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# Data-Driven Spatial Analysis: A Multi-Stage Framework to Enhance Temporary Event Space Attractiveness

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**Abstract:** Revitalizing Japan's remote areas has become an urgent challenge, particularly in regions with aging populations. Despite their rich cultural and natural resources, these areas struggle to attract younger demographics, including young families and children. To address this, local governments have introduced temporary events to enhance urban vibrancy and create inclusive spaces. However, research on optimizing event design faces significant challenges due to the vast amount of data required for comprehensive analysis, making it difficult to gain deeper insights into user experience. Recent advancements in natural language processing (NLP) and AI have opened new possibilities for analyzing large-scale, multi-person interview data. While models like ChatGPT-4 have enhanced data-driven decision-making, structuring user metadata and identifying shared themes across events remain key challenges. This research integrates visual segmentation, spatial perception analysis, and NLP-driven keyword extraction into a novel, scalable approach. Using Matsue City as a case study, the method enhances the visual attractiveness of temporary event spaces by optimizing spatial layout, product visibility, and user engagement, ensuring they remain appealing and inclusive despite demographic challenges. From a data perspective, the proposed model improves the analysis of complex qualitative datasets and supports a more accurate interpretation of public event experiences. This integrated approach not only bridges spatial design and participant engagement but also establishes a replicable AI-assisted framework for systematically enhancing temporary event spaces, overcoming current limitations in large-scale data processing.

**Keywords:** visual attractiveness; spatial perception; natural language processing (NLP); data-driven insights; temporary event space

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Academic Editor: Manfred Max Bergman

Received: 28 February 2025
Revised: 9 April 2025
Accepted: 15 April 2025
Published: 23 April 2025

**Citation:** Nguyen-Tran, Y.-K.; Majiid, A.; Mian, R.-u.-h. Data-Driven Spatial Analysis: A Multi-Stage Framework to Enhance Temporary Event Space Attractiveness. *World* **2025**, *6*, 54. https://doi.org/10.3390/world6020054



## 1. Introduction

Revitalizing Japan's remote regions has become a significant priority [1–3], and Matsue City serves as a key example of this effort, particularly through the creation of temporary event spaces that enhance urban vibrancy and foster interactions among residents and visitors. In this context, this research's objective is to explore how spatial and visual design influences user perception and engagement, aiming to develop effective strategies for enhancing the attractiveness and long-term success of these temporary spaces. Selected events under investigation, which have received positive feedback from 70% of attendees, have paved the way for other small-scale community gatherings, further promoting the city's potential and strengthening its local identity among both residents and tourists [4]. With a mix of organic foods, local goods, and family-friendly activities, the diverse range of stalls contributes to the visual appeal of these events, enhancing the overall participant experience [5]. However, concerns persist regarding the ability of temporary event spaces to maintain long-term engagement, as they often struggle to attract repeat visitors due to a lack of sufficient interaction [6]. This issue is frequently attributed to a misalignment between the expectations of visitors and the objectives of event organizers. Such misalignment highlights a cognitive and cultural divide, particularly between unmarried visitors and families, who show differing motivations for attending, such as exploring culture, seeking novelty, socializing, or fostering social connections [7]. Additionally, cultural background plays a role in how attendees perceive event spaces—while individuals familiar with Japanese culture tend to interpret visual environments holistically, international visitors are more likely to focus on distinct objects, especially in settings where multiple visual stimuli compete for attention [8].

These observations raise important questions about the impact of spatial configurations on participants' perceptions of temporary event spaces, leading to an exploration of how visual attractiveness is interpreted across different cultural and demographic groups. Therefore, this research seeks to answer the following key questions: How do specific spatial and visual design elements of temporary event spaces in Matsue City influence the perception and engagement of diverse user groups, including residents and visitors with varying cultural backgrounds and demographics? And what data-driven design strategies, informed by user feedback and leveraging NLP-enhanced analysis of spatial and visual perception, can be developed to enhance the attractiveness and long-term success of these temporary event spaces in Matsue City and potentially other remote regions in Japan?

In addition, recent advancements in generative AI, such as ChatGPT-4, have demonstrated the ability of natural language models to analyze voice or text extracted from voice [9,10]. The application of natural language processing (NLP) has also been successful in evaluating and decoding user perceptions, offering valuable insights into participant feedback [11,12]. More than ever, the increasing integration of digital and AI-driven tools has introduced new challenges in adopting data-driven design methodologies to enhance user experiences (UX) [9]. By combining visual segmentation and spatial perception analysis with our innovations and support from NLP, this research aims to improve the quality of temporary event spaces while identifying design strategies to enhance their visual attractiveness. Ultimately, these findings will contribute to a replicable framework that can be applied to enhance temporary events in Matsue City and other remote regions across Japan.

*Outline of the Study*

The rest of this paper is organized as follows: Section 2 provides a comprehensive literature review on urban livability and Data-Driven AI applications in spatial analysis. Section 3 details the proposed multi-stage framework and the methodology employed in this study, including case study selection and data collection methods. In Section 4, we present data-driven insights into environmental dynamics affecting event spaces. The proposed algorithm, designed to mitigate the challenges of using NLP by leveraging interviewer text from different personnel, is also addressed in Section 4. Section 5 explores the impact of spatial arrangements and data-driven results on the visual attractiveness of temporary event spaces. Section 5 also explains the scaling impact of adding new participants to the existing pool and examines the correlation between spatial factors and user engagement metrics. Finally, in conclusion, Section 6 summarizes the key findings and discusses implications for urban planners and event organizers.

## 2. Literature Review

This literature review examines the relationship between urban livability, event-based revitalization, and data-driven analysis, focusing specifically on Matsue, Japan. It addresses challenges related to demographic shifts and economic factors, emphasizing urban design strategies to liven up urban livability (Section 2.1), particularly in the case of Matsue (Section 2.2). The review further explores the role of temporary events in urban revitalization (Section 2.3), spatial cognition in perceiving event spaces (Section 2.4), challenges in analyzing user feedback (Section 2.5), and how AI and NLP can enhance data-driven analysis of user perceptions (Section 2.6).

### *2.1. Urban Livability in an Aging and Remote City*

Many remote regions across the globe face increasing pressure from demographic decline, economic stagnation, and urban shrinkage. Countries in Europe, North America, and East Asia have experienced similar patterns, where rural or secondary cities struggle to retain younger populations due to limited opportunities and services. These challenges have prompted discussions on urban livability and resilience in shrinking contexts [13]. Urban livability—often framed around accessibility, inclusiveness, and quality of life—has become a critical framework for rethinking the development of remote cities [14]. Building on this global discourse, this study turns to Japan—a country facing some of the most accelerated demographic changes—as a critical context to explore how urban livability frameworks are being applied in regional settings.

Japan faces significant demographic challenges due to low birth rates and an aging population, particularly in regional areas [15]. This has led to an ongoing outflow of younger individuals to metropolitan cities, leaving behind aging communities and struggling local economies [16]. In response, national and local governments have introduced various policies aimed at improving urban livability and attracting younger populations back to these regions [17]. These efforts include promoting reverse migration, enhancing job opportunities, and improving services for the elderly [18]. Recent studies on aging cities in remote regions have underscored the critical role of livability in ensuring that older populations can continue to thrive in these areas. Livability in such contexts is often shaped by access to essential services, healthcare, and social engagement opportunities. Research has shown that cities facing population decline and aging populations can improve livability by focusing on inclusivity, mobility, and the creation of spaces that foster social interaction while also addressing the specific needs of elderly residents [19]. Despite these efforts, many younger people continue to migrate to larger cities.

One major initiative, the Compact City strategy, aims to create more accessible, high-density urban centers that improve residents' quality of life [18,20,21]. Matsue City, classified as a Multipolar Network Type Compact City, has been part of this initiative, benefiting from infrastructure improvements and urban restructuring to the development of regional public systems and the integration of digital technology [22]. However, the expected increase in urban compactness has not fully materialized, as younger populations continue to prefer metropolitan areas [23,24]. The local economy of Matsue has also undergone significant transformations, with a shift from manufacturing and construction to the medical and welfare industries [25]. Such changes present new economic and social challenges that impact urban livability. To address these challenges, urban policies have increasingly focused on fostering creative industries, organizing events, and leveraging digital technologies to revitalize the city [26].

### *2.2. Urban Livability and Attractiveness in the Case of Matsue*

Studies on urban attractiveness indicate that environmental and cultural factors strongly influence perceptions of livability. Matsue, as one of 138 major Japanese cities assessed in the Japan Power Cities—Profiling Urban Attractiveness initiative by the Mori Memorial Foundation, ranks among the top cities for Cultural Interaction and

Livability [27]. For instance, from 2018 to 2023, Matsue ranked among the top 40% of cities with high ratings in terms of Cultural Interaction and Livability/Daily Life and among the top 10 cities in terms of Environment. The composition of the population has also shifted from a mix of families, seniors, and tourists toward greater diversity, with increased in-migration of single employees. Public Perception Surveys further indicate that the city's natural environment and historical landmarks remain its strongest assets, reinforcing its cultural and visual appeal [28].

Given these characteristics and its ongoing efforts to adapt to demographic changes, Matsue presents a compelling context for examining how spatial and cultural initiatives can improve livability in aging regional cities. In particular, its active integration of event-based urban strategies provides an opportunity to explore how temporary gatherings can strengthen community identity, stimulate local engagement, and enhance urban appeal.

### *2.3. The Role of Events in Urban Revitalization*

Events have become a crucial tool in urban revitalization by fostering a sense of community, attracting visitors, and stimulating local economies [29,30]. Matsue has leveraged cultural festivals, sports events, and other public gatherings to enhance its city's appeal. The post-pandemic period has further emphasized the role of events in strengthening urban identity and engagement [31]. Following a global approach to engage diverse communities and re-establish urban vibrancy [32], Matsue have been reinvesting in public spaces and hybrid event models combining physical and digital experiences aiming to re-engage communities, attract visitors, and encourage younger generations to see these cities as vibrant and livable places to settle and work [33,34].

However, the success of event-based urban revitalization depends on more than just creating events; it also requires effective engagement with the local community. Studies show that community participation in the planning and execution of events is essential for their success and long-term sustainability. Local involvement helps ensure that events reflect the needs and preferences of residents, thus strengthening social cohesion and urban identity. Furthermore, the absence of structured user feedback mechanisms in remote regions, such as Matsue (explained in Sections 2.1 and 2.2), makes it difficult to gather meaningful insights on public engagement and event formats [5].

### *2.4. Spatial Cognition and the Perception of Temporary Events*

Spatial cognition plays a significant role in understanding how individuals interact with and perceive urban environments. Lynch's framework on the image of the city [35] identifies five key urban form characteristics—paths, edges, nodes, districts, and landmarks—that shape an individual's perception of space. Temporary events, however, often introduce new visual cues and alter the familiar layout of urban environments. These events create dynamic, temporary visual experiences through signage, product displays, and activity zones [36,37]. Cullen's concept of townscape further explores how urban settings enhance the visual experience by highlighting aspects such as color, texture, and scale [38]. This is particularly relevant to temporary events, where organizers strategically place displays and structures to create a visual narrative [39]. Temporary events disrupt the everyday urban fabric by introducing novelty and contrast, often through vibrant colors and dynamic arrangements [40]. This disruption not only attracts attention but also contributes to a heightened sense of excitement and engagement [41], building upon the affective appraisal discussed by Nasar [42]. Furthermore, Russell's approach to cityscapes [43] emphasizes how the identity and structure of urban spaces are shaped by personal and collective experiences.

In addition, recent research has strengthened the link between visual attractiveness and user behavior, particularly in informal or event-driven urban settings. Nasar and Holleran found that visually engaging environments, marked by complexity and care, positively affect emotional responses and perceptions of safety [44]. Building on this, Mehta emphasized that the visual richness of street-level design—including storefronts, temporary displays, and signage—encourages social interaction and lingering behaviors [45]. This is particularly relevant in the context of street events, where temporary arrangements can reshape behavioral patterns. In a more event-specific context, Gehl and Svarre highlighted how even small changes in spatial setup or visual stimulation can influence how long people stay, where they gather, and how they interact in public spaces [46]. Similarly, Franck and Stevens (2007) observed that the success of temporary urban interventions depends on how well they appeal to the senses and invite users to engage with their surroundings [47]. These findings suggest that visually curated elements—such as product arrangements, colors, and structures—are not just aesthetic choices but behavioral cues that can activate space and draw participation. In Japan, studies of traditional shopping streets have shown how coordinated shopfront displays, banners, and local motifs contribute to both wayfinding and the sense of community, encouraging pedestrians to slow down and engage with their surroundings [5]. Likewise, research on regional streetscapes in rural Japan highlights how the integration of natural scenery, seasonal decoration, and traditional architectural details enhances visual attractiveness, fostering a strong sense of place and supporting local tourism and community events [48].

In the context of temporary events, the arrangement of product displays, information booths, and interactive zones all contribute to the event's identity, enhancing its visual appeal and engaging participants [49,50]. The careful consideration of these visual elements is crucial for designing successful, attractive temporary events. Furthermore, the inclusion of activities for all ages, from interactive installations to performance areas, creates visual focal points and adds dynamism to the event space [51], contributing to a richer sensory experience and enhancing the overall attractiveness of the event for a diverse audience [52].

### *2.5. Challenges in Analyzing User Feedback for Event Improvements*

While the visual appeal of temporary events is essential, a key challenge lies in effectively collecting and interpreting feedback from users. Traditional tools such as surveys, interviews, and field observations often fall short in capturing the full range of participant opinions and preferences [5,53]. This issue becomes more pronounced in compact cities like Matsue, where feedback systems are limited and aging demographics further complicate outreach and participation.

Recent studies have attempted to overcome these limitations through post-event evaluations using virtual environments and interactive platforms [54,55]. These approaches yield richer insights but also contribute to data overload, especially in constrained urban contexts like Matsue [48]. Hence, the absence of structured feedback systems in remote areas, as discussed in Section 3.1, makes it difficult to extract actionable insights that could guide the improvement of future events. In response to these limitations, this research proposes a new method that leverages artificial intelligence to analyze user feedback. The goal is to create a more scalable and structured approach for understanding how users perceive visual attractiveness in temporary event settings.

### *2.6. A Data-Driven Approach for Keyword Extraction*

Data-driven methods have become increasingly central in event management and urban design, helping planners interpret environmental dynamics and participant feedback more effectively. Recent advancements in semantic keyword extraction and natural language processing (NLP) have led to the development of powerful NLP models such as ChatGPT, Claude, Gemini, DeepSeek, and Copilot [10,56–59]. These models have significantly improved data-driven decision-making in urban planning, public engagement, and event management [60,61]. They allow for the systematic processing of large volumes of user-generated content, enabling event organizers to distill actionable insights. The integration of machine learning (ML)- and artificial intelligence (AI)-assisted analytical techniques enables efficient extraction of keywords, themes, and contextual insights from interview data [62–65]. These tools have been applied across domains, such as cultural event evaluations [66,67], market analysis [68], and socioeconomic studies [69,70]. Core methods like sentiment analysis [71], network modeling [72], and keyword categorization [73] have proven essential for interpreting human experiences in complex urban settings. However, bias in qualitative data processing, particularly in interview-based studies, remains difficult to analyze objectively. The challenges remain around subjectivity, inconsistency, and potential bias in both data collection and processing [74–76].

A range of keyword extraction algorithms have emerged to address these challenges. YAKE! [61] employs a five-step process, including text pre-processing, feature extraction, and ranking, to identify keywords efficiently. Similarly, RAKE [77] focuses on co-occurrence-based scoring, while TextRank [78] uses graph-based centrality measures for keyword ranking. TF-IDF [79] remains a classic method, relying on term frequency and document rarity, whereas KeyBERT [60] leverages BERT embeddings for context-aware keyword extraction. However, all of these existing models do not address a critical need: they are not particularly designed for processing interview texts from many individuals on the same topic, nor do they focus on weighted keyword extraction tailored to such data. To address these gaps, the proposed algorithm is specifically designed to target keyword extraction from multi-person interview data, emphasizing weighted keywords to capture shared themes and responses across participants more effectively. Although data-driven methods have advanced, capturing human behavior remains difficult due to the complex, nuanced nature of language [80,81]. Variations in word choice, tone, and implicit meaning can introduce ambiguity, and traditional NLP tools often struggle to distinguish between facts, opinions, and sentiments [82]. Our algorithm addresses these concerns by incorporating adaptive keyword scoring mechanisms, which reduce interpretative bias and improve the reliability of qualitative analysis. This ensures a more robust and context-sensitive interpretation of user input, particularly in settings with diverse stakeholder voices.

## 3. Methodology

This methodology section introduces the multi-stage research framework (Section 3.1) developed to examine temporary event spaces in Matsue, Japan. It outlines the case study selection (Section 3.2), data collection process (Section 3.3), and the adaptive keyword extraction approach used to analyze user feedback (Section 3.4). The framework integrates spatial observation with data-driven analysis to better understand how spatial arrangements influence user perception and event attractiveness.

### 3.1. Multi-Stage framework

To investigate the spatial quality of temporary event spaces, focusing on the relationship between visual attractiveness and user feedback, the framework is built upon the above literature review (detailed in Section 3.3), such as how the placement of event elements influences visitor movement and understanding of the space, how the unfolding of views contributes to the overall atmosphere and perception of the event and how visual attractiveness is not simply aesthetic but also tied to user emotions and perceptions. The survey observation examines how temporary events, as discussed in [36], utilize visual elements like product displays [49], stationary spaces [50], and activity zones [51] to shape user experience. This spatial analysis is then integrated with user feedback data, recognizing that visual attractiveness is not only a design consideration but also a matter of user perception and experience. Traditional NLP models often struggle to differentiate between factual statements, opinions, and implied sentiments within interview responses without explicit contextual understanding. To address this challenge, and the broader difficulties of analyzing large and diverse datasets from dynamic urban environments [53,54], this research leverages a novel AI-assisted data-driven approach. As detailed in Section 4.1, the algorithm was designed for multi-person interview data and weighted keyword extraction. This method enhances keyword analysis by dynamically adjusting keyword weighting based on contextual relevance and occurrence patterns, mitigating inconsistencies and bias in NLP-driven qualitative data analysis, and allowing for a more accurate and representative interpretation of user input. This approach is particularly relevant in the context of regional cities like Matsue, where structured user feedback mechanisms may be limited due to its challenging social and urban context (see Section 3.1) and given the increasing use of data-rich platforms like virtual environment in event post-evaluation [48,55]. The detail of the framework is shown in Figure 1 below.

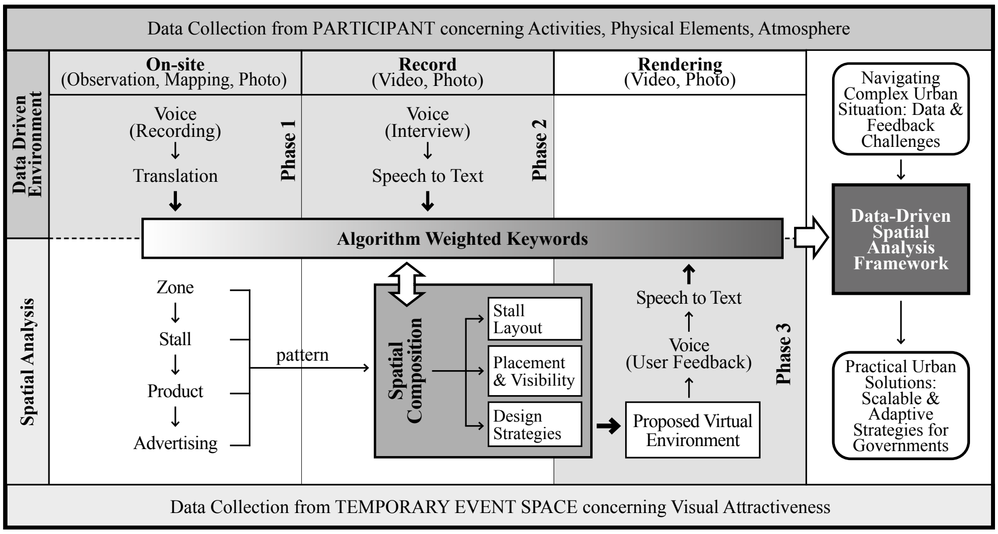


**Figure 1.** Framework data-driven spatial analysis.

### *3.2. Target Events*

The three events, thriving during and after the pandemic, contribute to urban revitalization by fostering community engagement, promoting local businesses, and providing family-friendly spaces. Each event has a distinct character that ties into the fabric of the local community, supporting different aspects of Matsue's cultural and economic life.

EV-1 as Imagine Coffee Morning Market is a monthly morning market event aimed at young generations, combining coffee culture with a dynamic pop-up store atmosphere. Attracting 20–30 visitors per session encourages the creation of new habits by introducing a lively, coffee-centric morning routine. Local coffee vendors, along with a rotating selection of pop-up shops, provide a platform for small businesses, offering unique local products and experiences [83]. This initiative revitalizes the local neighborhood by fostering a sense of community around a morning coffee culture that resonates with younger audiences eager to connect, socialize, and explore new trends in a relaxed, vibrant setting.

EV-2 as Yonagomachi Festival is held bi-annually in the historic district surrounding Matsue Castle and the nearby historical museum. With 30–50 visitors per session, the event takes place in the afternoon, offering families a chance to enjoy cultural activities before or after lunch. The district's rich heritage and frequent nearby events, such as exhibitions and performances, provide a perfect backdrop for this celebration of local arts and history [84]. It promotes local artisans and businesses while encouraging families and children to learn about the region's cultural history in an interactive, community-centered environment.

EV-3 as Matsue Farmer Market takes place further from the city center, focusing on promoting the local products of farmers from the surrounding Matsue area. This city-led initiative, attracting around 100–150 visitors per month, emphasizes sustainable practices and supports regional agriculture [85]. With a broader reach, it offers a platform for local farmers to showcase their fresh produce and products while providing an opportunity for residents and visitors to engage with the area's agricultural community. By highlighting the efforts of local farmers and their contribution to sustainability, the market serves as a key part of Matsue's urban revitalization efforts, teaching sustainable living practices and fostering connections between city residents and rural producers.

Each event brings something unique to the research. Imagine Coffee nurtures a young, coffee-driven culture with a focus on pop-up stores, Yonagomachi celebrates the region's cultural heritage in the heart of a historic district, and Matsue Farmer Market bridges the gap between urban residents and rural farmers, supporting local agriculture and sustainability. Together, they contribute to a vibrant, interconnected community that values both tradition and innovation. These events were strategically chosen to provide diverse contexts for investigating the relationship between visual attractiveness, spatial design, and user feedback in temporary events within a regional city.

### *3.3. Data Collection*

Data collection was conducted in three different periods:

On-site observation, mapping, and interview (August–October 2024): During each event, on-site observations and video recordings were conducted to capture the dynamic interplay between visitors and the event space. Stall Layouts, decorative elements, and store owners' design intentions were mapped. These data, analyzed through the lens of Lynch's framework [35], Cullen's concept [38] provides a basis for understanding the spatial organization and visual characteristics of each event. Initial on-site interviews were also conducted to gather preliminary impressions and inform the direction of subsequent interviews.

Post-event interviews (November 2024): Video recordings from the on-site events were used as stimuli for post-event interviews with eight participants (three long-term residents and three short-term residents, balanced for gender, marital status, and family structure). These interviews, guided by the initial on-site observations and interviews, explored visual and spatial aspects of the events, based on Nasar's evaluation of visual aesthetics [42] and Russell subjective perception [43] detailed feedback on user experiences and perceptions.

Post-evaluation interviews (December 2024–January 2025): Based on the analysis of the post-event interviews, virtual environments simulating the event spaces were created, incorporating design modifications aimed at enhancing user experience and wayfinding [86]. A replicated 3D model of each event was first built using on-site mapping and video recordings. User feedback from eight participants was analyzed to identify key themes such as spatial comfort and visual clarity, which informed the design improvements. These modifications were applied to the 3D models, and rendered views with similar frames to the original events were used for the post-evaluation interviews. The updated environments were presented to the same participants, and their feedback was collected to assess the perceived effectiveness of the design changes.

### 3.4. Adaptive Keyword from Interviews

This section focuses on the categorization and semantic analysis of keywords extracted from interviews of three environments, ensuring that they are systematically classified into distinct pre-determined categories.

The methodology for keyword extraction and analysis was developed to systematically extract, categorize, and analyze keywords from interview data related to all events, ensuring they align with predefined classification criteria. In this stage, the NLP model is supported with the actual interview data along with metadata about the event and participants. To maintain objectivity and prevent any bias from prior interactions, the analysis began with a fresh session, effectively resetting the context to avoid interference. This analysis is conducted in three phases. In all phases, the input data were organized in a structured Microsoft Excel format, including columns that detailed participant information with name, nationality, parental status, gender, age group, and their qualitative responses for each event, as shown in Table 1. This structured approach facilitated consistency and traceability throughout the analysis process. Providing background information (metadata) about each event was essential to contextualize the data. Details about the event's purpose, activities, and target audience helped ensure that the keyword extraction remained relevant and grounded in the specific context of each community event.

**Table 1.** Event and participant data summary.

| Interview Phase | Event Name | Target Attend. | Stalls (No.) | Avg. Dur. | Voice Data * Volume | Inter-Viewees (No.) | Male/ Female | JP/ Non-JP | Single/ Married | With/ Without Kids |
|---|---|---|---|---|---|---|---|---|---|---|
| On-site | Ev-1 | 20–30 | 8 | – | – | 11 | 6/5 | 11/0 | 6/5 | N/A |
| | Ev-2 | 30–50 | 11 | 4 m 12 s | 647 | 15 | 5/10 | 15/0 | 3/12 | – |
| | Ev-3 | 80–100 | 22 | – | – | 11 | 6/5 | 11/0 | 3/11 | – |
| Video | Ev-1 | 20-30 | N/A | 16 m 06 s | T:25745<br>I:20096<br>S:5649 | T:8<br>I:6<br>S:2 | T:5/3<br>I:5/1<br>S:0/2 | T:3/5<br>I:2/4<br>S:1/1 | T:3/5<br>I:2/4<br>S:1/1 | T:4/4<br>I:3/3<br>S:1/1 |
| | Ev-2 | 30–50 | | | | | | | | |
| | Ev-3 | 80–100 | | | | | | | | |
| Virtual | Ev-1 | 20–30 | N/A | 12 m 30 s | T:26790<br>I:19753<br>S:7037 | T:8<br>I:6<br>S:2 | T:5/3<br>I:5/1<br>S:0/2 | T:3/5<br>I:2/4<br>S:1/1 | T:3/5<br>I:2/4<br>S:1/1 | T:4/4<br>I:3/3<br>S:1/1 |
| | Ev-2 | 30–50 | | | | | | | | |
| | Ev-3 | 80–100 | | | | | | | | |

* T = Total After Scaling, I = Initial Before Scaling, S = Extended/Scaling.

The event and person data table provides a summary of data collected from three phases corresponding to three types of environments (Onsite, Record, and Rendering) in Matsue City, focusing on participant demographics, stall distribution, and engagement patterns. The total participants are split into two groups—before and after scaling—since the framework was developed to be scalable following the initial analysis. Accordingly, we also examine the impact of scaling on the framework's performance and applicability. The Record environment interviews, using post-event videos, elicited more reflective and detailed qualitative feedback from the participants. In the Rendering (virtual) environment interviews, participants interacted with digitally simulated event spaces, allowing us to evaluate their reactions to potential design modifications. These three phases offer a comprehensive view of how spatial design, demographic characteristics, and engagement patterns interrelate. Key findings show that family participation drives the need for kid-friendly areas, while stall visibility and event layout play a crucial role in attendee engagement. The synthesized insights from all three phases clarify user priorities and help identify which spatial and visual features enhance or hinder engagement. This analysis offers valuable insights for improving event design and making spaces more accessible and engaging for diverse audiences.

Following the analysis of data collected from onsite interviews with visitors, the responses were professionally translated into English by human (native Japanese translators) for subsequent processing. At this stage, apart from NLP keyword analysis, the collected data were also manually analyzed for each event to identify key themes and formulate questions for the offsite interviews (Record and Rendering), which were conducted while reviewing event video recordings (details are explained in Section 3.3). The remaining analysis was conducted in three major phases (see Figure 1), as outlined below:

#### 3.4.1. Phase-1

In Phase-1, keywords were categorized into three distinct classifications: Activities, which include actions performed or observed like eating, walking, and buying; Physical elements, referring to tangible objects or items such as sweets and farm products; and Atmosphere, capturing ambiance or emotional impressions like lively, fun, and natural.

Clear definitions for each category were established to maintain semantic precision and ensure that the keywords accurately reflected the content and nuances of the interviews. Then, a keyword extraction matrix was employed, mapping the keywords into a six-column structure comprising the keyword and its definition for each of the three categories: Physical Elements, Activities, and Atmosphere.

Definitions were crafted to highlight the key purpose and contextual relevance of each keyword, focusing on their core meanings and referencing the original context from the interviews. This step was crucial in preserving the semantic integrity and ensuring that each keyword was directly traceable back to the source text. Figure 2 summarizes the Phase-1 total (bar) and unique keyword frequencies (inner bar) of three categories across events. The top list of unique keywords for each event is provided in Table 2. The table shows that some cases exactly match the keywords, while others are different.

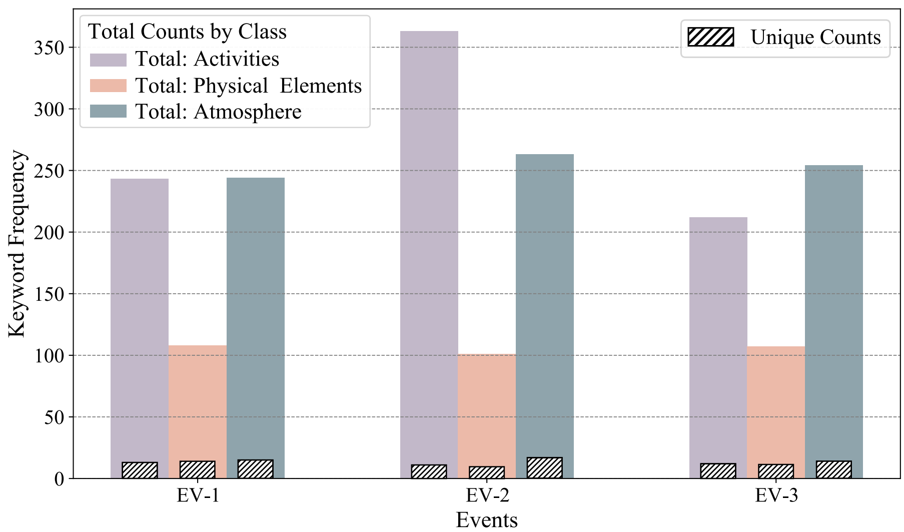


**Figure 2.** Categorized three distinct classifications of keywords.

**Table 2.** Top unique keyword activities, physical elements, and atmosphere by event.

| Event | Activities | Physical Elements | Atmosphere |
|---|---|---|---|
| Ev-1 | do, move, eat, drink, sell, buy | chair, drink, farm, table, cooler | color, attention, seem, festival, experience |
| Ev-2 | do, drink, eat, sell, buy, sit | drink, table, notice, yummy, fruits | color, lively, hot, experience, festival |
| Ev-3 | do, drink, eat, move, sell, buy | chair, drink, packaging, back, table | color, seem to be, expect to see, hot |

Note: Some keywords, such as *drink*, appear in multiple categories due to their contextual dual usage. For example, *drink* as a physical element refers to beverages available at event stalls (e.g., coffee), while as an activity, it reflects visitor actions like drinking with family or friends. This classification ensures that both object-based and behavior-based perspectives are captured in the analysis.

#### 3.4.2. Phase-2

In Phase-2, the data were analyzed without predefined classification, and NLP API self-generated identification was adjusted to identify potential correlations with the Phase-1 outputs. Through structured methodology, interview content was analyzed using keyword extraction, categorization, and thematic analysis. In both phases, keywords were systematically extracted per person based on predefined criteria to ensure accuracy and relevance.

#### 3.4.3. Phase-3

In Phase-3, the analysis is extended through the use of a developed virtual environment, which is based on the outcomes of Phase-1 and Phase-2. This phase is essential as it facilitates an unbiased continuation of the four predetermined keywords identified in Phase-2, enabling a more comprehensive evaluation of their impacts. Similar to Phase-2, the analysis in Phase-3 is systematic and relies on structured methodologies to ensure consistency and reliability. Like the video interview, here, the proposed algorithm for custom weights is also applied to the keyword frequency counting. It ensures the human behavior-related error during the counting of the keyword, as discussed in Section 4. The ultimate goal is to validate the video interview sessions by assessing how these sectors impact or align with the thematic outcomes.

## 4. Data-Driven Insights for Analyzing Environmental Dynamics

Understanding environmental dynamics within the context of community events used in this study requires a structured approach to data collection, processing, and analysis across several stages. Such a multi-stage framework not only relies on visitor feedback but also incorporates surveys, on-site interviews, video interviews, and interviews on virtual environment, along with the analysis of video content, images, and the developed virtual environment, as outlined in Section 3. This section presents a comprehensive analysis to extract meaningful insights from interview data by systematically analyzing keywords and themes across all three events described in Section 3.4.

The analysis is carried out in two major parts. Part-1, in Section 4.1, discussed details of our proposed algorithm for keywords analysis while in the Part-2 in Section 4.2, we detailed analysis of the key findings of our models outcomes.

### *4.1. Proposed Algorithm for Suitable Keyword Weighting in Text Analysis*

In analyzing human behavior, preliminary findings revealed that both the interviewer's (participant) and interviewee's words significantly influence the conversation. For example, participant P4's conversation response to the interviewer is higher than self-interested talking. This category of participants responds to the interview by saying "No" or "Yes" to a particular keyword. Thus, to ensure that no potential keywords are missed, we include the interviewer's keywords in the set of keywords attributed to the person being interviewed (participant). This approach eliminates the consideration of the interviewer as a participant while capturing all relevant keywords from the conversation.

However, there is a high chance of incorrect keyword counts in this approach when interviewer keywords are included. To prevent this, the combined keyword set undergoes the proposed weighting algorithm, ensuring that appropriately weighted keywords are used for analysis.

The proposed algorithm is illustrated in Figure 3. Two specialized modules, the top candidate module and the final weighting module, are used to determine the actual keywords and their corresponding weights. This algorithm is partially designed to address two major challenges in working with NLP. Since NLP statistically calculates keyword frequency, human behavior can introduce biases. This algorithm ensures that each person (Participant-1, Participant-2, ..., Participant-$n$) and their corresponding keywords (Keyword-1, Keyword-2, ..., Keyword-$r$) are correctly processed. The weights for each keyword are adjusted to mitigate these biases. Keywords are weighted based on their frequency and relevance within a defined range ($\alpha_{\max}$ and $\alpha_{\min}$), as shown in Algorithm 1.

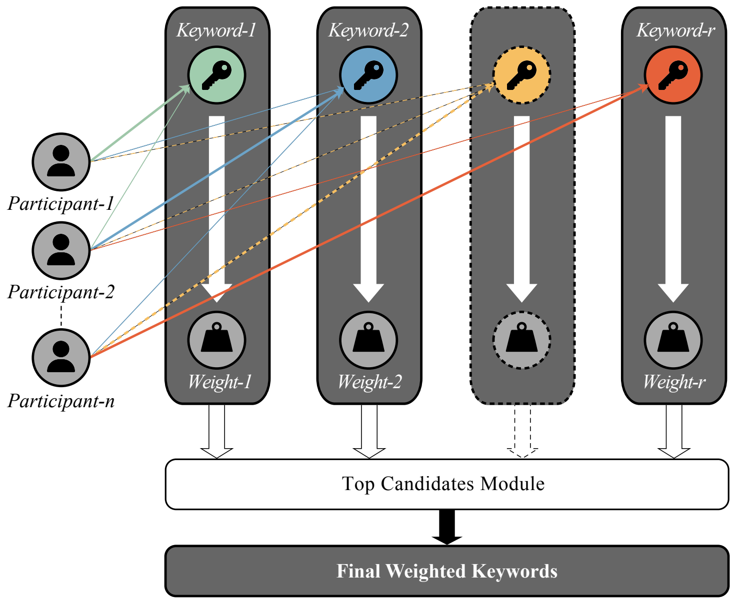


**Figure 3.** Proposed adaptive keyword analysis model architecture.

**Algorithm 1** Proposed Keyword Weighting Algorithm

**Require:** Keyword frequencies $f_k$, weight factor $\omega$, range $\alpha_{min}$, $\alpha_{max}$
**Ensure:** Weighted keywords $W_k$
**for** each keyword $k$ **do**
  Compute $temp \leftarrow 1 + (f_k \times \omega)$
  **if** $temp > \alpha_{max}$ **then**
    Set $W_k \leftarrow \alpha_{max}$
  **else if** $temp < \alpha_{min}$ **then**
    Set $W_k \leftarrow \alpha_{min}$
  **else**
    Set $W_k \leftarrow temp$
  **end if**
**end for**
**return** Weighted keywords $\{W_k\}$

As the keyword frequency can be significantly biased due to human behavior, disproportionately impacting certain keywords. For instance, in Figure 4, the keyword "see" in the activity category has a much larger influence compared to others. To address these biases, keywords are identified using the GPT-4 API, categorized based on relevance, and their quantitative frequencies are analyzed to determine occurrence. The proposed algorithm, illustrated in Figure 3, calculates weights for each keyword within a defined range ($\alpha_{max}$ and $\alpha_{min}$), streamlining classification and prioritization. $W_k$ is calculated using the formula Equation (1), where $f_k$ represents the frequency of keyword $k$ and $\omega$ is the calculated weight factor.

$$W_k = \begin{cases} \alpha_{max}, & \text{if } 1 + (f_k \times \omega) > \alpha_{max} \\ \alpha_{min}, & \text{if } 1 + (f_k \times \omega) < \alpha_{min} \\ 1 + (f_k \times \omega), & \text{otherwise} \end{cases} \tag{1}$$

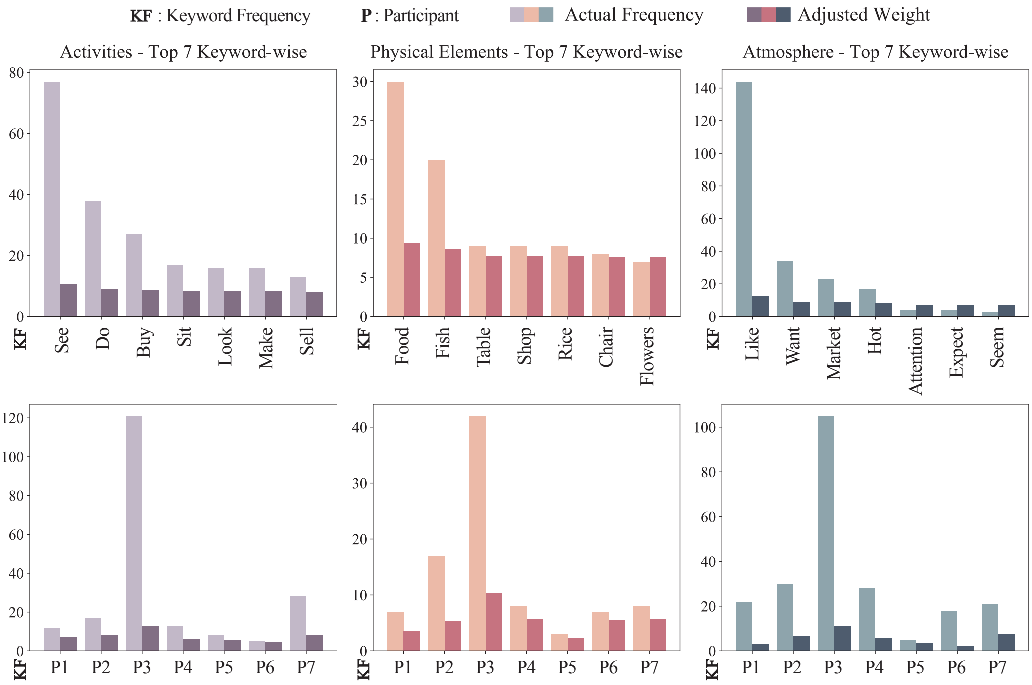


**Figure 4.** Actual and adjusted keyword frequencies for EV1 using the proposed algorithm. In this adjustment, the weight factor $\omega = 0.08$.

The proposed algorithm ensures fair weight distribution, assigning higher significance to frequently used keywords while maintaining proportionality. As shown in Figure 4, the top seven keywords and each person's keyword frequency are adjusted based on the proposed algorithm. Each participant's keyword frequency is adjusted based on the proposed algorithm illustrated in Figure 3, using a weight factor $\omega = 0.08$, with the adjusted weight bounded by $\alpha_{\text{min}} = 1.0$ and $\alpha_{\text{max}} = 2.0$. The small difference between $\alpha_{\text{min}}$ and $\alpha_{\text{max}}$ is intended to treat all participants equally. However, a larger value of $\alpha_{\text{max}}$ can be used if prioritizing certain participants' keywords is desired. In that case, $\omega$ has a big role as our difference is less; we keep small $\omega = 0.08$.The results show that although a particular keyword, such as "see", or a specific participant, such as "P3", had a high impact in terms of frequency count, after applying the adjustment, it was weighted within the defined range.

### 4.2. Analysis and Key Findings of Data-Driven Environment

Figure 5 illustrates the network graph depicting relationships among themes, events, and participants. The four themes are shown along with their connections to events and interviewees, highlighting their inter-dependencies. In the graph, the size of each node (circle) represents its occurrence or frequency, with larger nodes indicating higher frequency. Different colors are used to distinguish the themes, as specified in the figure legend. Solid lines connect the events to the four themes, whereas dotted lines indicate connections between individuals and themes. The degree of relationships is measured by the number of lines between each node. The figure reveals that some individuals, such as P5 and P2, exhibit higher engagement compared to others like P1 and P6. The themes Child-Friendly Space, Product Display, and Event Layout received more attention than Advertising. These insights derived from the proposed algorithm ensure the actual weights, as described before.

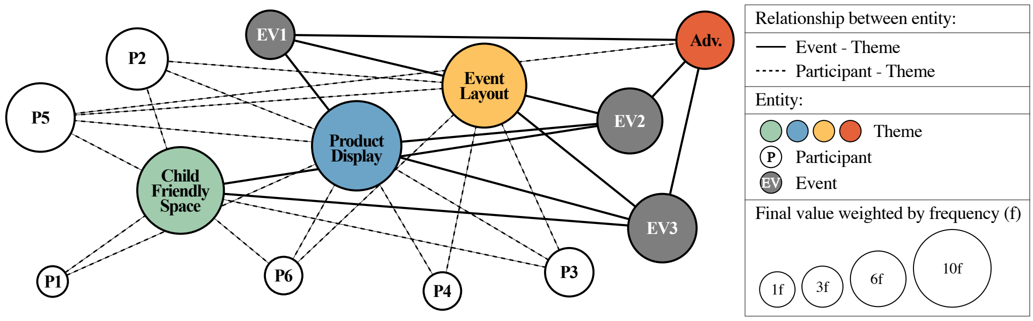


**Figure 5.** Network graph showing relationships among themes, events, and participants during interviews conducted while viewing a video recording of the event.

Figure 6 presents the network graph under virtual conditions, illustrating the evolving relationships between themes, events, and individuals. In this graph, interview keywords remain connected to their respective interviewees, maintaining the same node sizing structure as before (video interview), where the circle size corresponds to the frequency of occurrence. However, in contrast to Figure 5, an increase in theme size is observed across all categories, suggesting that engagement levels have improved within the virtual environment. Notably, EV-2 exhibits a significant rise in attention, as indicated by its strengthened connections and larger node size compared to other events. This suggests that the immersive nature of the virtual environment has amplified user interaction with particular themes. While the core themes—Child-Friendly Space, Product Display, and Event Layout—continue to dominate in user engagement, their prominence is more pronounced than in the physical setting. Advertising remains a less dominant theme, but its increased connectivity suggests a heightened awareness among participants within the virtual setting. Overall, the results confirm that the virtual environment impacts keyword associations, leading to a more accurate reflection of participant opinions.

Following the network graph analysis from both the video interview (Figure 5) and the virtual environment interview (Figure 6), we extend our evaluation to a direct comparison of the event–theme relationships under these two conditions. Figure 7 illustrates the cumulative comparison between the two network representations, identifying areas where engagement increased in the virtual environment and those that remained unchanged. The transition from a traditional interview while watching the video of the event to an interview while watching a virtual environment led to an overall increase in engagement with core themes, particularly Product Display, Event Layout, and Child-Friendly Space. In this particular network graph, the person impact is not shown, and also the event circle is not scaled as the key objective is the determine the impact of the theme. This suggests that participants found the virtual setting to be more immersive, leading to deeper interactions. The virtual environment also refined the representation of participant sentiment, allowing attendees to express opinions in a more structured and thoughtful manner. Event-specific engagement patterns indicate that EV-2exhibited the most significant increase in attention, with a +2 impact on child-friendly space and a +1 impact on the product display. In terms of the most impactful event, EV-3 is considered the most influential as it shows a positive impact across all keywords (advertisement, child-friendly space, and product display). However, it has a negative impact on child-friendly spaces.

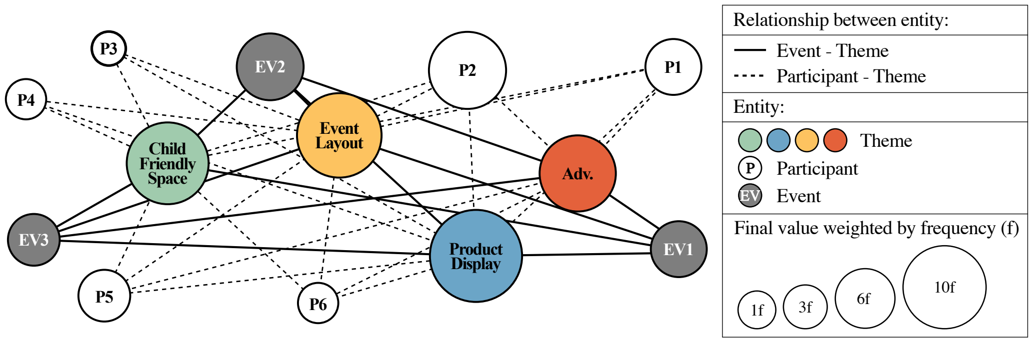


**Figure 6.** Network graph showing relationships among themes, events, and participants during interviews conducted while experiencing a virtual environment.

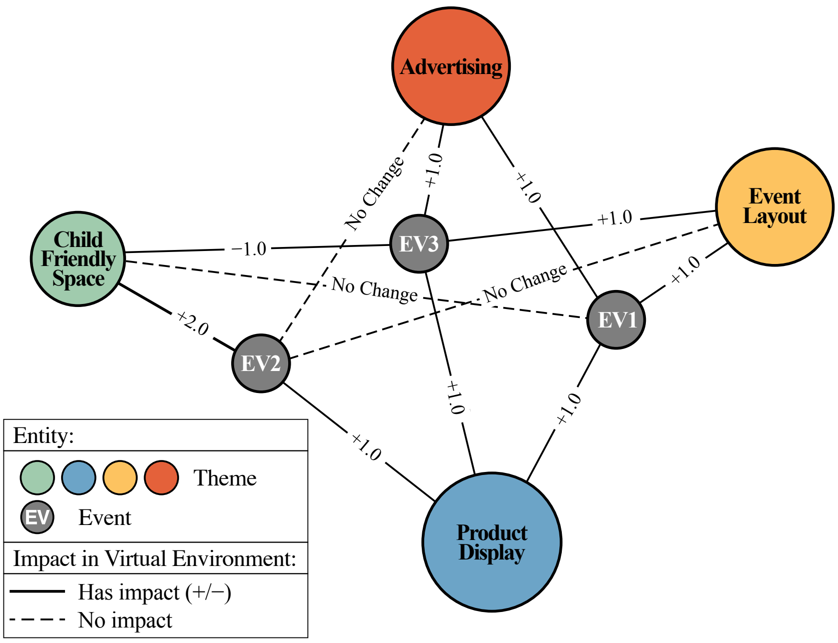


**Figure 7.** Network graph illustrating the impact of virtual engagement on event–theme relationships.

In terms of keyword analysis, as shown in Figure 7, product display has the highest impact across all three events, with a positive relationship. This indicates that architectural involvement is of high importance, as it is relevant to all the events. Child-friendly space, advertisement, and event layout also show significant impact, but not symmetrically across all events. For example, in EV-2, the impact of advertisement and event layout remains unchanged, whereas product display and child-friendly space exhibit the highest positive impact. This network difference graph, where individual participant opinions are not considered, highlights the impact of the virtual environment. Notably, there are no significant negative impacts, except in EV-3, which shows one negative impact on child-friendly space. All remaining keywords either show a positive increment or no change.

The final weighted analysis, as shown in Figure 7, provides a consolidated view of these findings, marking areas of significant change and stability.

## 5. Impact on Visual Attractiveness of Temporary Event Space

This chapter shifts from purely data-focused analysis to exploring how spatial layout and display strategies influence visual attractiveness at events. It examines how stall arrangements, vendor positioning, and visual displays interact to shape the overall experience. Section 5.1 highlights how vendors tend to choose simple layouts due to organizer pre-set placements while using creative displays to attract attention in less favorable locations. Section 5.2 analyzes how different participant groups—based on factors like nationality, gender, age, and parental status—engage with specific event themes, such as child-friendly areas, product presentation, layout, and advertising. Section 5.3 introduces a data-driven model that combines keyword analysis, spatial feedback, and user perception to support better event planning. Finally, Section 5.4 tests the model with a broader participant pool, confirming its reliability and potential for wider application.

### *5.1. Spatial Analysis*

In order to understand the impact of visual attractiveness in terms of spatial arrangement, this study begins by analyzing spatial perception through three key categories: Stall Layout, Placement and Visibility, and Display Strategy. Stall Layout examines the spatial composition of elements, such as tents, tables, and display shelves, provided by event organizers, while vendors position them within their designated spaces. Placement and Visibility focuses on how each stall is positioned within the event perimeter and its visibility from main access points, an aspect influenced by organizers. Display Strategy looks at how vendors arrange physical elements to effectively display their products and attract customer attention, which is primarily determined by the vendors themselves. By exploring these strategies, this study reveals how the decisions made by both organizers and vendors impact the event's overall visual attractiveness.

Firstly, Stall Layout is classified into three types based on the layout within the designated area of the stall periphery under the tent (Table 3). SL1 places a display table at the front of the stall within this designated area. SL2 adds more display elements in front of the stall, extending beyond the designated area. SL3 incorporates additional furniture and display elements at the back of the stall, within the designated area, for vendor preparation and storage. Among the 42 stalls analyzed, 16 use SL1, 16 use SL2, and 10 use SL3, with SL1 and SL2 showing the least effort in terms of layout complexity, as they are used more frequently by vendors compared to the more complex SL3 (see Figure 8).

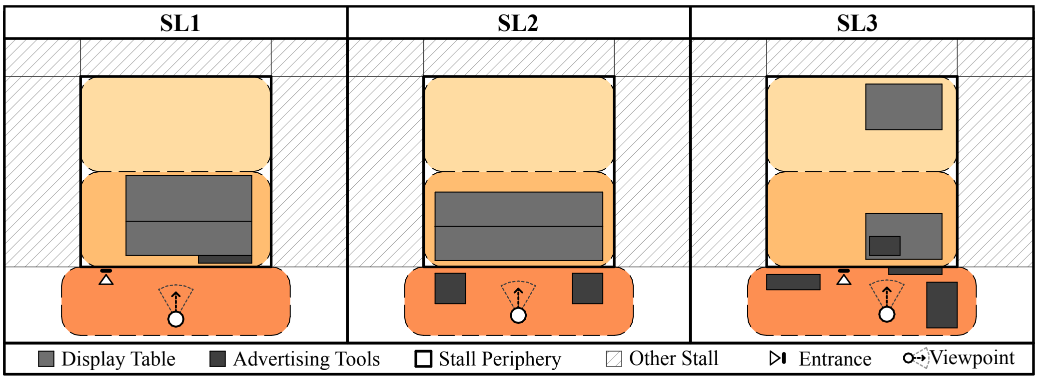


**Figure 8.** Stall Layout.

**Table 3.** Stall Layout in each event.

| Stall Layout | Events |
|---|---|
| SL1 (16) | EV1-02, EV1-06, EV1-07, EV1-09, EV1-10, EV2-01, EV2-09, EV2-10, EV2-11, EV3-03, EV3-09, EV3-10, EV3-12, EV3-15, EV3-16, EV3-20 |
| SL2 (16) | EV1-01, EV1-03, EV1-05, EV2-03, EV2-05, EV2-07, EV3-01, EV3-04, EV3-05, EV3-06, EV3-07, EV3-08, EV3-11, EV3-13, EV3-14, EV3-21 |
| SL3 (10) | EV1-04, EV1-08, EV2-02, EV2-04, EV2-06, EV2-08, EV3-02, EV3-17, EV3-18, EV3-19 |

Placement and Visibility are categorized into three levels: PV1 (least visible), PV2 (moderately visible), and PV3 (most visible), based on how easily each stall can be seen as visitors approach the event (Figure 9). In the EV-1 layout, outdoor stalls generally have PV2, except for the first stall located on the main street, which has PV3 due to its corner placement and prominent front position. The indoor zone has PV1, but despite this lower visibility, most gatherings occur indoors because the main coffee shop is located there, drawing the majority of visitors. In EV-2, stalls facing the street have PV3, while stalls positioned perpendicular to the street have PV2. Indoor shops, with PV1, attract fewer visitors, likely due to their less prominent location and unclear signage. The kids' zone, located behind the street-facing stalls, also has lower visibility. The eating area, with PV3, is highly visible due to its open design. Despite being positioned away from the street and the eating area, one kitchen car still attracts customers because it faces the eating area. In EV-3, the food area, facing the station, has PV3 and attracts the most customers. The large square, which connects the station to the event, offers better visibility of the stalls in the front. Shops located further back, with lower visibility, are less frequently visited but offer a more relaxing experience. Customers use the benches in this quieter area to eat and enjoy the contrast to the crowded spaces. This event also attracts the most elderly visitors, who prefer a peaceful environment.

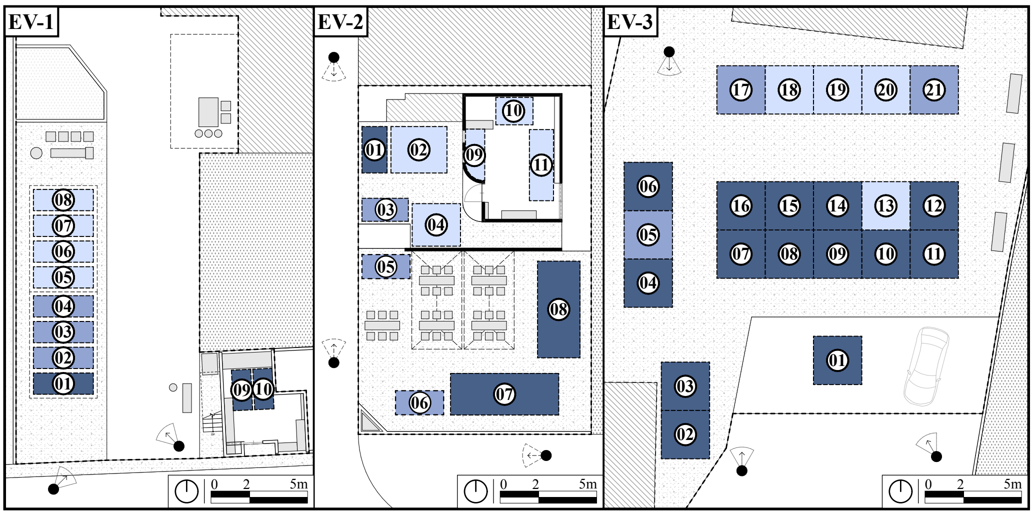


**Figure 9.** Placement and visibility. Note: The numbers indicate the stall numbering used in the event.

Finally, the Display Strategy analysis reveals how stores capture visitors' attention through factors such as the positioning of elements relative to eye level, banner placement, size, and color contrast. The strategies are categorized as follows: DS0 refers to the initial setup provided by the event organizer, without additional display elements added by the vendor; DS1 involves minimal advertising elements, such as banners attached to tablecloths or placed on tables, usually with text and price information; DS2 uses two banners placed in different positions on the store front, with a combination of text, photos, and pricing information; and DS3 utilizes larger banners with more color contrast and multiple placements to catch attention from various angles. As shown in Figure 10, DS1, which involves minimal advertising, was the most common strategy, used by 17 stalls. The second most common strategy, DS2, was used by 14 stalls, while DS3, which uses larger banners and more contrast, was employed by just seven stalls. DS0, which reflects the initial setup by the event organizers, was employed by only four stalls, indicating that most vendors made additional efforts to engage event visitors with their initial displays.

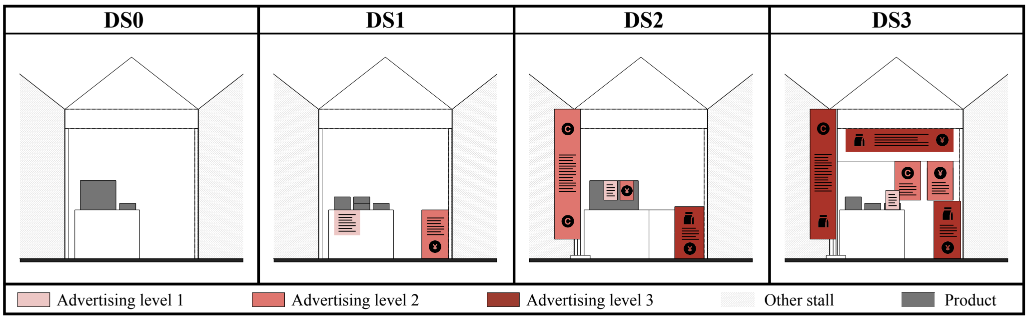


**Figure 10.** Display strategies.

### 5.2. *Visual Attractiveness from Data-Driven Spatial Analysis*

The analysis of 42 stalls from three event spaces reveals a strong correlation between spatial analysis and visual attractiveness (Figure 11). Vendors predominantly utilized the simplest stall layouts (SL1 and SL2), likely due to the ease of setup and cost-effectiveness. However, stall placement significantly impacted visibility and, consequently, the display strategies. Corner and peripheral stalls positioned along primary visitor pathways (PV3) consistently enjoyed higher visibility and natural foot traffic. Conversely, stalls located in less visible areas, such as those hidden from circulation or indoors (PV1, PV2), faced greater challenges in attracting attention. With the exception of the main store at EV-1, these less visible stalls often adopted more complex display strategies (DS2, DS3) to compensate for their less advantageous location. These strategies included bold color contrasts (e.g., black text on traditional fabric), larger text and pricing displays, and interactive elements (e.g., free samples, verbal promotion) designed to attract passing visitors.

From a spatial design perspective, enhancing stall visual attractiveness requires careful consideration of layout principles, perceived visibility, and the vendors' display efforts. In regional areas like Matsue, where event attendance may be smaller, optimizing event space quality to meet visitor expectations is crucial for boosting attendance and supporting stakeholder needs [87]. Although Matsue vendors and organizers often use social networks, brochures, and banners for promotion, the experience on-site, including route discovery and general event organization, can be inconsistent due to the limited resources and event management expertise of individual small stores [88]. This lack of structured event management, often exacerbated by limited communication between organizers and vendors, can negatively impact the visitor experience. Furthermore, the diverse goals of event organizers, ranging from community-based charity to profit-driven ventures [89], decisions regarding layout and vendor selection add another layer of complexity to event design. Therefore, integrating qualitative and quantitative analysis of visual attractiveness and understanding the correspondence between spatial design and user feedback is essential for creating successful and engaging temporary event spaces.

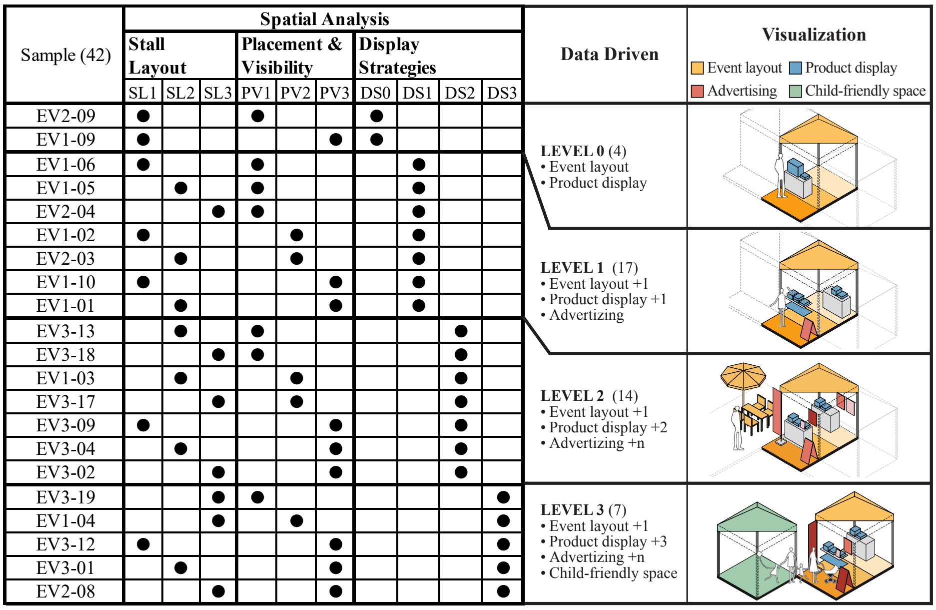


**Figure 11.** Level of visual attractiveness derived from data-driven spatial analysis.

### *5.3. Participant Behavior Analysis with Different Themes*

Having established the synergy of understanding visual attractiveness by correlating data-driven approaches and spatial analysis and recognizing its impact on bridging designer intent and user experience, we now delve into a deeper understanding of user behavior across various event themes to provide a more comprehensive picture of event engagement. We analyze the impact of participant behavior across all themes. Since the actual participant groups are not equally balanced, for example, as mentioned in Table 4, the dataset for the virtual and video interviews contains four Japanese and two non-Japanese participants. To overcome this issue, we normalized the data by averaging per person before comparison for all the themes. This approach allows us to obtain an actual picture of the influence of each participant group.

**Table 4.** Keyword count distribution with different themes

| **Participant Group** | | **Nationality** | | **Gender** | |
|---|---|---|---|---|---|
| | | **Japanese** | **Non-Japanese** | **Female** | **Male** |
| | Keyword Count | 206 | 678 | 418 | 466 |
| Participant Group | | Parental Status | | Age Group | |
| | | Has Child | No Child | 40 and Above | Below 40 |
| | Keyword Count | 310 | 574 | 310 | 574 |

As illustrated in Figure 12, the aggregate keyword count for each of the four participant groups is presented. Here, the themes and events were not considered separately to realize the overall impact of the participant group. This breakdown highlights the strong influence of participant groups on thematic engagement, except for the parental status “Child vs. No Child” group. The other three participant groups’ differences in keyword distribution emphasize that user group characteristics significantly shape interaction with themes. The keyword count in the Male vs. Female group and Japanese vs. Non-Japanese group has a significant difference, necessitating further investigation into the impact on each theme. In the case of the age group, a large difference appeared in child-friendly spaces where the young age seem to be less concerned than the old age while the vice versa impact exhibits in the product display.

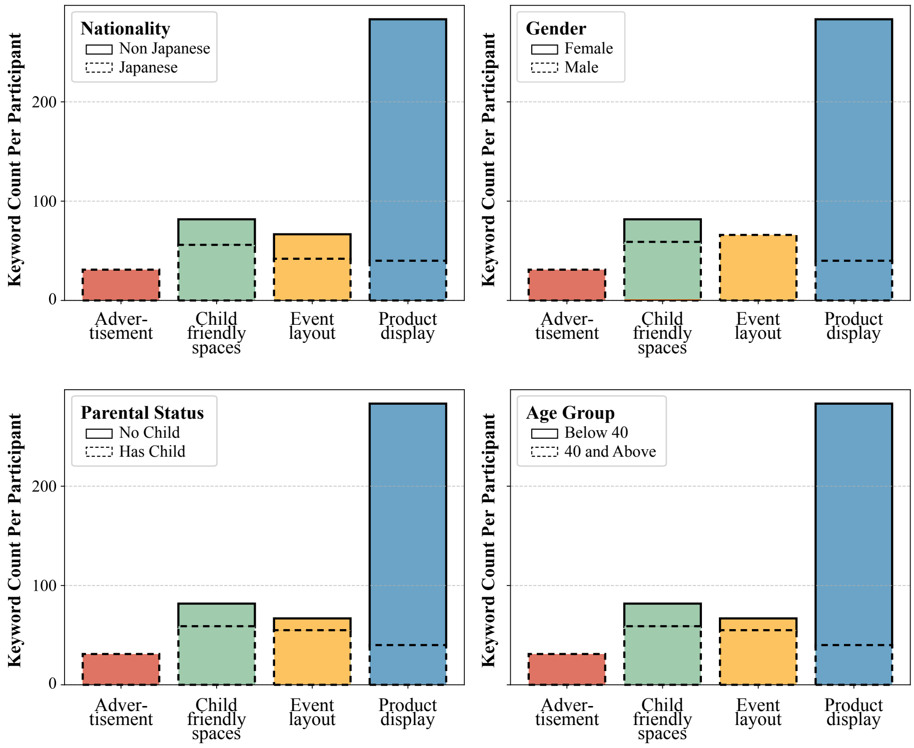


**Figure 12.** Average keyword count per person across themes, categorized by participant group Nationality (Japanese vs. Non-Japanese), Gender (Male vs. Female), Parental Status (has Child vs. No Child), and Age Group (below and above 40 years).

Figure 12 further examines the behavior of the group of participants in all themes. The bar charts provide insights into how different groups interact with various themes. This detailed breakdown allows us to assess which user segments are more active in specific contexts. In the Nationality group, while the Japanese nationals are not too concerned about the product display compared to non-Japanese, the other two themes regarding child-friendliness and event layout show competitive reactions. However, in terms of advertising, while the Japanese nationals are deeply concerned about the advertising, non-Japanese are not as concerned. Next is the Gender-based participants, where a big difference is observed in advertising, event layout, and product display. Males are more concerned about event layout and advertising, while females focus more on product display. Finally, in the Parental Status group, it is observed that parents with no children are more concerned about the product display and most advertisements and child-friendly space, while parents without children or those not married are more concerned about the product display. Concerning the event layout, both participants expressed nearly equal impressions.

Based on a thorough analysis of user interactions across various event settings, the final data-driven model is shown in Figure 13. The figure illustrates the structured framework that integrates keyword weighting, spatial perception analysis, and participant feedback to improve event planning strategies.The model highlights four core event themes: Child-Friendly Space (green), Product Display (blue), Event Layout (orange), and Advertising (red). The impact assessment methodology systematically evaluates participant engagement, weighting their responses based on frequency and contextual relevance.

**Figure 13.** Proposed data-driven model incorporating video interview insights, virtual environments, and comparative evaluation.

### 5.4. Scaling Impact of Interview Expansion

To further validate the proposed Framework's scalability, an additional phase of interviews was conducted by expanding the participant pool. As in the early steps, the imbalanced participant groups are averaged to ensure a balanced impact analysis. However, two new participants were newly included, considering more balanced participant behavior statistically. The new participant data are explained in Section 3, where Table 1 separately shows the participant information before and after scaling. Initially, six participants were interviewed, and later, two more individuals were included to assess the adaptability of the framework. Figure 14 compares the actual increase in engagement for video and virtual interviews after scaling with the expected impact range (35–55%), based on a 33% increase in participants and 35% increment of the keyword (see Table 1). The results show that most themes align with the expected impact, particularly in video interviews; all themes remain within the expected range. In the case of the virtual interview, the theme of child-friendly space and advertisement exceeded the expected boundary by only 2% and 5%, which can be considered as normal overflow. In this step, the proposed algorithm for the weighted keyword is applied to obtain the actual impact of the scaling, and the $\omega$ remains the same as before 0.08. This underscores the robustness and adaptability of the proposed framework for enhancing temporary event spaces.

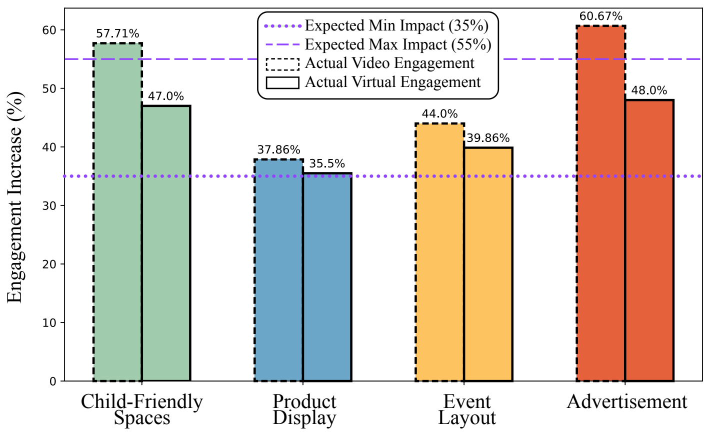


**Figure 14.** Actual vs. expected engagement impact after scaling (35–55% range).

## 6. Conclusions

This study explores the revitalization of regions facing demographic challenges through temporary events, emphasizing the enhancement of event environments by integrating architectural and spatial analysis with data-driven methodologies. The research highlights the significance of understanding and optimizing the spatial configuration of event spaces to improve user experience and engagement. By examining three distinct events, this study identifies key architectural and spatial factors that contribute to the success of temporary spaces: the strategic organization of layouts, the careful arrangement of product displays, and the creation of child-friendly spaces. These elements were found to positively influence user perception and engagement, playing crucial roles in making events more attractive and inclusive, demonstrating that thoughtful spatial design can significantly enhance the vibrancy and appeal of community gatherings.

Moreover, this study introduces a novel approach to data analysis by developing and validating an algorithm for keyword analysis in NLP, specifically tailored for processing multi-person interview data. This methodological advancement underscores the importance of incorporating user feedback and preferences in the design process, showcasing how data-driven insights can refine and improve event planning. The proposed algorithm's effectiveness in extracting meaningful patterns from qualitative data not only aids in the design of event spaces but also offers a scalable approach to data analysis that can be applied in various urban planning and social research contexts, ultimately contributing to strategies that enhance the attractiveness and long-term success of these events. This study's analysis of user feedback gathered from a diverse group of residents, including foreign residents, provided insights into how these spatial elements are perceived across different backgrounds.

The implications of this research extend beyond event planning, offering valuable insights for governance and strategic planning in regions similar to Matsue City. The challenges outlined in Section 3.1, such as the necessity for urban compactness and the revitalization of underutilized spaces, can be addressed through the strategic organization of temporary events. These events can serve as catalysts for broader urban revitalization efforts, testing and showcasing design and policy innovations in a temporary, low-risk format. For instance, the integration of digital technology in event planning, as explored in this study, can inform the development of regional public systems and enhance urban accessibility. Furthermore, this study highlights the importance of community-driven initiatives. By prioritizing events that actively engage residents in planning and decision-making, cities can foster a stronger sense of belonging and ensure that revitalization efforts are aligned with the community's evolving needs. The data-driven approach to understanding user experience, including the analysis of feedback and preferences, provides a model for how governments can incorporate community input into urban planning processes. This can lead to the development of more responsive and sustainable strategies that not only attract younger demographics but also improve the quality of life for existing residents.

In conclusion, this research demonstrates the potential of temporary events as a dynamic tool in urban revitalization, offering new perspectives on how data-driven design and community engagement can reshape the future of shrinking cities. By fostering a stronger connection between spatial design, user experience, and community involvement, this study contributes to the broader discourse on urban livability, particularly in areas struggling with demographic decline. While the current study involves a limited number of interviewees, its scalable framework is designed to incorporate future data seamlessly, ensuring broader applicability and adaptability across diverse urban contexts. The findings and methodology outlined here open avenues for future research, where the integration of architectural analysis, data-driven insights, and community feedback can be further explored to address the complex challenges faced by regions worldwide.

**Author Contributions:** Conceptualization, Y.-K.N.-T. and R.-U.-H.M.; methodology, Y.-K.N.-T. and R.-U.-H.M.; software, all authors; validation, all authors; formal analysis, Y.-K.N.-T. and A.M.; investigation, all authors; resources, Y.-K.N.-T. and A.M.; data curation, Y.-K.N.-T. and R.-U.-H.M.; writing—original draft preparation, Y.-K.N.-T. and R.-U.-H.M.; writing—review and editing, Y.-K.N.-T. and R.-U.-H.M.; visualization, Y.-K.N.-T., A.M. and R.-U.-H.M.; supervision, Y.-K.N.-T.; project administration, Y.-K.N.-T.; funding acquisition, Y.-K.N.-T. and R.-U.-H.M.; intensive data analysis, Y.-K.N.-T. and A.M.; architectural thought and design, R.-U.-H.M. and Y.-K.N.-T.; NLP analysis and algorithm development R.-U.-H.M. and Y.-K.N.-T., all authors. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by OBAYASHI FOUNDATION grant number Research 2023-40-105. The APC was funded by Shimane University, Matsue Japan.

**Institutional Review Board Statement:** Ethical review and approval were waived for this study due to the result from a preliminary assessment by the Ethical Review Board of Shimane University Interdisciplinary Faculty of Science and Engineering, which determined that a formal review was not required.

**Informed Consent Statement:** The authors have obtained informed consent from all participants involved in the interviews and related data collection for this research. Participants who took part in on-site visitor interviews, video interviews, and virtual environment interviews have given their consent for their provided data to be used in this study.

**Data Availability Statement:** The interview data, including videos and images used in this study, can be made available upon request to the corresponding author for non-commercial academic research, verification, and validation purposes. Please contact the corresponding author directly via the provided email for access to the data.

**Acknowledgments:** The authors would like to express their sincere gratitude to all associated personnel, including event organizers, stall owners, interview participants, Ochiai Wooden workshop, and the Matsue City public, for their valuable support and facilitation for the conduct of this research. The authors are also grateful to the OBAYASHI FOUNDATION and Shimane University for providing the funding and research facilities necessary to conduct this study. Additionally, special thanks go to the students of Khang's Laboratory for their tremendous cooperation and assistance throughout the research process.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| NLP | Natural Language Processing |
| EV | Event |
| P | Participant |
| SL | Stall Layout |
| PV | Product Visibility |
| DS | Display Strategy |
| GPT | Generative Pre-trained Transformer |

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