Gamified Mobile Guide Using iBeacon: Enhancing Informal Learning in a Taiwanese Science Museum

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Manuscript received April 24, 2025; revised June 5, 2025; accepted June 27, 2025; published October 14, 2025

***Abstract*—This study investigates the implementation of a gamified mobile guide system—iGuide—integrated with iBeacon indoor positioning technology in a real-world science museum in Taiwan. Using a mixed-methods design combining spatial trajectory analysis, on-site behavioral observation, and post-visit interviews, the study examined how such a system influences visitor behavior, engagement, and informal learning experiences. Participants were segmented into three types—leisure-oriented, goal-oriented, and learning-driven—based on their interaction patterns.**

Key findings indicate that app users visited approximately 33% mor exhibits, remained on-site for an estimated 40% longer duration, and demonstrated twice the number of high-engagement interactions—as defined by extended dwell time and task completion—compared to non-users. Gamified task and context-aware navigation effectively encouraged exploration of under-visited areas and increased overall participation. Interview data highlighted the need for a more intuitive interface, flexible content depth, and differentiated features for varying visitor profiles.

This study contributes to educational technology research by demonstrating how location-aware task-driven systems can foster adaptive and immersive learning in informal learning environments. Practical implications include design guidelines for personalized museum guidance, integration of real-time feedback and visitor modeling, and pathway toward AI-driven emotional analytics.

***Keywords*—gamified mobile learning, iBeacon, informal learning, museum visitor behavior, user experience design, visitor typology, educational technology**

I. Introduction

Museums are undergoing a transformation from static knowledge repositories to interactive smart environments that promote participatory and exploratory learning. As mobile technologies and indoor positioning systems become increasingly integrated into cultural space, mobile guide systems have emerged as powerful tools to enhancing visitor engagement and informal learning experiences [1].

Prior research has shown that mobile guide incorporating User Experience (UX) design and personalized content can deepen immersion and emotional connection with exhibits [2]. Additionally, gamification strategies—such as missions, challenges, and real-time feedback—effectively boost user motivation, particularly among younger audiences [3]. Advances in indoor positioning technologies like iBeacon have further enabled real-time location tracking and context-sensitive interaction, supporting dynamic and adaptive museum navigation [4].

However, most existing studies treats these elements—technical systems, UX design, and learning engagement—as separate components rather than exploring their integration in real-world settings. Limited empirical research examining how these systems can work together to support different types of visitors—such as casual browsers, goal-driven seekers, or learning-focused explorers, or how visitor typologies interact with spatial behavior, exhibit layout, and gamified tasks [5].

To address these gaps, the study presents the design, deployment, and evaluation of iGuide—Go to NTSEC, a gamified mobile guide system integrated with iBeacon indoor positioning, real-time behavioral tracking, and task-based learning modules at the National Taiwan Science Education Center (NTSEC). This system was implemented at full scale, with 474 iBeacon devices installed across eight museum floors, enabling fine-grained monitoring of visitor trajectories, task interaction, and engagement depth. The key contributions of this study are:

1) To evaluate whether the iGuide app increases exhibit coverage, spatial exploration, and visitor engagement.
2) To develop and validate a visitor typology model that explains behavioral differences across user types.
3) To analyze how task-based design influences spatial heatmaps, behavioral hotspots, and visitor flow.
4) To derive UX insights and optimization strategies based on qualitative visitor feedback.

By combining quantitative trajectory data with in-situ observation and post-visit interviews, this study provides a comprehensive mixed-methods investigation of how integrated, location-aware, gamified mobile guides can enhance informal science learning and support adaptive, inclusive museum experiences. The study's novelty lies in its real-world deployment of a unified system combining these elements and its empirical evidence of how such integration affects visitor behavior and learning engagement.

II. Literature Review

A. UX Design and Indoor Navigation in Smart Museum Applications

UX design is a central component in mobile guide systems, particularly when integrated with indoor positioning technologies such as iBeacon. iBeacon's low-energy Bluetooth signal enables accurate, room-level positioning that supports real-time content delivery and task triggering [6, 7].

The study shows that UX enhancements, such as map overlays, intuitive icons, and adaptive interfaces, improve user orientation and reduce navigational errors in complex exhibition spaces [8, 9]. Particle filtering, Gaussian-weighted models, and Kalman smoothing have all been applied to boost positioning accuracy and responsiveness [10, 11].

doi: 10.18178/ijiet.2025.15.10.2404

Moreover, smart guide interfaces that integrate 360-degree panoramic views or contextual hints are shown to support pre-visit planning and reduce cognitive load for first-time users [12].

B. Personalization and Behavioral Modeling in Mobile Guide Systems

Personalization in mobile learning systems involves tailoring both content and interaction modes based on user behavior and context. In museums, iBeacon can capture fine-grained spatial data—such as viewing duration, revisit frequency, and content selection—to model user intent [2, 13].

Interactive content delivery has also been explored through the integration of AR and iBeacon in Problem-Based Learning (PBL) models, enabling context-aware task triggering within exhibit zones [14]. Additionally, researchers have combined Bluetooth Low Energy (BLE) with Pedestrian Dead Reckoning (PDR) to improve positioning precision and reduce signal drift in mobile environments [15].

Additionally, user segmentation based on visit behavior has been proposed as a means to support adaptive interface delivery, particularly for institutions with diverse visitor demographics [16].

C. Gamified Interaction and Emotional Engagement

Gamification has gained prominence in educational technology as a motivational strategy that incorporates tasks, narratives, and real-time rewards. In museums, studies show that game elements promote memory retention and conceptual understanding, especially among students and young visitors [3, 17].

Advanced systems use location-based triggers to launch challenges or mini-games when visitors approach exhibits, improving interaction and dwell time [4, 18].

Emerging designs also incorporate affective computing—e.g., facial expression recognition or smartwatch-based emotion sensing—to dynamically adjust exhibit content based on visitor mood [19, 20]. These innovations offer new ways to adapt learning pathways in real time, although they remain underutilized in large-scale deployments.

D. Informal Learning and Visitor Motivation in Science Museums

Museums are key environments for informal, self-directed learning, offering multisensory experiences that foster curiosity, reflection, and collaboration [1, 21]. Studies show that emotional triggers—such as awe, humor, or surprise—can enhance learning, particularly in family or group visits [22, 23].

Gamified guides that integrate narratives and role-play elements have been found to increase conceptual understanding and visitor motivation [24]. Moreover, spatial layout and exhibit positioning play crucial roles in shaping visual attention and movement patterns, influencing both cognitive and affective engagement [25, 26].

E. Data-Driven Design and Adaptive Learning Systems

The convergence of learning analytics, indoor localization, and adaptive content recommendation is an emerging trend in educational technology. BLE-enabled guides now collect behavioral data that can be analyzed for improving personalization, content relevance, and exhibit flow [27, 28].

Artificial Intelligence and sensor integration are also being explored to assess physiological signals—like heart rate or skin conductivity—to model user engagement and stress levels [29]. Such emotionally aware systems are aligned with self-determination theory, which posits that autonomy and relatedness are key drivers of intrinsic motivation [30].

Despite these advances, many systems remain conceptual or lab-based. Few empirical studies examine how real-time behavioral sensing, gamification, and personalization can be jointly deployed at full scale in public museum contexts.

F. Summary and Research Gap

To date, most museum guide studies focus on either technical implementation or visitor engagement, but rarely explore how gamified mobile systems can integrate behavioral segmentation, spatial navigation analytics, and informal learning goals into a unified framework. While several representative studies have addressed individual components—such as BLE-based positioning, gamified content, or adaptive recommendations—few have combined all three dimensions in real-world deployments (see Table 1 for a summary of related works and their respective contributions).

Table 1. Representative studies in mobile guide systems and smart museums

Author	Technology Focus	Contribution
Giuliano *et al.* (2020) [6]	BLE + positioning algorithms	Real-time indoor localization with museum-specific deployment
Lin *et al.* (2019) [14]	AR + iBeacon + PBL	Triggered learning tasks in informal learning zones
Ivanov & Velkova (2023) [13]	NFC + iBeacon + personalization	Real-time path recommendation via behavior modeling
Dichev & Dicheva (2017) [3]	Gamification design	Theoretical foundations of game-based educational engagement
Kennedy *et al.* (2021) [23]	AR + emotion stimulation	Emotional design enhancing science concept learning
Álvarez-Merino *et al.* (2023) [27]	Behavioral trajectory clustering	Adaptive system design using mobility-based personalization
Aiuti *et al.* (2022) [19]	Facial micro-expression sensing	Affective feedback mechanisms for exhibit adaptation
Šumak *et al.* (2021) [29]	AI + physiological sensors	Emotion-aware adaptive interface design in cultural learning

This study addresses this gap through the design and evaluation of a fully deployed iBeacon-based guide system in a science museum, combining task-based gamification, real-time positioning, and user typology modeling. The approach provides practical implications for the next generation of adaptive, inclusive, and data-driven museum experiences.

III. MATERIALS AND METHODS

This study focused on the design, deployment, and evaluation of iGuide—Go to NTSEC, a mobile guide app co-developed by the research team and the NTSEC. The main objective was to assess the feasibility and impact of integrating indoor positioning and gamified task design in a convergent mixed-methods design, combining quantitative trajectory and interaction data with qualitative observations and interview feedback. This approach aligns with best practices in museum learning research for capturing both behavioral patterns and subjective visitor experiences [31–33].

A. System Design and Functional Architecture

The iGuide app is a mobile application specifically designed for on-site museum visits. Its core objective is to integrate mobile device capabilities, iBeacon indoor positioning technology, themed navigation modules, interactive tasks, and multimedia content to deliver a real-time, personalized, and participatory museum experience. The app employs a modular design and user-friendly interface to accommodate users of varying ages and levels of digital literacy.

The app comprises six core functional modules:

1) Position-based navigation

Utilizes iBeacon signals for real-time indoor positioning and exhibit information display. Users can easily identify their current location within the museum during their visit.

2) Multi-route guide

Offers multiple themed tour routes that allow users to select exhibits based on personal interest, with the flexibility to switch modes at any time.

3) Personal services

Provides access to user-specific information including visit history, preference settings, and task progress tracking, based on login credentials.

4) Visitor information

Includes essential museum details such as ticket prices, hours of operation, facility layout, exhibit introductions, and transportation guidelines.

5) Indoor panorama view

Offers a 360-degree panoramic view of each floor to help visitors familiarize themselves with the exhibition space and plan their visit prior to arrival.

6) Contextual trails

Features iBeacon-triggered interactive missions such as knowledge quizzes, treasure hunts, and immersive learning tasks to reinforce educational engagement through gamification.

The interface design employs color-coded categories and intuitive icons to lower the operational threshold. It also reflects a progressive functionality structure—from basic information delivery to highly personalized interactions—aligning with the study's goals of validating "personalized visiting experiences" and "immersive interactive guidance".

B. iBeacon Deployment and Positioning Application

To achieve high-precision indoor positioning, a total of 474 iBeacon devices were deployed throughout the exhibition areas of the NTSEC. The installation involved two phases, where the first phase implemented 239 beacons primarily across exhibition floors 1 through 4, and the second phase added 235 beacons to extend coverage from the B1 level to the 8th floor. The beacons were installed at an average density of one device every 6 m, resulting in a positioning accuracy with a margin of error within 1 m. This infrastructure enabled real-time location tracking and path recording throughout the museum. The positioning system utilized Kalman filtering to mitigate signal interference, and employed Received Signal Strength Indicator (RSSI) values to calculate the approximate distance between the user and the exhibit nodes. These calculations were used to trigger context-aware content, including exhibit-specific information and interactive tasks. Simultaneously, the backend system recorded user movement trajectories, timestamps, and exhibit interaction logs. These data were used to generate personalized route maps and visualize behavior heatmaps, supporting in-depth behavioral analytics and adaptive content delivery.

C. Field Implementation and Participant Recruitment

To evaluate the effectiveness of the iGuide—Go to NTSEC app in a real-world museum context, a series of field experiments and in-situ user observations were conducted across the 3rd to 6th floors of the NTSEC. Participants were assigned to two groups: naturally occurring visitors who did not use the app (Non-User Group, N Group) and a recruited cohort who actively engaged with the app (User Group, U Group).

1) Non-user Group (N Group)

This group consisted of 16 visitors (coded N-01 to N-16) who did not voluntarily download or interact with the iGuide app. Participants were recruited on-site using randomized sampling at the museum entrance, thereby reflecting the organic behavioral patterns of typical visitors. Observations were conducted over six sessions—three on weekdays and three on weekends—from 10:00 a.m. to 3:30 p.m. Trained researchers unobtrusively shadowed each participant for approximately 30–60 min, depending on their natural visit duration. Using printed maps, researchers documented exhibit visitation sequences, dwell times, and visible demographic characteristics (e.g., gender, approximate age, accessories). When feasible, demographic inferences were made post-observation. The estimated age range for this group was 18–40 years, with an education level inferred to range from high school to undergraduate. Gender distribution was relatively balanced (9 male, 7 female). Museum visit history was unknown due to the absence of post-visit interviews.

2) User Group (U Group)

The U Group included 15 participants (coded U-01 to U-15) recruited prior to the study and instructed to use the iGuide app throughout their museum visit. Recruitment targeted young adults aged 18–35 with high digital literacy and a propensity for informal learning. Channels included university bulletin boards, online forums, and social media communities related to science education. All participants confirmed that they were first-time NTSEC visitors.

Each participant used the app to explore the 3rd to 6th floors for approximately one hour. Observations mirrored the N Group protocol, with researchers documenting movement paths, task completions, and interaction behaviors.

Following their visit, participants engaged in a 60-minute semi-structured interview that explored: Usability: app interface clarity, navigation ease, positioning reliability. Engagement: motivation to complete tasks, depth of exhibit interaction. Learning experience: perceived knowledge gains, emotional connection. Suggestions: improvement ideas for app features and museum layout. Interview themes were informed by recent frameworks and research on multimodality, interactivity, and visitor learning engagement in museums [34, 35].

The User Group had an average age of 25.6 years (SD = 4.2), with gender evenly split (8 male, 7 female). Their education levels included 5 undergraduates, 9 graduate students, and 1 participant with a completed master's degree.

3) Summary of participant demographics and limitations

The sample size and composition were designed to balance analytical depth with feasibility, aligning with prior museum visitor behavior and engagement studies [25, 32]. A comparison of the demographic characteristics of the two participant groups is provided in Table 2. Data include either self-reported visually estimated variables, such as age, gender, education level, and museum visitation history. These attributes helped contextualize differences in behavior between unguided visitors and those assisted by the mobile guide app.

Table 2. Participant demographics of the non-user and user groups

Demographic Variable	Non-User Group (N = 16)	User Group (N = 15)
Age Range / Mean (SD)	Estimated: 18–40 years (visually observed)	18-35 years Mean = 25.6 (SD = 4.2)
Gender	9 male, 7 female (estimated)	8 male, 7 female
Education Level	High school to undergraduate (visually inferred)	Undergraduate to graduate (self-reported)
Museum Visit Frequency	Unknown (not collected)	All first-time visitors (self-reported)

While the methodology was comprehensive, several limitations should be noted. The use of manual observation may have introduced some observer bias despite extensive researcher training. The sampling was confined to a single institution and targeted primarily young adult age groups, which limits the generalizability of findings to other demographics or cultural contexts. Furthermore, visitor behavior could have been influenced by variables such as time of day, day of the week, or crowd conditions. Future studies are encouraged to address these limitations by incorporating automated sensor-fusion techniques, expanding demographic diversity of participants, and conducting longitudinal investigations across different sites and audience segments.

D. Behavioral Observation Data Integration, and Interpretation Model

To explore the effects of gamified mobile guidance on informal science learning, this study adopted a convergent mixed-methods approach, integrating quantitative behavioral data with qualitative interview and observation insights. All participants provided written informed consent, and the research protocol complied with ethical standards and personal data protection regulations. Participant data were anonymized using alphanumeric codes for analysis purposes only.

1) Multi-layered data collection

The study structured around a five-stage behavioral observation and analysis framework, adapted from audience typology theories [5, 36].

- Exhibit Interaction Logging: The iGuide system backend automatically recorded participants' exhibit selections, interaction frequency, and time spent per node, generating a quantitative foundation for identifying engagement hotspots.
- Behavioral Tracking: Trained research assistants conducted unobtrusive "shadowing" observations, manually tracing movement paths, dwell zones, and physical responses to exhibit stimuli.
- Persona Construction: Based on a synthesis of behavioral data and typology-aligned questionnaires, three visitor personas were constructed to reflect dominant motivation patterns and exploration strategies.
- Observation and Interview Integration: Researchers used an exhibit coding system to cross-reference each participant's visit sequence with both observational field notes and semi-structured interview transcripts. This integration supplemented the app's backend data by capturing subtle interaction moments (e.g., hesitation, social signaling) not detectable via digital logs.
- Data Triangulation and Semantic Analysis: Qualitative data from interviews were thematically coded using semantic unit analysis and then cross-referenced with movement data and usage metrics. This allowed for multi-dimensional validation of behavioral trends and informed targeted system refinements.

2) Quantification of engagement: dwell time classification

To systematically interpret visitor engagement depth, this study introduced a tiered classification model based on dwell time per exhibit, supported by heatmap visualizations. As shown in Table 3, the model categorizes behavior into three color-coded levels:

Table 3. Dwell time-based visitor behavior classification

Code	Dwell Time	Behavioral Interpretation
Yellow	30 s–2 min	Light interaction and exploratory engagement, indicating initial contact behavior.
Green	2:01–8 min	In-depth reading, task participation, and exhibit interaction, indicating medium-level immersion.
Red	Over 8 min	Co-viewing with companions, advanced learning, and contextual immersion, indicating high involvement and extended engagement.

This classification method, adapted from prior museum behavior studies [25, 37], supported downstream analysis such as path mapping, hotspot density comparison, and individual engagement profiling. For each visitor, the combination of entry/exit timestamps, dwell duration, and task interaction logs was visualized through color-coded spatial paths.

3) Integration of quantitative and qualitative data

Quantitative and qualitative data were collected concurrently and merged during the analysis phase, allowing for bidirectional interpretation:

App logs and heatmaps revealed what participants did—e.g., skipped exhibits, time spent on missions, frequent returns. Interviews explained why—e.g., "the UI confused me at Exhibit Z," or "the task motivated me to stay longer."

For instance, participants with longer mission completion times often described higher intrinsic motivation and perceived control, aligning with backend usage patterns. Conversely, areas with unexpected drop-off in app interaction were clarified through interview feedback citing usability barriers or content overload.

This triangulated analysis provided a more nuanced understanding of how gamified mobile guidance affects learning behavior—not just in terms of spatial flow, but also cognitive and motivational engagement.

IV. Result and Discussion

This section presents the outcomes derived from field observations, iBeacon backend data analysis, and user feedback on the mobile guide app, iGuide—Go to NTSEC. It explores the app's performance in real-world museum settings, focusing on variations across different visitor types, interaction behaviors, and overall satisfaction.

A. Behavioral Trajectory and Participation Intensity Analysis

This study aimed to visualize visitor movement patterns and identify engagement hotspots within the exhibition hall using iBeacon positioning and trajectory data. The third floor of the permanent exhibition at the NTSEC was selected as the primary area for analysis. The following findings are based on heatmaps of exhibit visits, visitor paths, app usage entry points, and demographic observations.

1) Heatmap of exhibit visits

Taking the Life Science Exhibition Zone on the third floor as an example, system logs recorded visitor positions and dwell times to generate a heatmap (Fig. 1). The heatmap visualizes the intensity of interactions based on color gradients from light yellow to red, indicating increasing density. The results show several "learning hotspots" clustered around interactive exhibits and task-trigger zones, highlighting the app's effectiveness in terms of guiding visitors and engaging them through location-based tasks.

This spatial behavior analysis suggests that the iGuide app not only influences the visitor's route but also enhances their dwell time at key educational nodes, thereby achieving the dual purpose of navigation and experiential learning.

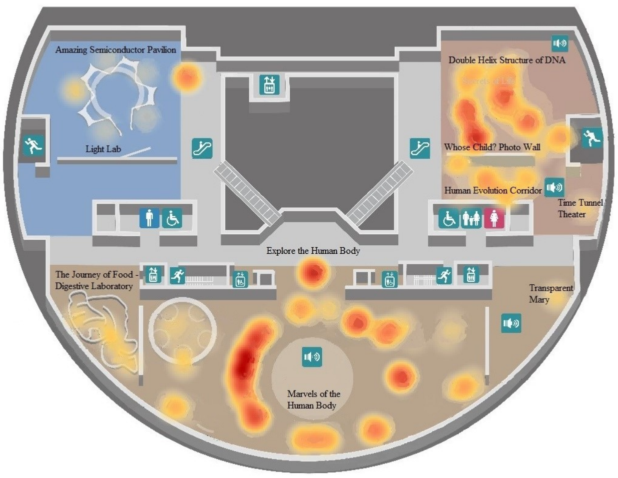


Fig. 1. Presents the heatmap of exhibit visits on the third floor, generated from the iBeacon data logs.

Most visitors were clustered in the "Secrets of Life" and "Marvels of the Human Body" areas, both located near the eastern side of the floor, directly adjacent to the escalator entrance. This confirms that the spatial navigation logic designed by the museum—where visitors tend to move "right upon entry" (right-up-left-down circulation)—aligns with actual visitor behavior. In contrast, western exhibits such as the "The Journey of Food - Digestive Laboratory" and "Light Lab" showed significantly fewer visitations, suggesting that entry path and exhibit location are strong determinants of audience flow.

Further analysis revealed that the most visited exhibit was "Whose Child? Photo Wall," followed by "Double Helix Structure of DNA." These exhibits are visually prominent and directly visible upon ascending the escalator, demonstrating how spatial positioning impacts exhibit attention. Interactive panels in the central area and the Human Evolution Corridor in the east also drew more attention, while peripheral zones and features like the "Time Tunnel Theater" experienced low footfall.

To address this imbalance, it is recommended that visual cues (e.g., lighting, signage) be enhanced for peripheral exhibits, and that directional guidance (e.g., ground markers or illustrated maps) be added near the theater to increase awareness and traffic.

In the "Marvels of the Human Body" area, the most popular exhibit was "Explore the Human Body," located at the entrance of the zone. Observational data showed this exhibit served as a frequent gathering and dwell point, making it one of the hottest zones on the floor. It is advisable to reposition high-priority exhibits like "Transparent Mary" closer to the entry area to increase visibility and engagement.

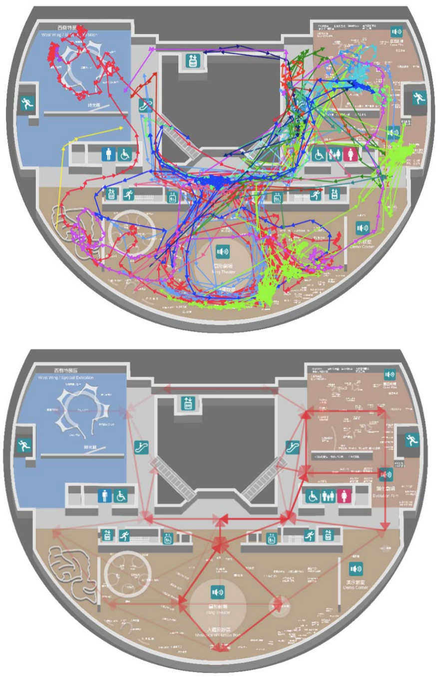
In the Special Exhibition Area on the west side, the "Amazing Semiconductor Pavilion" attracted the most visitors, largely due to the presence of a photo spot. However, this zone suffers from its peripheral location and the placement of the downward escalator, which encourages exit rather than further exploration. Path analysis confirmed that many visitors, upon completing their tour of the eastern and central areas, tend to return via the same route rather than proceeding westward. Enhancing directional signage and using attractive spatial elements such as entrance arches or illuminated pathways could help redirect visitor flow and improve spatial equity across exhibit areas.

2) Visitor pathways (raw and simplified models)

To further understand spatial behavior and exhibit engagement, this study adopted the approach proposed by [26, 38], which emphasizes the importance of constructing abstracted visiting models from complex raw data to gain Finsights into spatial planning, guidance design, and behavioral classification. Accordingly, both raw pathways and simplified directional maps were analyzed.

As illustrated in Fig. 2, the raw pathways represent visitors' actual movement trajectories and dwell points at exhibits, while the simplified paths abstract and generalize the primary directions of entry, circulation, and exit within the exhibition space. Taking the third floor of the National Taiwan Science Education Center as an example, the simplified path diagram reveals that visitor flow primarily concentrates in the eastern and central zones of the exhibition hall. Due to the NTSEC's architectural circulation layout—designed in a "right-up to left-down" pattern—visitors typically enter from the east after ascending the escalator, proceeding with a rightward bias, then transitioning to the central exhibition area. Without explicit directional signage or thematic motivation, few visitors continue into the western Special Exhibition Area.

Additionally, within the eastern exhibition zone, internal movement patterns also exhibit a strong right-turning preference, demonstrating a consistent spatial cognition and behavioral habit among museum-goers. This finding aligns closely with previous heatmap observations, particularly regarding the high-traffic zones near entrance points and prominent exhibit locations.



Raw Visitor Path (overlaid sample trajectories)

Simplified Directional Flow (aggregated patterns)

Fig. 2. Visitor path analysis—3rd floor.

B. Visitor Types and Behavioral Characteristics

This study observed a total of 31 visitor groups, using a combination of tracking observation data, exhibit dwell times, and movement trajectories, along with app usage logs and interview feedback. Drawing upon established visitor typologies in museum studies [5, 36, 39], three distinct audience types were identified. The classification criteria focused on: Dwell time per exhibit, Depth of app interaction, and Exhibit interaction and task completion rates.

These classifications were further validated through qualitative evidence obtained from field notes and interviews. The 31 visitor samples were categorized based on their behavioral patterns during the museum visit, and their interaction patterns within the mobile guide system (iGuide) were analyzed accordingly. As summarized in Table 4, the three identified visitor types include:

Leisure Browsers, who exhibited a fast-paced, surface-level viewing pattern, characterized by short exhibit dwell times and minimal engagement. For instance, observation cases N-06 and U-07 typically spent only a few seconds at each exhibit and did not interact with the app or complete any tasks. Interview responses frequently indicated motivations such as "just strolling" or "killing time."

Focused Explorers, who showed concentrated interest in specific exhibits, particularly those associated with gamified tasks. Participants like U-03 and U-04 actively triggered guided tasks and completed missions. They also responded positively to the app's recommendation features, noting that it "highlighted key areas worth visiting" and "helped me focus on the main points."

Immersive Learners, including U-01, U-06, and U-13, who demonstrated extensive exhibit exploration with prolonged visit durations. These participants engaged deeply with the app's features—including navigation, tasks, and multimedia—and even offered constructive suggestions for system improvement during post-visit interviews.

Table 4. Behavioral characteristics of three visitor types

Type	Avg. Number of Exhibit Stops	Path Density	App Usage Rate	Satisfaction	Visitor Traits
Leisure Browsers ($N = 4$)	11.3	Low	Very Low	Moderate	Brief stops at exhibits, minimal task completion, primarily exploratory visits.
Focused Explorers ($N = 10$)	22.7	Medium	Medium	High	Targeted interactions, task-focused behavior, favorable toward personalized suggestions.
Immersive Learners ($N = 17$)	35.1	High	Very High	Very High	Enthusiastic full-area exploration, deep engagement, often provided improvement suggestions.

In summary, the typology of visitor behaviors provides valuable insights into interaction patterns and can inform the future development of personalized content delivery and interactive guide design. The results suggest that the app effectively supports the needs of Focused Explorers and Immersive Learners, while its impact on Leisure Browsers remains limited. For the latter group, lightweight interactive features and alternative engagement strategies may be necessary.

C. Comparative Analysis: App Users (U Group) vs. Non-Users (N Group)

In order to evaluate the impact, the mobile guide app had on visitor behavior, we performed a comparative analysis of 15 app users (U Group) and 16 natural museum visitors who did not use the app (N Group). Behavioral differences were analyzed across three key dimensions:

1) Exhibit coverage and engagement scope

Participants in the U Group interacted with an average of 31.3 exhibits (SD=5.2), significantly higher than the 23.5 exhibits (SD = 4.8); this difference was statistically significant ($t\,(29) = 4.23$, $p < 0.001$). Heatmap visualizations revealed that the U Group's exploration covered a wider range of exhibit zones, especially those embedded with gamified tasks and digital interactions. In contrast, the N Group participants tended to cluster around default-route exhibits, particularly near the entrance and main corridors, showing limited deviation from the museum's designed path.

2) Dwell time and engagement intensity

Analysis of iBeacon dwell logs showed that the U Group recorded more than twice the number of red-zone visits (over 8 minutes) compared to the N Group, indicating significantly deeper engagement. Specifically, U Group participants averaged 5.6 red-zone stops per session, while the N Group averaged 2.3. Interview data further confirmed that app users were more intrinsically motivated to complete missions, interact with multimedia content, and revisit exhibits to gain rewards or complete tasks. In contrast, the N Group's visits were generally passive, with shorter, surface-level engagement driven more by physical layout than learning intent.

3) Navigation behavior and spatial orientation

The U Group demonstrated more complex and adaptive navigation patterns, often deviating from the museum's fixed "right-in, left-out" circulation route. Participants were guided by app-based missions that encouraged non-linear movement, resulting in a higher number of spatial nodes visited. Conversely, the N Group followed a relatively uniform path with minimal exploration into peripheral zones, as visualized in comparative trajectory maps.

In summary, the task-driven interactivity and content push mechanisms embedded in the mobile guide system significantly enhanced visitors' engagement—both in terms of breadth (coverage) and depth (dwell and re-engagement). U Group participants not only reported higher satisfaction with their visit experience but also showed more autonomous and motivated learning behavior. While positive overall, several participants noted that interface simplification and clearer exhibit-task alignment would improve usability in future iterations.

D. User Feedback and System Optimization Recommendations

Based on semi-structured interviews with 15 app users, key themes emerged that reflect differentiated needs among the three identified visitor types. These insights inform practical directions for system improvement:

1) Navigation and positioning are useful but visually overwhelming

Several users reported difficulties navigating the map interface due to overlapping elements and excessive visual layers. Visitors with a "Leisure Browsing" profile tended to avoid using the app for navigation due to interface complexity. For instance, participant U-07 noted, "There were too many points on the map—I didn't know where to click". It is recommended to simplify the map layers and introduce intuitive features such as "One-Tap Mission Start" or "Suggested Tour Paths" to support quick onboarding for light users.

2) Scenario-based tasks are engaging but need better guidance

Both "Focused Visitors" and "In-Depth Learners" showed strong interest in gamified tasks, particularly those involving storylines or role-playing elements. Participant U-03 shared, "The gene-hunting task was fun—it made me want to complete it." However, several participants expressed confusion about unclear instructions or exhibit locations. Improvements could include enriched visual cues, voice instructions, and blinking path indicators for task navigation.

3) Content hierarchy should allow flexible depth of learning

For "In-Depth Learners", current exhibit content in the app was perceived as overly basic. Participant U-13 suggested, "It'd be better to have beginner and advanced modes, so we can choose how much we want to read". This study recommends implementing a dual-layered content model featuring both summary and extended information, with clearly labeled depth levels to support personalized exploration based on time and interest.

4) Interactive design and achievement feedback are well received

Many users appreciated feedback elements such as sound cues, achievement badges, and mission-completion screens, which contributed to motivation. Participant U-06 commented, "The mission-complete screen was great—it felt like passing a challenge." Future enhancements could include a personalized learning dashboard that accumulates progress history and achievements over time.

These recommendations provide strategic insights for tailoring the guide system to varied user types and improving both usability and engagement across different learning profiles.

E. Discussion

This study reinforces the growing role of mobile guide systems as facilitators of exploratory learning, engagement, and adaptive navigation in museum environments. The findings showed the app users demonstrated significantly broader spatial exploration, deeper exhibit interactions, and greater dwell time compared to non-users. This suggests that gamified digital tools can effectively foster self-directed yet structured learning behaviors by blending autonomy with guided tasks [31, 40, 41].

From a UX design standpoint, the app's mission-based navigation, content prompts, and spatial guidance align with frameworks that emphasize the importance of intuitive interfaces, service flow, and task clarity in cultural settings [2, 12]. Our results extend these frameworks by demonstrating how location-aware design directly influenced movement patterns and learning hotspots, particularly in under-visited peripheral zones when supported by digital guidance. Positive participant feedback regarding usability and satisfaction confirms that structured digital interventions enhance orientation, engagement, and the perceived education value of museum visits [16, 42].

In terms of gamification, the system's use of real-time feedback, goal-driven missions, and interactive progression points exemplifies "gameful design" principles that transform passive museum visits into purposeful journeys [43]. These features align with critical reviews highlighting that well-designed gamification can significantly influence motivation and learning engagement, especially when task is contextually meaningful [3, 17].

Learning theories further contextualize the results. The combination of autonomy and embedded guidance exemplifies the principles of guided play, where learners explore at their own pace within structured environments [44]. This mirrors earlier findings that mobile learning systems integrating problem-solving and mission-based strategies promote deeper cognitive engagement [40, 45].

Our visitor segmentation analysis further illustrated how audience typologies influenced spatial and task engagement patterns. The app's adaptive features supported diverse visitor motivations and behaviors, as advocated in typology-based personalization frameworks [5, 33, 46]. Behavioral clustering enabled us to align content delivery with motivational profiles, showing how personalization strengthens identity-driven engagement and learning outcomes [1, 21].

Finally, this study highlights future directions for scalability and intelligent adaptation. Integrating multimodal sensing, emotion detection, and physiological monitoring—as demonstrated in real-time affective learning systems—could further personalize learning trajectories and reveal hidden emotional engagement [19, 20, 47]. These developments may eventually support museum systems that respond dynamically to visitors' cognitive states, interests, and affective feedback, enabling a richer, more human-centered museum experience [22, 48].

In summary, the iGuide system illustrates how mobile technology can blend UX, gamification, and learning theory to cultivate adaptive, inclusive, and meaningful informal learning. By linking real-world visitor behaviors with interactive design, this research contributes to the evolving paradigm of smart museum engagement.

V. Conclusion

This study summarizes and reflects on the key findings of this study while offering actionable suggestions for future development and application. The results aim to contribute both practically and theoretically to the domains of digital museum guide design, visitor behavior research, and smart environment implementation. Grounded in real-world museum settings, this study employed field-based tracking, iBeacon heatmap analysis, and user feedback to comprehensively assess the actual impact of a digital guide system on visitor behavior. The findings indicate that the iGuide—Go to NTSEC app significantly enhances visit efficiency, promotes spatial exploration, and increases interaction and participation. Notably, app usage resulted in a clear increase in the number of exhibits visited, time spent on-site, and task completion rates. These outcomes suggest that the app functions beyond a simple navigational tool, effectively serving as a digital intermediary that guides learning and facilitates engagement.

From an academic perspective, this study introduces a behavioral model of three visitor types, addressing the current design gap in mobile guide systems regarding the cognitive and interaction needs of diverse audience groups. It also contributes to ongoing discourse about interpreting positioning data and participation depth by triangulating heatmap findings with interview-based semantic content, thereby enhancing data validity and interpretability.

Regarding spatial layout and exhibit popularity, the study highlights that when task design aligns with spatial flow and exhibit distribution strategies, visitors can be effectively guided to peripheral or less-visited zones, leading to more balanced visitor traffic and enriched user experiences. Moreover, achievement feedback, voice navigation, and exhibit-based tasks within the app were found to stimulate intrinsic motivation among certain users, demonstrating the value-added impact of digital guides for deep-participation audiences. In summary, the results support the integration of context-aware and gamified mobile systems in museum environments as a means to enhance personalized learning pathways, spatial interaction, and user satisfaction. Future developments should continue to incorporate multimodal feedback, adaptive interfaces, and personalized recommendation mechanisms to support inclusive and learner-centered digital experiences.

A. The Major Findings

1) Effectiveness of iBeacon-based Positioning: A total of 474 iBeacon devices were deployed throughout the museum, enabling the successful visualization of visitor movement patterns and dwell durations using heatmap analysis.
2) Impact of Gamification on Engagement: The incorporation of scenario-based enhanced user interaction and motion within the exhibition space.
3) Personalization through Visitor Segmentation: Behavioral clustering revealed distinct visitor types, allowing for the development of adaptive content delivery strategies tailored to different user needs.
4) Enhanced Learning via Integrated app Features: Features such as real-time prompts and interactive tasks contributed to deeper and more meaningful user engagement.
5) Strengthened Research Validity through Mixed Methods: By combining quantitative positioning data with qualitative interview insights, the study achieved a more comprehensive and nuanced understanding of visitor engagement.

B. Practical Implications and Future Directions

1) App Optimization: Future versions of the systems should prioritize simplified user interactions, voice-assisted navigation, and intelligent, context-aware content recommendations. Adding audio-based descriptions for exhibits could further stimulate user curiosity.
2) Strategies for Cold-Zone Engagement: Utilizing AI-analyzed heatmap data can help identify under-visited areas, allowing for the deployment of incentives or environmental cues to encourage more balanced visitor distribution.
3) Affective and Physiological Feedback Integration: Incorporating real-time data such as heart rate or facial expressions can support dynamic content adaptation based on users' emotional and cognitive states.
4) Scalability Across-Domain: The framework developed in this study can be extended to other cultural and commercial spaces, promoting a wide range of personalized, location-aware experiences.

This study confirms that the integrating mobile navigation, sensing technologies, and user-centered design effectively creates a novel museum visiting experience. Future guide systems should combine perception data, semantic guidance, adaptive recommendation engines, and context-aware gamified tasks to deliver flexible, segmented, and immersive learning journeys. Ultimately, such systems have the potential to enable intelligent, interactive, and human-centered guide ecosystems that respond dynamically to diverse visitor needs and preferences.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

CL & YN conducted the study together; YN analyzed the data; CL wrote the paper and submitted it for publication, and all authors approved the final version.

FUNDING

This research was funded by the Digital Humanities Program, Ministry of Education, Taiwan.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Director Shu-Wen Cheng of the Information Division at the National Taiwan Science Education Center for her valuable support. Special thanks are also extended to the research team members Wei-Ling Wu, Sheng-Yan Lin, Yi-Chu Chen, and Ming-Rong Chia for their assistance in observation, interviews, and data collection efforts throughout the study.

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