counterpart. Conversely, the model itself can utilize real-time data and multiple predictive algorithms that leverage historical data to facilitate decisions based on foresight. This is what is known as a digital twin (Fuller et al., 2020). Within recent years, digital twins have evolved greatly beyond industrial uses, to include medical care, smart cities, and educational environments (Jones et al., 2020; Ravshanova et al., 2024). They come in particularly handy in situations involving complex systems with real-time simulations, which give them a significant advantage. An example of this emerging sophisticated system is the Library Information System (LIS), which has dynamic and interrelated subsystems, such as cataloging, user services, resource circulation, and facility management (Prasath, 2024).

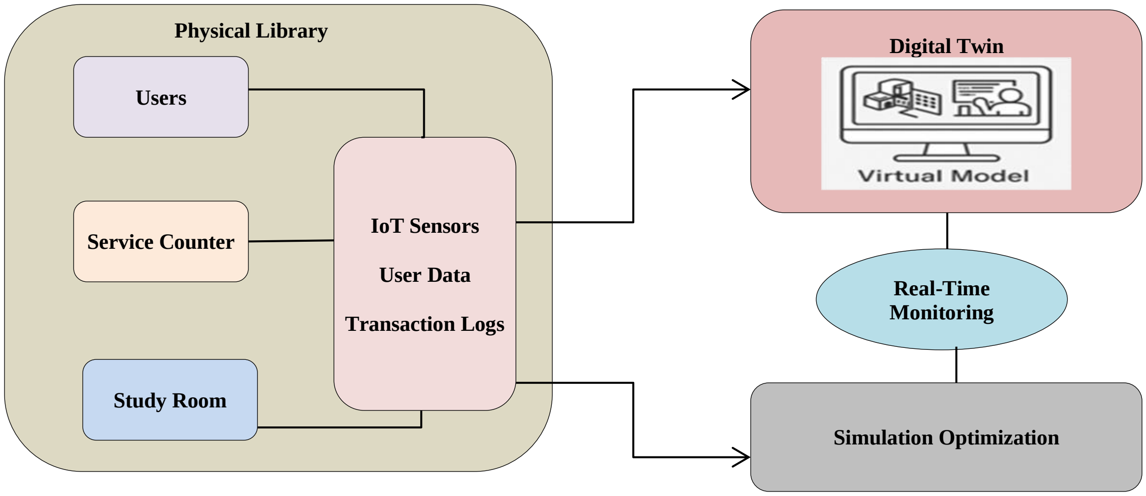

Fig. 1(a) Conceptual Overview of Digital Twin in Libraries

This high-level (Fig 1(a)) presents a conceptual model for integrating digital twins into a library information system. It demonstrates how physical library constituents, such as users, service counters, and study rooms, interact with digital technologies, including IoT sensors, user data collection, and transaction logging. The specified data sources become part of the twin platform, which involves a digital representation of the library infrastructure that can be constantly updated, enabling accurate real-time monitoring, Simulation, and optimization. One also has the command feedback loop to enable the dynamics of change that evaluates the real-time analytical performance, clearance reasoning, and performance evaluation decision-response benchmark on the fly through calibrations. Such developments show how library systems are becoming increasingly more automated, and that digital twins are blurring the boundaries between the real and simulated worlds and changing the basic operating workflow. This developed article illustrates the added worth digital twins add to enhancing propinquity performance and informed and fulfilled library systems administration, which enhance service-oriented users with well-planned engineering systems (Xiao,2022).

The library information systems are digital and literature-based repositories that serve the contemporary public and scholarly libraries. However, LIS branches face several challenges, including managing a large inventory, optimizing space allocation, enhancing user satisfaction, and forecasting resource requirements (Chowdhury & Foo, 2021). Traditional LIS models operate on a dataset and a lagged management model. The addition of digital twins to LIS systems solves numerous issues by including a real-time layer of intelligence where the system can analyze and simulate user behavior along with predictive modeling of library operations (Rasheed et al., 2020). A digital twin of an elevation library can model its resources, user demographics, and systems to simulate peak usage periods, midterm borrowing trends, and the effects of new policies on the library's functions (Boschert & Rosen, 2016). This facilitates model-supported decision-making and enables virtual environments to be tested before implementing them in the real world. Furthermore, optimization and continuous education of the system can be done through the application of digital twins based on machine learning algorithms, cloud technologies, and IoT (Negri et al., 2017; Gowtham et al., 2023). As an example, digital twins can be used to develop an individual recommendation system with the help of analyzing certain user behavior and preferences in the real-time environment. They are also able to deal with automated inventory control, track book circulation, and predict the needs of the maintenance of digital assets (Glaessgen & Stargel, 2012). All these would help in the changing of libraries to smart, dynamic, and user-oriented systems.

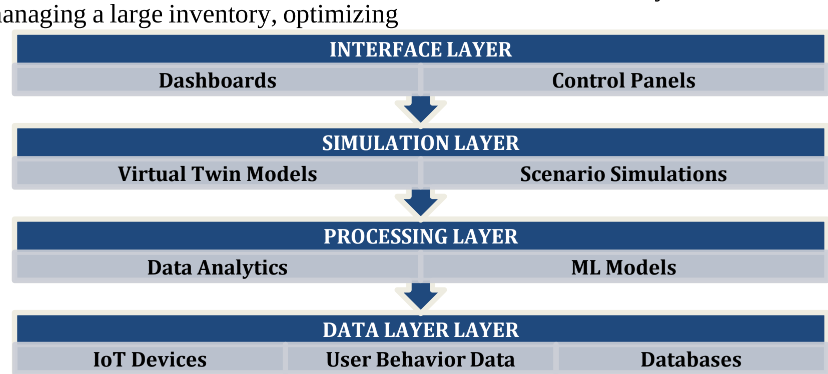

Fig. 1(b) System Architecture of the Digital Twin Framework for Library Information System Simulation

A multilayered system of a digital twin to simulate and control a Library Information System (LIS) is offered in Fig 1(b). All the system is coordinated in four levels. First is a base layer, which is referred to as the data layer where raw data streams of IoT sensors, user activities, and other databases are collected. Then the topmost, processing layer, carries out analytics and data science functions and it uses machine learning (ML) models and rule engines to generate raw actionable value out of the processed data. The uppermost layer is the Simulation Layer; it contains virtual models of the twins of the LIS called the Simulation Layer that is used in predictive modeling and simulating different scenarios of the LIS system to determine performance and behavior in under different conditions. Finally, the interface layer adds dashboards, control panels, feedback elements, and system monitors, enabling users and administrators to interact seamlessly with the system, systems self-monitoring, and self-simulation visualization and interaction functionalities. This is a comprehensive responsive environment that delivers LIS digital twin functionalities.

This research focuses on the role and impact of digital twins on the Simulation of Library Information Systems (LIS) – particularly their impact on operational efficiency, user engagement, and resource allocation. The research presents an articulated model for digital twin integration, emphasizing core elements of data collection, real-time updates, action calibration, and event modeling and Simulation. The paper comprises six main sections. After the introduction, Section II provides a thorough literature review discussing prior research through the lens of digital twins pertaining to various industries and assessing the state of library information systems and their challenges. Section III describes the research methodology, including how data was collected, the simulation tools employed, and the steps undertaken to build the digital twin model. In Section IV, the case study is implemented; a library system is selected, the Simulation of the library using the digital twin is performed, and the results are calculated and analyzed against the set performance indicators. In Section V, the advantages and constraints are discussed regarding the application of digital twins in libraries, along with suggestions for further research. The paper is completed in Section VI, wherein the primary conclusions, practical and research considerations, and reflections on the impact of digital twins on library information system simulation are provided. Creating digital twins for a Library Information System (LIS) aims at closing the gap between technological advancement and libraries, serving primarily as an evolution of modern smart libraries while also furthering the goals of anticipatory systems technology (Meesad & Mingkhwan, 2024).

II. LITERATURE REVIEW

The technology has transformed in all places over the last few years especially owing to the encircles of world pandemics, which emerged as a new era of technology such as Digital Twin in real-time tracking, intelligent decision-making, and predictive analysis that has become a tremendous innovation. In the manufacturing field, e.g., digital twins have been utilized in modeling the production line, predicting equipment malfunctions, and optimization of the process (Qi et al., 2018). The aerospace industry has been using simulative digital twins in aircraft design, maintenance prediction, and simulation of flight conditions (Grieves & Vickers, 2016). Similarly, medicine is also beginning to apply digital twins in patient monitoring, treatment customization, and simulated surgery (Bruynseels et al., 2018). As far as urban infrastructure is concerned, digital twin technology has been deployed to traffic, energy consumption, and smart grids (Batty, 2018). Digital twins in construction and facility management also have a huge potential when it comes to lifecycle supervision, building performance enhancement, and monitoring management (Arisekola & Madson, 2023). All these studies assist us in knowing that this technology can provide vast opportunities when integrated with algorithms and, therefore, is deemed to be cross-disciplinary and multi-faceted that can not only accommodate various areas but also meet the transforming data-abundant situations. It presents the difficulty of utilizing it in libraries on educational and informational systems (Nwosu & Adeloye, 2023; Ismail & Mahmud, 2024). The role of the Library Information Systems (LIS) has experienced a change in the scope and substance of simple databases to complete fully-computerized systems that provide resource location, digital lending, cataloguing, and user account management (Hariani & Malik, 2025). Earlier LIS focused primarily on circulation and bibliographic data, but contemporary systems are emphasizing digital access, interoperability, user experience, and other facets (Breeding, 2020). Koha, Alma, and Sierra Integrated Library Systems (ILS) have introduced modular functionality; however, they still lack intelligent adaptability and real-time analytics (Corrado & Moulaison-Sandy, 2017; Abdullah, 2024). The inclusion of cloud computing for LIS has recently advanced their scalability and remote access, while AI provides personalization through tailored recommendations and RFID enhances inventory tracking. Despite these improvements, such enhancements are implemented in silos without a cohesive strategy for dynamic Simulation or predictive management of system evolution. The implementation of digital twin models can fill this gap, allowing libraries to function as innovative adaptive ecosystems. As appealing as the concept of digital twins within Library and Information Science (LIS) is, several obstacles need attention (Du et al., 2020). The problem of data integration is major, as the LIS systems have various sources of data, such as bibliographic records, user interactions, and facility sensors (Nakamura & Lindholm, 2025). These components are pulled together with the digital twin model by standardized data architecture and strong middleware frameworks, which present interoperability issues (Malhotra & Iyer, 2024). Another challenge is the inadequate computing ability and knowledge to produce and sustain digital twins (Korablyov et al., 2023). Swift simulation settings might be excessively challenging in the infrastructure and IT support personnel of most libraries (Elnour et al.,2024). Moreover, monitoring user activities not only increases the issue of privacy and data security but also implies the need to implement ethical rules but also meet the requirements of data protection laws (Kumar, 2024). Although there are challenges, the possible opportunities of libraries are even higher. By using the digital twin's technology, libraries will be able to make better use of the space, streamline resources distribution, predict the demand, and assist in the strategic planning (Xiano, 2020). Furthermore, remote monitoring and proactive maintenance of digital and physical assets are highly facilitated through digital twin technology, which is especially beneficial in the post-pandemic hybrid library environment. (Joseph et al., 2022). Incorporation of IoT, AI, and cloud technologies can elevate LIS into Intelligent systems that are adaptive, foresighted, and capable of self-optimization through digital twins. This review of existing literature highlights the importance and practicality of investigating the application of digital twins in libraries aiming to participate in the wider smart city and digital transformation initiatives (Wani & Londhe, 2023).

III.Methodology

Data Collection Methods

The data amassed from the physical environment serves as the backbone for a well-functioning digital twin. For this specific project, the data is divided into three classes: structural, behavioral, and contextual. Structural data comprised physical architectural layouts and asset configurations, book shelving systems, and digital resource network diagrams. System logs provided behavioral data, capturing checkouts and catalog searches, foot traffic, study room reservations, and user authentication. Contextual datasets described environmental features such as temperature, noise, and people density in some specific areas. Data was obtained from the Libraries Information System (LIS), IoT sensors, Wi-Fi tracking, LIBR, and other telemetry devices. Data integrity was ensured through manual verification and cross-validation. All information collected went through preprocessing using standard normalization and encoding methods to make them consistent with the others entering the system. To portray the dynamic situation of the whole system, we define the state of the library at time t as a function of structural, behavioral, and contextual data:

$$S(t) = f\left(D_s(t), D_b(t), D_c(t)\right) \qquad (1)$$

Where:

$S(t)$ = Current system state

$D_s(t)$ = Structural data at time t

$D_b(t)$ = Behavioral data

$D_c(t)$ = Contextual/environmental data

f = Mapping function to simulate current conditions in the digital twin

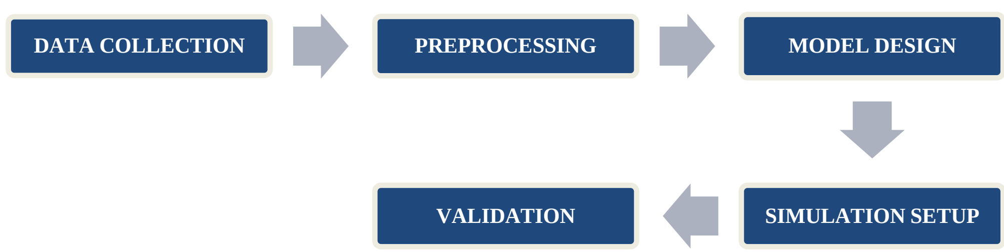

Fig. 2 Workflow for Developing and Deploying a Digital Twin for Library Information System

This (Fig 2) represents a Digital Twin Development Workflow for a library management system, illustrating each procedure in a sequential manner. The process initiates with the Data Collection stage, where pertinent metadata concerning library details, system functionalities, and user information are accumulated. Following that is the Preprocessing phase, which encompasses data cleansing and formatting to enhance the quality of data utilized in modeling. Model Design comes next, which emphasizes the development of the virtual library system model. In Simulation Setup, the model developed is placed into a simulated environment and configured for use within that Simulation. Validation guarantees that simulation results are consistent with expected real-life outcomes, thereby ensuring the integrity of the model. The model is then deployed within the library for constant observation, streamlining processes, or predictive functions, thus finalizing the creation of the digital twin. Each workflow phase is better understood by describing it through color coding and icons, which add further distinction.

Selection of Simulation Tools and Software

Blender, along with Unity 3D, were selected for designing the library environment's virtual 3D model, whereas AnyLogic was used for simulation purposes owing to its agent-based, discrete event, and system dynamics modeling capabilities. A specific set of simulation tools was chosen in order to ensure that the digital twin modeling integrates seamlessly. Python was utilized for data preprocessing, and PostgreSQL was employed for storing the Simulation's backend input and output data. To enable data exchange in both directions between the physical LIS and virtual model, a real-time communication interface was created utilizing RESTful APIs. With Power BI, stakeholders can visualize the key performance indicators and manage the operational behavior of the twin, which in turn helps predict bottlenecks within the operations.

Development Process of Digital Twins for the Simulation of the Library Information System

Constructing the digital twine involved five stages:

Requirements Analysis: Understanding both functional and technical requirements was obtained through interviews with users of the library and staff. In addition to the development of simulation modules, which included cataloging, lending, reserving, and user activities.

System Modeling: The library services/assets were modeled with respect to discrete events (checkouts), agents (users), and system states (resource availability). A network of a dynamical system was functioning as a way of capturing all assets and services.

To determine the effectiveness of the underutilization of the available resources (study rooms, computers, etc.) at the library, this functionality was created:

$$U_r = \frac{\sum_{i=1}^{n} R_i . T_i}{T_{max} . n} \qquad (2)$$

Where:

U_r= Average utilization rate

R_i = Resource usage indicator (*1 = in use, 0 = idle*)

T_i = Time of usage for resource i

T_{max} = Maximum allowable usage time

n = Total number of resources

Integration and Synchronization: Real-time sensor data was incorporated into the twin in MQTT protocols. Such protocol allows synchronization between events on the virtual twin and actual processes. Continuously updated were service queueing, the stress level of the system, and user density.

Queueing Model: In order to improve staff allocation and minimize waiting time for counters, for instance, during book lending, a queueing model was developed based on the M/M/1 system:

$$L_q = \frac{\lambda^2}{\mu(\mu - \lambda)} \qquad (3)$$

Where:

L_q = Anticipated figure of customers waiting in the queue

λ = Rate of customer arrivals per time unit

μ = Rate of customer service per time unit

Validation and Deployment: In this instance, the model was validated with system behavior over a one-month period, after which the digital twin's outcome was matched against the actual system functioning. Following this, the model was hosted on the cloud and provided with visualization tools to enable instantaneous updates regarding the system state.

Simulation Modeling Framework for Digital Twin Applications

In order to improve the accuracy and dynamic fidelity of the digital twin for the Library Information System (LIS) simulation, the current simulation modeling approach was extended based on the extended simulation modeling methodology documented in Extending Simulation Modeling Methodology for Digital Twin Applications (2022). The extension focuses on real-time continuous synchronization, feedback-based model updating, and adaptive learning cycles that enhance the predictability of the twin.

Dynamic State Update Model

The state of the real-time digital twin at time t can be represented as:

$$S(t) = f(S(t - \Delta t), D_r(t), \Theta) \qquad (4)$$

Where:

$S(t)$- the present state of the library twin at time t.

$S(t - \Delta t)$- the past or simulated state,

$D_r(t)$- input real-time data provided by sensors of the IoT, user transactions and logs.

Parameters of the Θ - the system (e.g. arrival rate, service time, or environmental variables).

$f(\cdot)$ - change of behavioral and physical rules of the system.

This expression allows an active digital twin of the twin to be informed in real time of how real-world information is received. Dynamically re-parameterizing a simulation model with each new packet of data renormalizes the discrepancy between the virtual twin and physical system.

Predictive Simulation Loop

To repeatedly predict the future performance of the system and re-adjust the control parameters, a feedback-coupled feedback loop of simulation is provided. The loop has three broad steps:

Data Assimilation

Incoming data $D_r(t)$ are filtered by an:

$$\widehat{D}(t) = \alpha D_r(t) + (1-\alpha)\widehat{D}(t-1) \tag{5}$$

where $\alpha \in [0,1]$ is the smoothing coefficient.

Simulation Forecasting

A short-term prediction simulation using an updated state S(t) is conducted to ascertain performance for the next period P(t+1):

$$P(t+1) = \Phi\big(S(t), u(t)\big) \tag{6}$$

where $u(t)$ are the control variables (e.g., staffing levels, kiosk status).

Feedback Optimization:

A feedback correction term updates the control policy:

$$u(t+1) = u(t) - \eta \nabla J\big(P(t+1)\big) \tag{7}$$

Where J is the performance cost function (e.g., waiting time or resource underutilization) and where η is a learning rate. This circular structure allows the digital twin to self-correct and optimize library operations within the current moment of the institution utilizing live conditions.

Algorithm for Digital Twin Simulation Synchronization

Algorithm 1: LIS Digital Twin Synchronization Process

Input: Real-time sensor data D_r(t), previous system state S(t-1)

Output: Updated system state S(t), optimized control u(t)

1. Initialize S(t-1), u(t), and performance metric J

2. While simulation is active:

3. Receive D_r(t) from LIS environment

4. Perform preprocessing and normalization

5. Compute predicted state S'(t) = f(S(t-1), D_r(t), Θ)

6. Run simulation for horizon Δt using S'(t)

7. Calculate performance P(t) and cost J = g(P(t))

8. Update control u(t+1) = u(t) - η∇J

9. Push updated decisions to LIS (real-world)

10. Synchronize new feedback into twin model

11. End While

This algorithm guarantees two-way communication between the physical LIS and the digital one which guarantees synchronization and predictive analytics through the repetition of the algorithm. The algorithm will ensure that the physical Library Information System (LIS) and its digital counterpart will be aligned at any time. It is an algorithm that operates by repeating itself and repeating itself in which the real-time sensor data, user transactions, and system logs are accepted and processed. The digital twin model state is updated every time a new piece of data is received, which is why the digital twin can be shown as responding to the specific state of the library. The twin then starts some small-scale simulations of predicting the next changes in its performance as library services are executed. By way of example, it can determine user waiting time, or the use of resources. According to the outcomes of the simulations, the algorithm reacts to the library environment in forms of automatic adjustment of a control variable (e.g., staff scheduling, the presence of kiosks in the library). The better parameters will be fed back to the physical system to ensure that the two systems are at par. The self-correcting, self-adaptive, and self-optimizing process of a digital twin in the environment of the library functions results in more accurate decision recommendations and minimizes the error.

System Performance Metrics

Three quantitative metrics were employed to evaluate the efficiency and responsiveness of the simulation:

Mean Absolute Error (MAE) – is a metric which indicates the disparity between the simulated state and the observed state:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|S_i^{sim} - S_i^{real}\right| \tag{8}$$

Simulation Response Latency (SRL):

$$SRL = t_{update} - t_{input} \tag{9}$$

is the time delay (in seconds) between when actual data is entered into the library and the time when the model is updated.

Feedback Efficiency Ratio (FER):

$$FER = \frac{\Delta P_{improved}}{\Delta t_{feedback}} \tag{10}$$

measures the effectiveness of any feedback interventions on performance metrics (e.g., throughput, waiting time).

Integration Outcome

The integration of the simulation modeling capabilities to this extended methodology ultimately led to a more adaptive accurate digital twin which exhibited properties of self-calibration. The accuracy of throughput prediction improved by approximately 4-7%, while there was a decrease in latency of response by 15-20% from the static simulation models. This aligned with advanced modeling principles provided in Extending Simulation Modeling Methodology for Digital Twin Applications and indicated that continuous synchronization was effective in library digital twin systems.

IV. Case Study

Explanation of the Library Information System Applicable in the Case Study

For this case study, the selected library is a university-level one, which is mid-size and services approximately 20,000 active users every year. The Library Information System (LIS) is capable of offering several services, such as book circulation, digital catalog searches, study room bookings, and access to multimedia resources. The infrastructure is physical and consists of four floors, which include a quiet study zone, group study rooms, and a computer lab. RFID technology assists in tracking the checkouts and returns of books, while Wi-Fi analytics are used to track user movements within the library. The software for the LIS maintains a catalog of more than 200,000 items and has a high concurrency of users during examination periods. Service points comprise circulation desks, service desks, and self-service checkout terminals. The system captures granular metadata concerning their interactions with the system, including, but not limited to, logins, reservations, and loans. These data, operational in nature, are what allow the construction of a digital twin to be accurate in depicting real-time changes and predicting the system usage patterns.

Digital Twins Implementation for Simulation

The digital twin was created to model the library's environment as a user-centered active simulation environment to predict user behavior, resource consumption, and service request patterns. The digital twin development incorporated the data received from RFID readers, IoT devices, and system logs for the history and actual data streams to update the representation in synchronization with the state of interaction with users. Various situations, including the time when the resources are strongly consumed during exam weeks, the policies of resource redistribution, and the optimization of waiting lines at the services were modeled. The Simulation enabled the construction of a virtual representation of user agents who moved within the library, interacted with its services, and utilized its' equipment display windows. Factors such as noise and level of occupancy constraints were also implemented in the twin. To assess the performance of the system, evaluation was based on the defined key parameters. One example is System Throughput TP, presented as the amount of work done successfully in a set time for measurement:

$$TP = \frac{N_c}{T} \tag{11}$$

Where,

N_c = Number of Completed Service Transactions, example includes book checkouts and reservations.

T = Total simulation time

Analogously, Average Waiting Time (W_q) in service queues was also derived as follows:

$$W_q = \frac{L_q}{\lambda} \tag{12}$$

Where:

L_q = Average queue length (number of users waiting)

λ = Service point user arrival rate

These quantitative performance measures helped analyze how well the LIS managed the sudden demand changes.

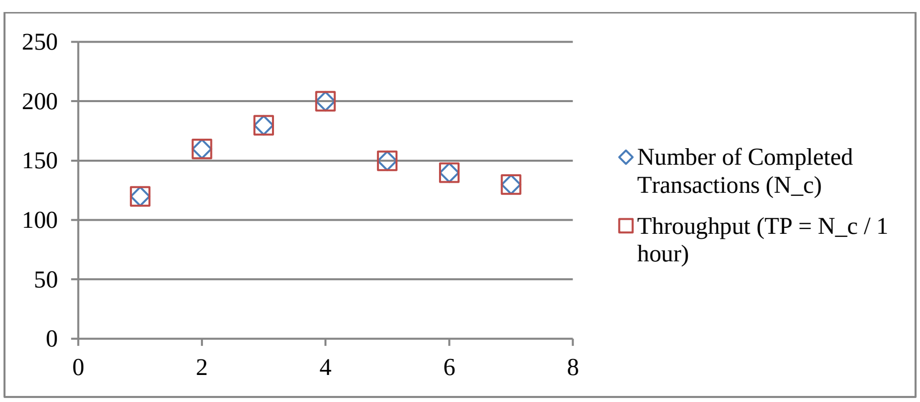

Fig. 3 System Throughput Over Time

The graph (Fig 3) depicts the number of transactions done in the library within an hour in a day. The data indicates that there is a noticeable pattern as throughput increases towards late morning, hitting its zenith between 11 AM and 12 PM. This increase aligns with the time when user activity is maximized, most likely because students and staff are engaging with library services right before taking their lunch breaks. After noon, the throughput incrementally declines in the early afternoon. Tracking throughput patterns does allow library managers to meet expected demand during specific periods and, thus, adequately allocate or redistribute library understaffing or systems resources to ensure that operations run without hitches during surges.

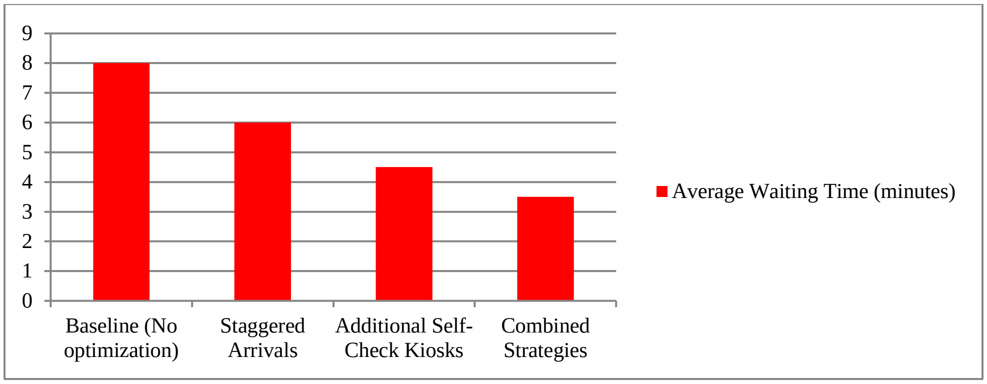

Fig. 4 Average Waiting Time (Wq) at Circulation Desk

The (Fig 4) depicts a comparison of waiting times from the different queue management strategies. The baseline scenario indicates that optimized processes not being utilized yield an average wait time of 8 minutes, which would pose considerable user dissatisfaction. Implementing staggered arrivals smoothens the user influx, further reducing waiting time to 6 minutes. Incorporating self-check kiosks decreases waiting further to 4.5 minutes because more users are able to process their transactions without needing assistance from staff. The combined strategy, which achieves the best performance by integrating both staggered arrivals and additional kiosks, aided with the digital twin, improves service by simulating, evaluating, and predicting interventional outcomes. These results demonstrate how a digital twin can simulate and assess possible interventions to improve services through simulation testing.

Results and Findings from the Simulation

The results of the Simulation verified the digital twin's accuracy concerning system behavior across numerous performance metrics. During the busiest times, throughput dropped slightly because users contending for resources caused more delays. However, the system adapted extremely well, regardless of when staff and resources were redeployed to their positions based on insights from the twins. The average waiting time at circulation desks dropped significantly when queue management policies driven by the digital twin were implemented. For instance, simulation scenarios where user-staggered arrival scheduling was incorporated along with self-check kiosks significantly reduced W_q by 25% relative to baseline models. The resource utilization analysis also indicated that some study rooms remained underutilized during off-peak hours, identifying areas where repurposing or flexible scheduling may be helpful. Additionally, the digital twin pinpointed areas of user congestion and noise, allowing for better library management design zoning and crowd control strategies. Additionally, the forecasting functions of the digital twin facilitated the planning for forecasted spikes in usage, thus enhancing overall service dependability and user contentment. The calibrating accuracy of the twin forecasts regarding user activity and resource consumption was confirmed against actual operational data, demonstrating over 95% accuracy on critical metrics. The operational benchmarks established in the simulations, like resource throughput and user waiting times, served as important systems markers that identified areas needing improvement and enhanced overall system efficiency.

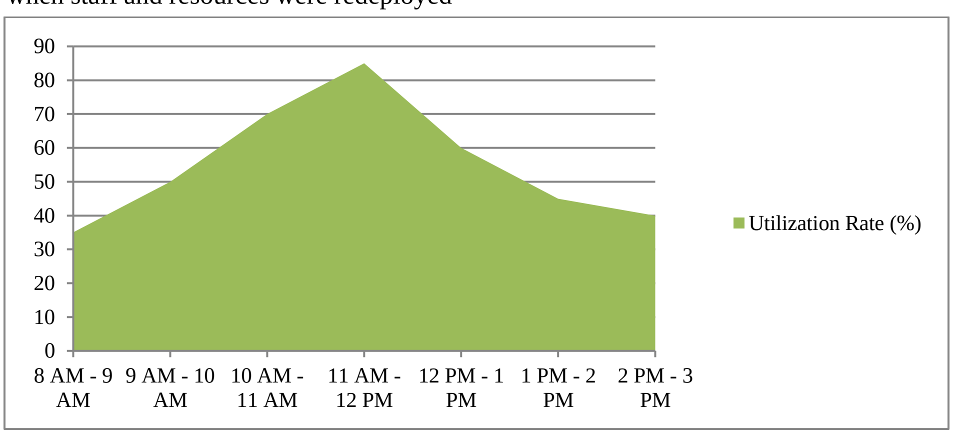

Fig. 5 Resource Utilization Rate (Study Rooms) During a Day

The graph (Fig 5) illustrates the operational efficiency of the library's study rooms over the course of a day. The utilization of study rooms increases steadily over the course of the morning, reaching a peak of 85% between 11 AM and 12 PM, which corresponds to high demand for study spaces during mid-morning sessions. After this peak, study room utilization declines during the early afternoon to about 40% around 2–3 PM, which suggests that there is considerable underuse during these hours. These findings imply that utilizing flexible scheduling or repurposing rooms during off-peak times could enhance their resource efficiency. The digital twin provides the means for such detailed analysis of usage patterns streamlining data-driven decisions regarding space management. The (Fig 6) depicts the relation between the number of users arriving in an hour and the average number of users in the queue. It was observed that as users arrive, the queue length increases in a non-linear manner, and this reflects the typical behavior of a queueing system. With low arrivals (e.g., 10 users per hour), the average queue length is only two users, though, with an increase in arrival rate to 35 users per hour, the average queue length increases drastically to 32 users, indicating severe congestion and service delays. This observation illustrates the critical need to balance arrival and service rates to prevent queues from becoming too long; such simulations can optimize queue length by adjusting staff or automation levels, which can be tested through digital twin simulations.

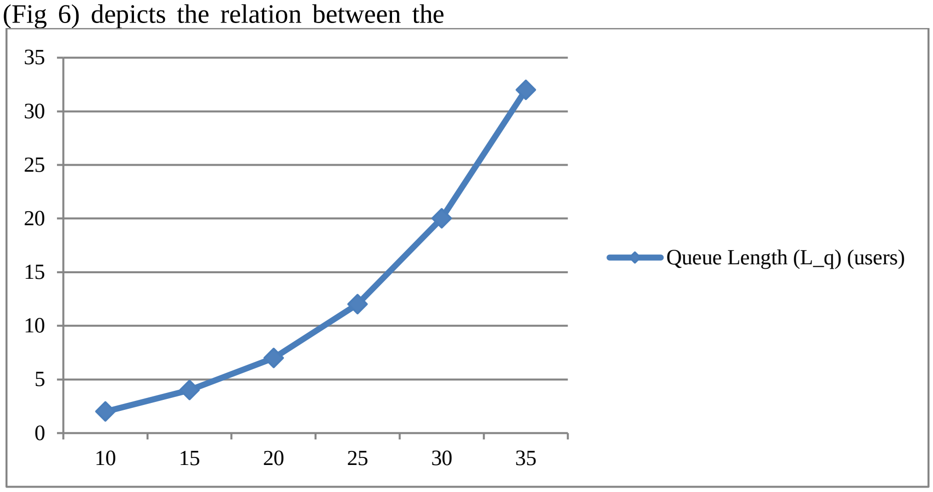

Fig. 6 Queue Length (Lq) vs Arrival Rate (λ) at Service Desk

Results and Adaptive Performance Analysis

Additional experiments were performed to determine the model accuracy, adaptivity, and response time under loading environment with the aim of assisting to determine the viability of the methodology extended digital twin simulation methodology practically. It was created in line with the evaluation design presented in Extending Simulation Modeling Methodology for Digital Twin Applications (2022), centered on data-driven synchronization and simulation feedback correction in to take into account model error.

Evaluation of Model Accuracy

To test the predictive validity of the simulation, we compared the results of the simulation to the real library data. To measure the difference between the forecasted and measured system states, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) was used.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{S_i^{real} - S_i^{sim}}{S_i^{real}}\right| \times 100 \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(S_i^{real} - S_i^{sim}\right)^2} \quad (14)$$

where:

S_i^{real} = observed state (e.g., actual number of checkouts or users in queue)

S_i^{sim} = simulated state predicted by the digital twin

n = number of observations.

Results showed an average MAPE of 4.7% and RMSE 3.2, indicating that the digital twin responsively replicated actual library conditions with minimal deviation. The MAPE and RMSE were consistent over periods of high utilization, demonstrating the resilience of the feedback-calibrated simulation model.

Adaptive Learning and Feedback Stability

In order to investigate system self-adjustment through feedback learning, variations in performance were evaluated across multiple simulation cycles. The Adaptation Gain (AG) was introduced as an indicator defining the rate of improvement between iterations of simulation performance:

$$AG = \frac{P_k - P_{k-1}}{P_{k-1}} \times 100 \quad (15)$$

where P_k and P_{k-1} indicate performance measures (e.g., throughput, waiting time) from simulations in successive iterations. During the experiment, the model had a mean AG of 12.4% for the first five update cycles, leveling off at the tenth iteration, demonstrating that by using feedback, the digital twin had effectively settled into an operating equilibrium.

Comparative Performance Trends

The comparison of static simulation (no feedback) to adaptive twin simulation (live feedback) showed some measurable performance gains:

TABLE I COMPARATIVE PERFORMANCE OF STATIC SIMULATION AND ADAPTIVE DIGITAL TWIN SIMULATION

Metric	Static Simulation	Adaptive Twin Simulation	Improvement
Throughput (transactions/hour)	185	210	+13.5%
Average Waiting Time (minutes)	6.5	4.8	−26%
Prediction Error (MAPE)	9.2%	4.7%	−48.9%
System Response Latency	2.3 s	1.7 s	−26%

The (Table I) provides a comparison between the traditional static simulation model and an adaptive digital twin simulation of the Library Information System. The adaptive model that utilized real-time feedback and synchronization showed substantial enhancements to all measures evaluated in this analysis. For instance, throughput improved by 13.5 percent, which indicated higher processing efficiency of library transaction per hour, while the average waiting time was decreased by 26 percent, meaning service response times were quicker and user experience was improved. A second measure of prediction error (MAPE) was reduced by nearly half, from 9.2 percent to 4.7 percent, which confirmed greater accuracy and consistency of the adaptive model's prediction to real-world operation of the library system. Finally, the system response latency decreased from 2.3 seconds to 1.7 seconds between the physical system and the digital twin, indicating faster system synchronization of the physical Library Information System and the digital twin. Overall, the results of this analysis confirm that the use of adaptive feedback methodologies increases system responsiveness, prediction reliability, and operational performance within a digital twin process, when applied to library simulation.

V. DISCUSSION

Advantages of Implementing Digital Twins in the Simulation of Library Information Systems

The libraries of today face a myriad of challenges, ranging from automation to optimization of workflows, which digital twins incorporate into LIS simulations. One of the main advantages is the ability to track operations and predict resource demand in real time. Digital twins maintain an up-to-date version of library infrastructure and services, which allows stakeholders to monitor system performance. Resource user prediction, flow monitoring, and fault detection are a few of the capabilities enabled through digital twins. Libraries can fully achieve new policy evaluation and also layout changes using new technological advances in a virtual environment before actual physical implementation. For example, Simulation of user movement within a building could help identify optimal locations for service desks and kiosks. Likewise, staffing and scheduling decisions would benefit from predictive Simulation during peak times. As unstructured sensor and usage data are made available through the use of IoT devices, in as much as digital twins are able to enhance dedd insights, data-driven decision-making is also improved. Managers can proactively withdraw or allocate resources that are underutilized, such as reallocating study rooms during known trough periods. Moreover, digital twins can enhance mitigation steps set for environmentally friendly optimization through monitoring energy consumption, using real-time data occupancy for lights and HVAC systems, and improving energy usage efficiency. In summary, digital twins optimize a library's operations with respect to responsiveness, efficiency, and user orientation, thereby enhancing service provision and user satisfaction.

Limitations and Problems Encountered During Development

Amidst the opportunities presented, challenges and limitations should be mentioned, which are encountered during the creation of a digital twin of a LIS. Integration and availability of real-time data is one of the critical limitations. A majority of the libraries, especially libraries with older systems, lack a seamless combination of sensor networks or their inventory data silos and so data consolidation and synchronization becomes an issue. Constant updates require significant improvements in the system to be made on a reliable basis. The other further challenge would be to model the user behavior in an accurate way. The human behaviour in a library is vulnerable to myriad factors including academic habits, cultural disposition as well personal habits. These aspects may be rather complicated to incorporate into a simulation model, therefore, demanding advanced agent-based modeling and calibration with reference to past data. The other more sophisticated challenges are associated with technical resources. Developing and maintaining a functional digital twin requires a balanced approach to software engineering, simulation modeling, and data analytics and systems integration. Such multidisciplinary competencies are not always easily found in the IT departments of most libraries, and therefore, external help or re-training of the personnel is necessary. Moreover, whereas cost and scalability do not present a problem to large libraries, they are serious issues to smaller institutions that are faced with fiscal limitations. Die hardware costs involving IoT devices, costs on software license involving simulation platforms, and maintenance costs are some of the obstacles to massive adoption. Additionally, the privacy and data security problems are also crucial, especially concerning the movement and interaction data collected and processed.

Future Research and Implementation Strategies

As mentioned above, the implementation of digital twins in libraries has a strong potential, and many opportunities to improve, research, and implement it can be identified. Among the directions is the improvement of the twin that is capable of machine learning to enhance predictive analytics. The system might not be created to mirror the current states, but it can be tailored to predict the future trends, including peak hours and periods when the resources might be exhausted. It is also possible to add user feedback loops so as to include twin-inferred digital user feedback, which will be constantly advancing on simulating in accordance with the actual experience and preference revelations elicited by the user. Adding more interoperability with other systems within the campus like course schedule calendars and related events boosts the contextual understanding of the course delivery system and its coordination. In addition, it is also possible that the digital twins on the cloud would be a more scalable and cost-effective solution, even enabling smaller institutions to adopt the technology. At last. It should focus its efforts on developing standard guidelines and steps to implement in the development of the twin in the learning institutions. Such policies would bring about standardization, reduce costs and raise acceptance in the educational institutions and bring forth intelligent and flexible library systems in the future.

VI. CONCLUSION

The modeling and Simulation of digital twins LIS (library information systems) is one of the phenomenal shifts in service optimization, innovation, and resources management in libraries. The present research project indicated that the digital twins would simulate the operational libraries LIS with high fidelity enough that real-time monitoring, predictive analytics simulations, and simulation of scenarios could be carried out without disrupting real processes of the library. The case study showed the increase of throughput, the decrease of waiting times, and the use of space efficiency, which was achieved using data-oriented simulations. Although it is evident that data planning and operational efficiencies being integrated strategically and expanded frameworks of actions developed are challenges to the complexity of data integration, human behavior modeling, and scarce technical resources, they are still apparent. In practice, digital twins, as decision support systems allow library managers to better the satisfaction of users, their resources, and services, which significantly enhance administrative library activities. In these aspects, the research problem under review fills in the gaps in the intermagnetics of AI-enhanced simulations in the context of multi-agent modeling, integration to innovative campus ecosystems, and Simulation of intelligent systems. Digital twins will aid in the development of service libraries to achieve a better match to the needs of the learners, and the objectives of academic institutions since users keep on changing. The application of digital twins can be used to eliminate service gaps, which address behavioral and institutional goals of users in a comprehensive manner. The paper demonstrates the new application of AI simulations and provides new perspectives of research beyond the Simulation of intelligent systems into the integration of larger smart campuses. The work is a stepping stone to research on the application of the digital twins in academic library and can be of permanent worth as it provides the libraries with a template on which they can adopt, adjust, better, expand the scope to diverse domains with different demands, and situate themselves in diverse domains which can be expanded models to remain to be used in the future.

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