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Quantifying crowding perception at large events using beacons and surveys

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Given the increasing urban population and frenetic mobility, understanding how individuals perceive crowding at large-scale events is crucial for effective crowd management and safety. This study focuses on Tokyo Big Sight in Japan exhibitions to examine participants' perceptions of peak crowding times, locations, and local density, and compare them with the actual measurements. Our methodology integrated questionnaires with beacon tag data. The results showed that participants' perceptions of crowded times and locations aligned well with the actual (measured) crowding data, demonstrating that people can pick crowded moments and locations with better accuracy. However, when asked to select images that closely reflect crowding density conditions within the facility, the association was mostly relative (i.e., context-depending) and lacked absolute accuracy. Furthermore, perceptions of time tend to be biased towards exit times. This study underscores the necessity for event organizers and urban planners to account for the subjective and relative nature of individual crowding experiences, thereby emphasizing the need for adaptive management strategies that consider personal perceptions.

Keywords Crowd managements, Bluetooth, Questionnaire, Large scale events, Crowding perception

Urbanization and mass transportation have drastically made cities and public facilities crowded. To implement green and eco-friendly mobility solutions[1,2], more emphasis is placed on pedestrian areas, with vehicular traffic being increasingly penalized and pedestrian traffic promoted, especially in city centers[3]. This trend is prompting a thorough reevaluation of pedestrian facilities. Public pedestrian areas are now expected to do more than just comply with legal norms; it is normal as a branding strategy to promote locations and attract crowds[4]. Furthermore, the increasing number of people attending mass events also requires stringent safety measures. Accurate capacity computation and constant monitoring by facility operators are essential to prevent overcrowding. However, it is not easy to maintain safety in public spaces with large crowds. Therefore, recognizing crowds possessing both physical and psychological dimensions is crucial[5]. In particular, when measuring crowding as a physical quantity and using it as a reference, it is vital to ascertain whether subjective perceptions of crowding align with objectively measured crowding and understand the nature of any deviations.

The psychological dimension related to crowding is explored from the perspective of perceived crowding, which assesses whether people's perceptions of crowding aligns with objective measurements. It is commonly assumed that higher measured crowd density leads to increased perceptions of crowding, however, the relationship is more complex. Research on the relationship between an individual's perception of crowding and objective measures of crowd density in recreational areas has yielded mixed results. Some studies suggest that the measured visitor density can be the main factor for perceived crowding[6,7]. In contrast, some show perceptions of crowding are more influenced by expectations, preferences, and previous experiences[8–13], which is consistent with pedestrian experimental research[14]. Consequently, perceived crowding is influenced by the physical density of the crowd as well as individual factors that affect coping strategies and overall experience, thereby enhancing or reducing the impact of the relationship. However, these studies do not consider the temporal and/or spatial variations in crowding. Therefore, the accuracy of estimating crowding in both time and space remains unclear, which limits the applicability of these findings to the dynamic management of actual recreational events.

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A major challenge in qualitative measurements of time, location, and density is that excessive crowding can hinder the accurate counting of individuals, particularly in urban settings with high pedestrian traffic. Moreover, in densely crowded environments, increased interactions can lead to complex, nonlinear phenomena, complicating traditional analysis methods. However, recent technological advancements offer promising solutions; Various sensors now enable real-time counting and tracking of people's movements[15–17]. Additionally, large-scale analysis of crowd dynamics, from controlled laboratory experiments with hundreds of participants[18] to observations of millions of individual trajectories in real-world settings[19], captures the complex phenomena at play. Moreover, computer simulations are being used for creating what-if scenarios and calculating facility capacities[20,21]. For example, the study of human movement during evacuations has been integral to the development of building codes ensuring safe egress, supported by recent standards for validating computer simulation codes for evacuation simulations[22,23].

We believe pedestrian perceptions of crowding are set to improve by integrating recent technological advancements with traditional psychological approaches. Recent studies emphasize the significance of personal space[24–27], highlighting its influence on crowd perceptions. Additionally, factors such as collision avoidance and pedestrian attention are crucial[28,29]. Despite these advancements, determining a clear correlation between perceived and actual crowding at large-scale events, derived from extensive surveys within real facilities, remains a challenge.

To clarify the accuracy and deviations in the perception of crowding at large-scale events, we investigated the relationship between measured and perceived crowding based on location, time, and crowding density among individual of mass events (Fig. 1). By utilizing a methodology that integrates questionnaire-based data collection with sensor measurements-via beacon tags-we examined the discrepancies between actual measurements and participants' reported experiences in discerning time, location, and crowd density in a large event space covering approximately 30,000 sq. m. We found that majority of participants had perceptions regarding time and location that were more accurate than random selections. Furthermore, perceptions of time appear biased towards exit times. In contrast, perceptions of crowding density lacked accuracy, indicating that individuals do not perceive crowding quantitatively but rather base their assessments on relative comparisons (context-based evaluation).

In the upcoming sections, we begin with an analysis of how perceptions of crowding time, location, and density align with each measurement. We also explore biases in time perception and the differences between perceptions of time and location versus density. The study concludes by synthesizing these insights in Discussion that highlights the complexity of perceived crowding at large-scale events. This comprehensive understanding aids in developing strategies to enhance crowd experiences and ensure safety. Lastly, we provide a detailed account of the methodologies employed in our research.

Results

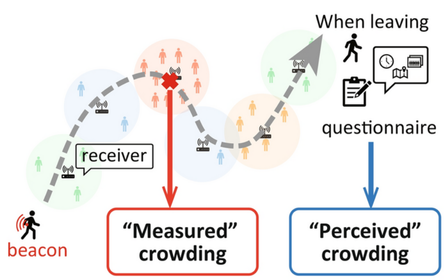
Brief summary of methodology

To comprehensively capture individual experiences and perceptions of crowding at large-scale events, we examined a technological event held at Tokyo Big Sight, one of the largest exhibition venues in Japan. We employed a dual-method approach, integrating beacon tag measurements with questionnaire-based surveys (Fig. 1).

The beacon tags facilitated continuous time recording and provided estimates of participants' positions within the venue. We assumed that the number of beacons detected by each receiver within specified time intervals would correlate with the local population density. By cross-referencing each participant's trajectory with the crowding data across different locations and times, we identified the measured peak crowding in terms of time, location, and density.

Conversely, we asked participants about the specific times and locations where they experienced crowding. Additionally, we requested participants who reported experiencing crowding to select, from a series of photographs, the one that most accurately depicted the crowding situation.

To collect this data, we approached participants at the exhibition entrance to explain our research objectives. Participants who showed interest and provided consent were given beacon tags, each with a unique identification (ID) number. Some participants engaged further by completing questionnaire surveys. To ensure data consistency and minimize potential biases related to the time of day, we aimed for a steady distribution of



	"Measured" crowding	"Perceived" crowding	Research questions
Method	Beacon measurement	Questionnaire	
Time	T_m	T_p	How accurately do T_p match T_m? Are there any notable biases in T_p?
Location	A reciever at (x_m, y_m) within zone A_m	Select zone A_p on map	How closely do A_p align with the actual measured crowding locations (x_m, y_m)?
Density	Approximated crowd size: ρ_m	Select an image	Do participants experiencing higher crowd density select images depicting larger crowds?

Fig. 1. A conceptual overview of this study, illustrating the definition of variables used in this paper.

respondents throughout the event. The unique ID of each beacon was noted on its corresponding questionnaire, linking the beacon measurements with survey responses.

To compare individual experiences and perceptions, we defined "perceive" and "measured" crowding. The perceived crowding time and location refer to the time and location reported by participants in response to the survey question: "What time and where did you feel the most crowded during the exhibition?" On the other hand, the measured crowding time and location correspond to the times and locations where the largest "approximated crowd size" (as detailed in the Overview of crowding section) was recorded along participants' trajectories.

It is important to note that most participants did not visit all areas within the venue. Therefore, the identification of both perceived and measured crowding for each participant was influenced by their specific movements-i.e., the areas they visited and the times they were present.

Detailed aspects of this methodology are elaborated in the "Methodology" section.

Overview of crowding

In 2022 and 2023, the number of visitors were 10,607 and 31,137, respectively (Fig. 2c). The number in 2023 was about three times larger than that in 2022. This difference was primarily due to changing attitudes towards infectious diseases[30]. Figure 2a presents the time distribution of people inside the venue as measured by LiDAR sensors (see the "Methodology" section for details). In both years, the venue was generally more crowded around one hour before and after noon.

While the number of visitors fluctuated between 2022 and 2023, the distribution of beacons remained relatively stable, with 2824 beacons deployed in 2022 and 2599 in 2023 (Fig. 2c). Consequently, we estimate that each beacon corresponded to approximately 3.76 visitors in 2022 and 11.98 visitors in 2023, a relationship denoted as $a^{(Y)}$ where Y can be either 2022 or 2023.

We hypothesize that the number of beacons detected by each receiver correlates linearly with the local population density in the vicinity of the receiver (see the "Methodology" section and Ref.[17]). Then, we define the "approximated crowd size" at a specific time t and location x, denoted as $\rho_{t,x}$, as the product of $a^{(Y)}$ and $n_{t,x}$, where $n_{t,x}$ indicates the count of beacons detected at that location: $\rho_{t,x} = a^{(Y)} \cdot n_{t,x}$ (Fig. 2d).

When we limit location x to the place of receivers, we can analyze the time evolution of the crowding around the receivers. Figure 2b illustrates the time evolution of the approximated crowd size from all receivers on the 2nd day of 2023 as an example. For a visual guide, three receivers are highlighted according to their average approximated crowd sizes over the entire day: red for the highest average, blue for the lowest average, and green for the median average. Specifically, the approximated crowd size of the lowest average exceeded the one of the highest average around 14:00. Therefore, identifying the highest crowding point varies depending on the participants' location and timing during the event.

Each participant's movement within the venue is captured as a trajectory by analyzing the beacon data, represented as a sequence of time-location pairs $(t_1, x_1), (t_2, x_2), \ldots, (t_r, x_r)$. This approach help identify

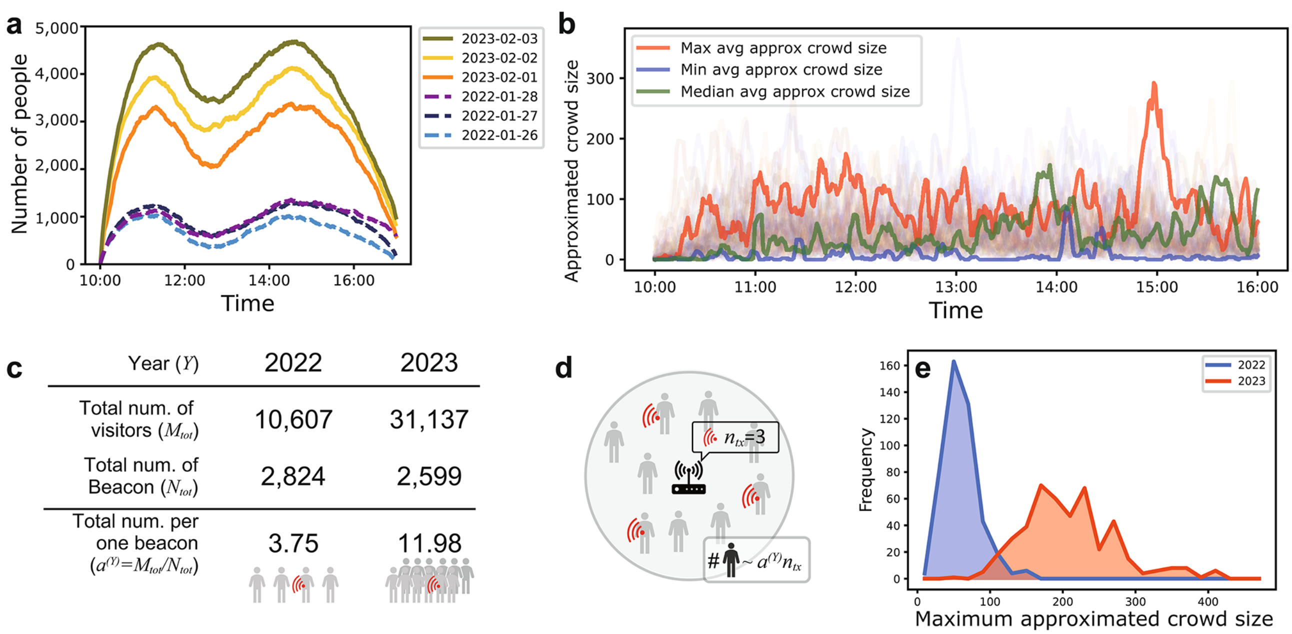


Fig. 2. The number of people and approximated crowd size. (**a**) Time evolution of the total number of people within the venue, depicted for each day. (**b**) Time evolution of the approximated crowd size measured by each receiver on the second day of 2023. The faint-colored lines represent all other samples. (**c**) Table depicting the estimated number of visitors represented per beacon. (**d**) Illustrative depiction of the approximated crowd size calculation, approximating the crowd size around each receiver from the number of beacons. (**e**) Distribution of the maximum approximated crowd size for each survey respondent.

moments of peak crowding for each individual by detecting the highest approximated crowd size recorded along their trajectory. To further examine individual experiences of crowding, we analyzed the maximum approximated crowd size observed for each participant. Figure 2d displays the distribution of the maximum approximated crowd size encountered by each participant within the venue. Notably, the data range from 0 to 100 in 2022 and from 100 to 300 in 2023, it extends from 100 to 300, indicating a significant increase in the overall crowding in 2023, aligned with the threefold increase in the total number of visitors compared to 2022.

Respondent profile

First, we discuss the profile characteristics of the respondents based on their questionnaire responses. Table 1 provides an overview of the respondents' characteristics for 2022 and 2023. A notably higher proportion of male respondents compared to female respondents. The largest groups of respondents were in their 50s and 40s but were distributed among all generations. Over 80% of respondents identified as office workers. Additionally, the majority of respondents indicated that they visited the venue alone, thus limiting effects related to (in-) group dynamics. This distribution of respondent profiles aligns with the target participants anticipated by the technology event organizers and the characteristic human images used in the composite photographs presented in the questionnaire.

Crowded time recognition

Accuracy of time detection

First, we examined the ratio of responses to the crowding time question to investigate the qualitative perception of crowding. Some participants were unable to answer the crowding time question because they felt they had not experienced any crowding. This ratio is specifically defined as the ratio of responses provided to the question about crowding time.

We calculated this ratio within each bin, where each bin is determined based on a specified width of the maximum approximated crowd size encountered by each participant within the venue. This binning method helps in grouping the data points effectively. As shown in Fig. 3a, the ratio of responses for identifying crowding time increases with the maximum approximated crowd size. The correlation coefficient is 0.87 with the p-value of t-test for linear correlation is 0.001. The blue dashed line represents the linear approximation as $y = 0.002x + 0.22$ with p-values for the coefficients being 0.0016 and 0.0002, respectively and, an R^2 value of 0.76. This suggests that if the perception of crowding is considered qualitatively or through a binary choice of whether participants felt crowded or not, the higher the maximum approximated crowd size, the higher would be the accuracy rate.

Next, we explored the relationship between the quantitative perception of crowding and the measured crowding. When we compared the times of perceived crowding with the times of maximum approximated crowd size (measured crowding), we identified a strong alignment in the trends of both sets of data, as depicted in Fig. 3b. A consistent pattern emerged, with peaks in both perceived and measured crowding levels occurring around 11:00 a.m. and 1:00 p.m.

We examined the correlation between the perceived crowding and measured crowding time for each participant, as shown in Fig 3c. The horizontal axis represents the perceived crowding times (T_p) and the vertical

	2022		2023	
	n	%	n	%
Total	498	100.0	499	100.0
Gender				
Male	450	90.4	453	90.8
Female	48	9.6	46	9.2
Age				
10s	3	0.6	8	1.6
20s	64	12.9	67	13.4
30s	83	16.7	107	21.4
40s	128	25.7	115	23.1
50s	129	25.9	109	21.8
60s	70	14.1	76	15.2
Over 70s	21	4.2	17	3.4
Occupation				
Office worker	425	84.3	425	85.2
Public servant	15	3.0	16	3.2
Researcher	17	3.4	16	3.2
Entrepreneur	23	4.6	21	4.2
Student	8	1.6	13	2.6
Other	10	2.0	8	1.6

Table 1. Characteristics of respondents in 2022 and 2023.

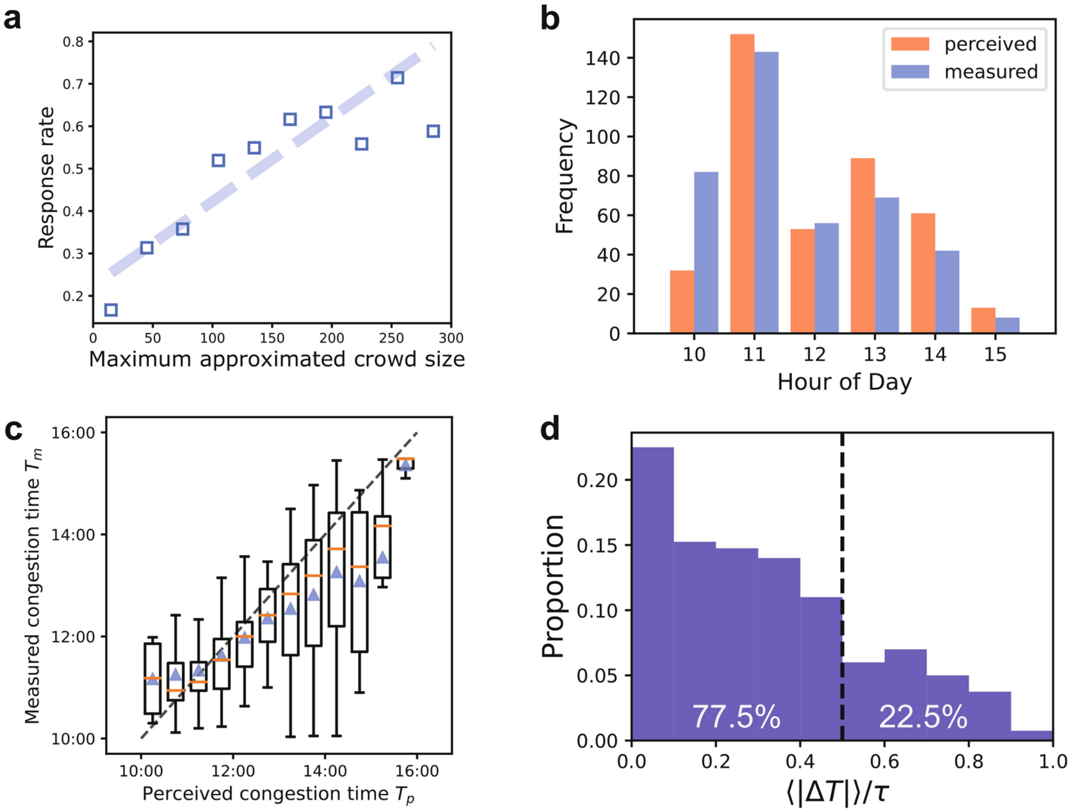


Fig. 3. Qualitative perception of crowding and the temporal accuracy of perceived crowding (**a**) Correlation between the response rate regarding crowding and the maximum approximated crowd size. (**b**) Histogram comparing perceived and measured crowding times. (**c**) Box plot depicting the relationship between perceived and measured crowding times for each individual. The boxes are generated for each one-hour interval of perceived time. Orange lines represent the median. Blue triangles represent the mean. The broken line in the plot represents the line of equality, where the perceived crowding times would match exactly with the measured crowding times. (**d**) Histogram of the absolute differences in perceived versus measured crowding times, normalized by the duration of stay. The black dashed line represents the expected differences for random responses. 77.5% of participants reported times of crowding that were more accurately pinpointed than what would be expected from random responses.

axis represents the measured crowding times (T_m). Points along the dashed diagonal line indicate instances where a participant's perceived and measured crowding times coincide. Overall, the data reveals a positive correlation between these two variables. The center orange line of eachbox indicates the median value of T_m for each hour of T_p, demonstrating an increase alongside T_m. Additionally, the correlation coefficients for 2022 and 2023 are 0.40 and 0.67, respectively, with a combined correlation coefficients of 0.58 for the 2-year data. The p-values from the t-tests for these correlations are all smaller than 10^{-6}. This suggests a consistent correlation between perceived and measured crowding times across different years.

There appears to be a significant correlation between the perceived (T_p) and measured (T_m) crowding times, however, the accuracy of participants' responses regarding the timing of crowding is influenced by the length of their stay (τ). As the stay duration increases, accurately pinpointing the exact time of crowding becomes more difficult. To analyze this relationship, we calculated the discrepancy between the times of perceived and measured crowding, expressed as $\Delta T = T_p - T_m$, and normalized this discrepancy by the stay length as $|\Delta T|/\tau$. In this representation, $|\Delta T|/\tau = 1$ would represent, for example, an attendee picking up a crowded time at the beginning or end of her/his visit, while the most crowded moment happened at the end or beginning, respectively. Attendees, with $|\Delta T|/\tau$ close to 0 were very accurate in identifying the most crowded moment.

Figure 3d presents a histogram of $|\Delta T|/\tau$. The black dashed line indicates $|\Delta T|/\tau = 0.5$, representing the expected discrepancy if participants answered randomly. Interestingly, 77.5% of participants reported a smaller discrepancy than this random expectation, while 22.5% reported a larger discrepancy. This indicates that participants had a clear tendency to accurately identify times of crowding.

Time perception discrepancies in crowding reports

While a positive trend is observed between T_p and T_m, the median of T_m indicate a discrepancy from the precise time, as highlighted by the orange lines in Fig. 3c. Participants who perceived the most crowding in the morning generally reported their T_p to be closer to T_m. Conversely, participants who experienced the most crowding in the afternoon reported their T_p to be later than T_m. We hypothesize that these afternoon participants were likely those who stayed for longer durations and reported later times than those measured.

To verify this, we examined the difference between the times participants perceived and measured crowding relative to when they completed the questionnaire. We defined T_{ans} as the time of questionnaire completion and calculated $\Delta T_{ans,p} = T_{ans} - T_p$ and $\Delta T_{ans,m} = T_{ans} - T_m$, quantifying the discrepancies between the questionnaire response time and both T_p and T_m (Fig. 4a).

Figure 4b presents the mean values of $\Delta T_{ans,s}$ and $\Delta T_{ans,p}$, calculated for each one-hour interval of stay. Intriguingly, for stay durations longer than three hours, $\Delta T_{ans,m}$ tends to be larger than $\Delta T_{ans,p}$. This finding suggests that the time participants perceived as most crowded was closer to the time when they completed the questionnaire compared to the measured time of crowding. Our additional analysis using Cohen's d values supports this observation, indicating that for stays longer than 3 h, participants' perceived crowding times are generally reported as earlier than the measured crowding times. Additionally, the large Cohen's d value for the 0–1 hour stay duration suggests that participants might have perceived congestion at the beginning of their visit, possibly during a high-density period at the entrance.

This pattern is further illustrated in Fig. 4c, which shows the approximated crowd size over time for two participants. The magenta and lines represent participants with the smallest and largest $|\Delta T|$ on that day, respectively. Triangles and circles on the respective lines mark their perceived and measured crowding times. Notably, consistent with the suggestion of Fig. 4b, the perceived crowding time (green triangle) is closer to the time when they completed the questionnaire than the measured time of crowding (green circle). Note that the reason why participants chose the specific time as the perceived congestion time remains unclear. This time is not aligned with the second or third measured peak in crowding (see Supplementary Fig. S2).

Crowded location recognition

Next, we investigated participants' ability to recognize crowded locations. We divided the venue into several zones and allowed participants to select multiple crowded zones in the questionnaire (see the "Methodology" section). Then, we compared these zones with the measured-crowding zone where maximum approximated crowd size was measured (Fig. 5a). Overall, the proportions of respondents who correctly selected the crowding zone were 0.243 and 0.291 for 2022 and 2023, respectively, which were higher than choosing randomly. It should be noted that the proportion of correct answers when choosing randomly is 1/12 and 1/14 for 2022 and 2023, respectively, due to the number of selection zones being 12 and 14 for each year.

Figure 5c,d illustrate the spatial distribution of both the measured and perceived crowding areas, in 2022 and 2023, respectively. The orange circles represent the proportion of zones selected as perceived-crowding

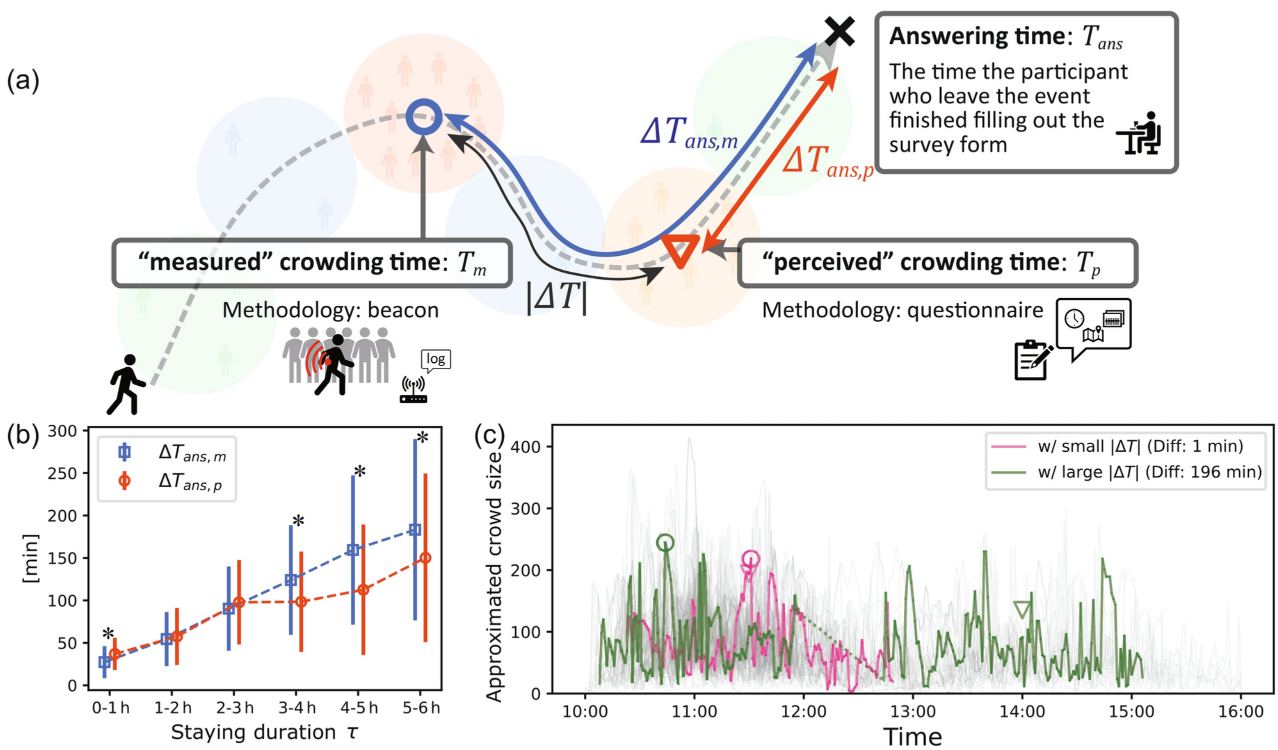


Fig. 4. Discrepancy of perception of crowding times. (**a**) Schematic illustration explaining the definitions of $\Delta T_{ans,p}$ and $\Delta T_{ans,m}$. (**b**) Graph displaying the discrepancies $\Delta T_{ans,s}$ and $\Delta T_{ans,m}$, plotted in relation to stay duration. Star markers indicate Cohen's d values greater than 0.3, highlighting significant differences between the discrepancies in the two measures. (**c**) Time evolution of the approximated crowd size of each person on the second day in 2023. The faint-colored lines represent all other samples.

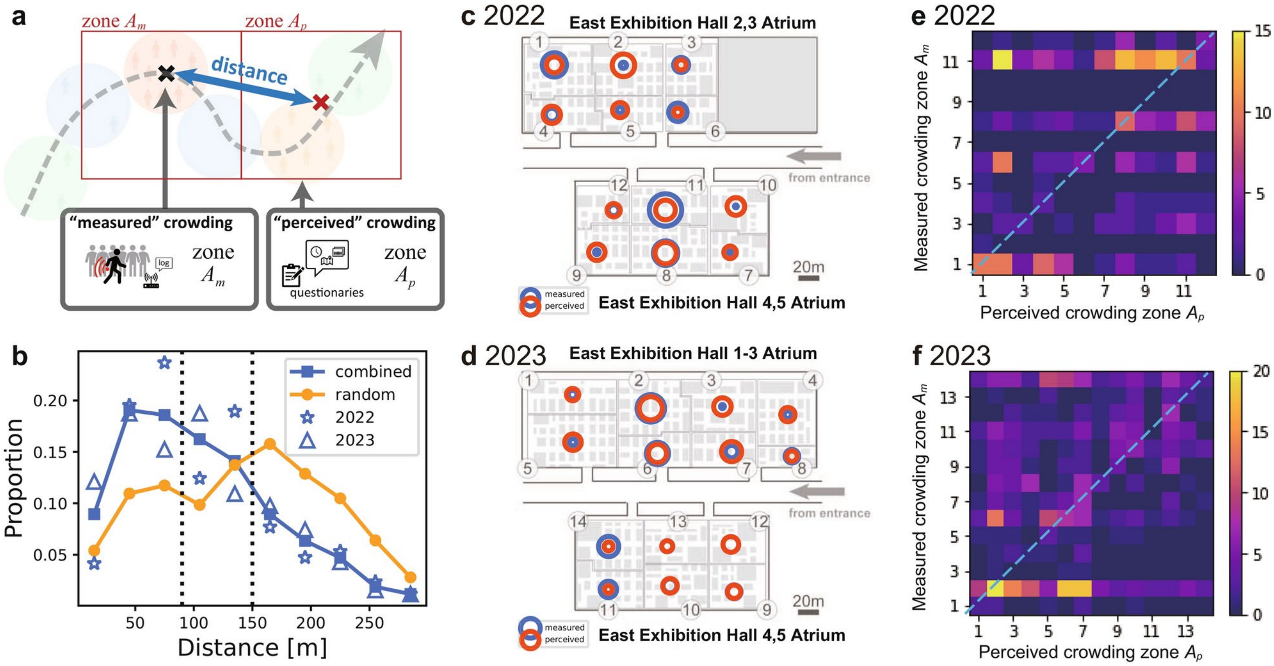


Fig. 5. Spatial accuracy of perceived crowding. (**a**) Schematic of the distance between measured and perceived crowding locations. (**b**) Proportion of each distance between measured and perceived crowding locations, calculated in 30-meter increments. (**c**–**f**) Distribution of questionnaire-based zone selections. (**c**, **d**) illustrate the spatial distribution of responses for 2022 and 2023, respectively, overlayed on a map. (**e**, **f**) detail the specific proportion of selections for each zone for 2022 and 2023, respectively.

areas, calculated as the number of answers that selected a specific zone divided by the total number of answers. Similarly, the blue circles represent the proportion of areas identified as the measured crowding areas, calculated as the number of samples whose measured crowding area was a specific area divided by the total number of measurement samples. For both years, the distributions differ considerably.

In Fig. 5e,f, the correlation between the perceived and measured crowding is evaluated for the various zones within the venue for 2022 and 2023, with the p-value from t-test for the correlation coefficient being 0.1. The matrices display the frequency with which zones were reported as crowded by participants against the crowding measurements obtained from beacon data. The absence of a pronounced diagonal trend in these matrices indicates a disparity between perceived and actual crowding on a 20×20 m scale, in contrast to time-based analyses which showed clearer patterns.

To determine whether participants could perceive crowding on a larger scale, we analyzed their ability to correctly identify the hall, which spans approximately 100×100 m, rather than specific zones. In 2022 and 2023, the proportions of participants who correctly identified the hall, excluding non-respondents, were 0.678 and 0.693, respectively, indicating a degree of alignment between perceived and measured crowdings on a larger scale. This shows that most participants had a general sense of more expansive crowded areas.

Given the different venue sizes in 2022 and 2023, it was essential to not only compare the ratio of answers for each specific area but also apply a consistent measurement approach. Therefore, we analyzed the spatial discrepancy between the locations of maximum measured crowding and the areas participants identified as most crowding.

We calculated the distance as the Euclidean distance between the xy coordinates of the measured crowding location and the perceived crowding location (Fig. 5a). The measured crowding location is determined by the coordinates of the receiver position with the highest recorded density. For the perceived crowding location, we used the center of mass of the receivers located within the participant-selected zone, calculated by averaging the coordinates of all receivers in that zone. The proportion distribution of this distance is represented by blue square markers, which differ from the distribution when answers are selected randomly, as illustrated by the yellow circle markers (Fig. 5b). Notably, at distances shorter than 150 m, this proportion is significantly higher than what would be expected if participants had randomly selected their answers for each measured crowding location, as illustrated by yellow circle markers. The dashed lines at 80 m and 150 m indicate typical distances between the nearest neighboring zones within the same hall, respectively. This indicates that while many participants mistakenly chose neighboring zones as crowded, a majority accurately identified locations within the same hall.

In summary, a significant majority of participants who identified a crowded zone could accurately perceive the location of crowding at the scale of a hall, approximately 100×100 sq. m in size. The proportion of participants who correctly identified the hall aligns closely with the proportion of those able to pinpoint the time of crowding more accurately than a random guess.

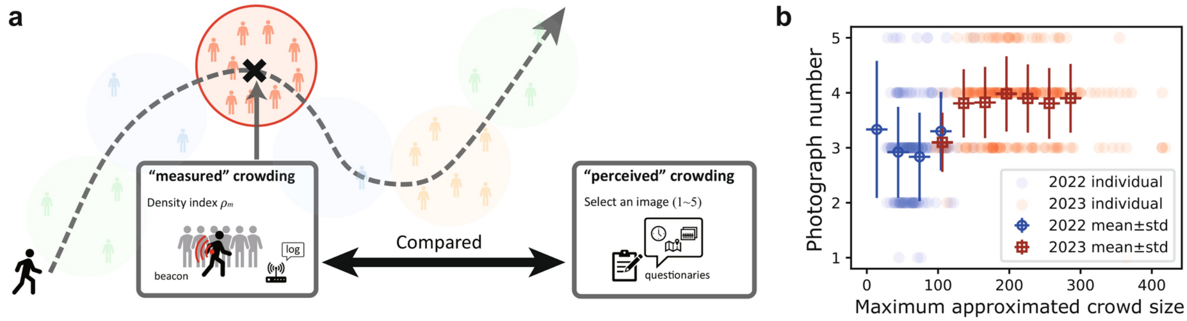


Fig. 6. Accuracy of perceived crowd density. (**a**) Schematic illustration explaining the investigation of participants' recognition of crowding density compared to the measured crowding. (**b**) Distribution of photograph choice numbers from Fig. 7c in relation to the maximum approximated crowd size.

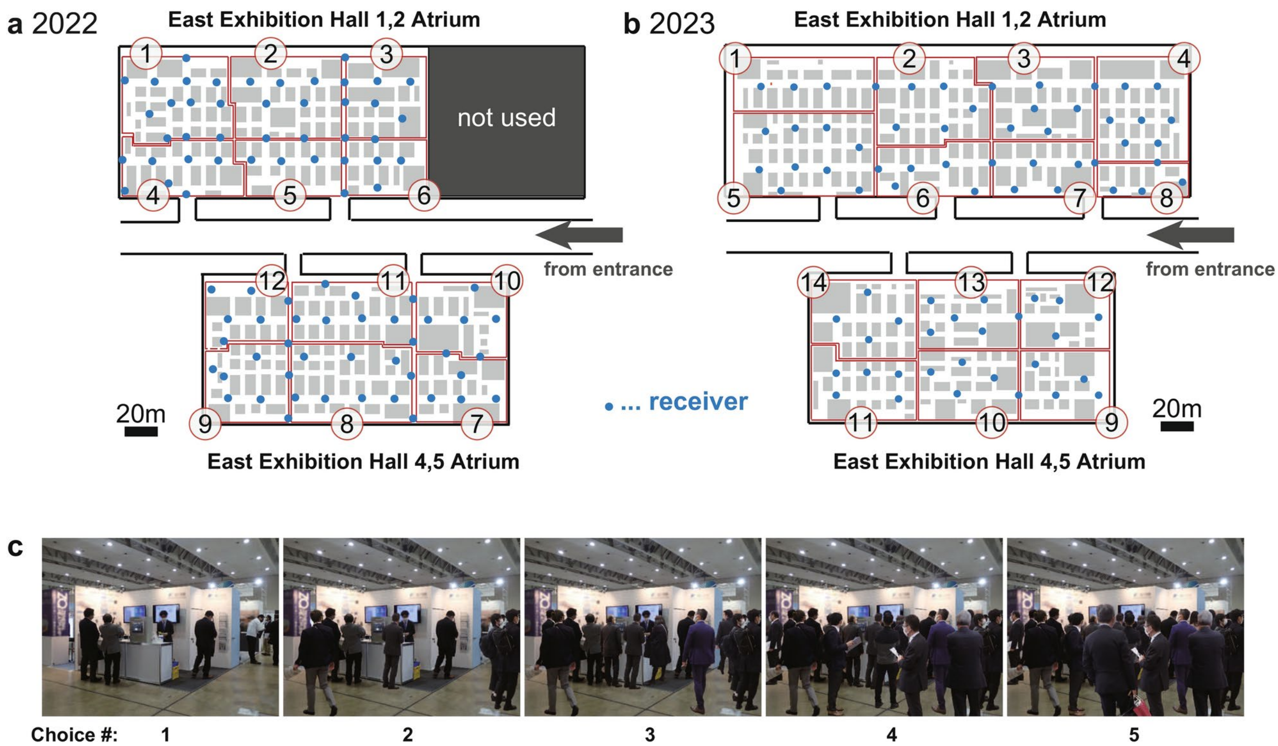


Fig. 7. Exhibition hall layout and visual aids for crowding analysis. (**a**, **b**) Exhibition hall layout for 2022 and 2023, with red lines indicating the segments used for crowding analysis in the questionnaire. Blue circles represent the positions of beacon receivers, and arrows highlight the primary entry routes of participants. (**c**) Photographs were utilized to assess participants' perception of crowding. The numbers of people are 7, 11, 16, 21, and 25.

Crowding density recognition

Finally, we investigated how participants perceived crowding density and its relation to the measured density, as shown in Fig. 6a. Participants selected from a set of photographs, each representing different crowd densities, the one they felt best matched the density in the area where they experienced crowding. The photographs, numbered from 1 to 5, depicted crowds of 7, 11, 16, 21, and 25 people, respectively (see Fig. 7c for reference). See the "Methodology" section for details.

Figure 6b correlates participants' photograph selections to the maximum approximated crowd size they encountered. Photograph choices, averaged into bins of 30 for the maximum approximated crowd size, are represented by circle and square markers for 2022 and 2023, respectively. These choices increase with the maximum approximated crowd size, suggesting an overall trend where higher densities lead to the selection of more crowded images (correlation coefficient: 0.40, p-value of t-test: $< 10^{-3}$). The differences between the two years may be due to the threefold increase in congestion. However, within each year, the correlation coefficients and p-values of the t-test are 0.11 and 0.16 for 2022, and -0.04 and 0.47 for 2023, respectively. Therefore, we cannot conclude that people quantify the congestion strictly on pedestrian numbers in the surroundings.

Discussion

This study employs a novel approach that combines questionnaires and beacon data, and represents, to the best of our knowledge, the first attempt to compare perceptions of crowding with actual crowding at an event with over 10,000 visitors. This method not only advances our understanding of crowding dynamics but also provides actionable insights that are valuable for event management. The findings reveal two relationships that are crucial for comprehensively understanding crowding at large-scale events.

First, our results indicate that participants were more accurate in identifying the time and location of crowding than if they had answered randomly. However, their perception of crowding did not consistently align with the measured crowding density. This indicates that while individuals may not quantify crowding, they develop a relative understanding based on personal experiences. Essentially, people can discern relatively crowded times and places. However, density perception did not strongly align with measured density. While perception reflected a threefold difference in density between years, differences within a year would be clearer with continuous selection options. The minimum and maximum selections are generally avoided, and hence, offering a wider range of options would help. Additionally, participants might remember locations like corridors or areas near gates that aren't represented in the photographs. Consistent with previous studies[8–14], it is likely that subjectivity strongly influences these perceptions of crowding.

This insight is vital for event organizers and urban planners, who often depend on quantitative data to evaluate and manage crowd density. It is important to note that perceived crowding levels can differ significantly due to influenced by personal experiences, emotions, and expectations. While average responses may indicate noticeable differences in crowd sizes across various events, interpreting crowding density on an individual basis from these responses can be misleading. Therefore, recognizing the subjective and relative nature of individual experiences of crowding is crucial in planning and managing large-scale events.

Second, our findings revealed a notable bias: participants' recollections of crowding times were often closer to their leaving times than the measured crowding times, particularly for those who stayed for more than three hours, as detailed in the "Time perception discrepancies in crowding reports" section. This finding can be interpreted in light of the "recency effect," where individuals are more likely to remember recent events more vividly[31]. Additionally, the observed lower perceived crowding in the 10:00 time slot (Fig. 4b) can also be explained by this effect.

This suggests that participants' perceptions of crowding are significantly influenced by their recent experiences. Consequently, event organizers should focus on managing crowding effectively during the latter part of the event, as this period may disproportionately affect participants' overall impressions of crowding. Ensuring adequate crowd management towards the end of the event could help control the impact of recent crowding experiences and guide practical adjustments such as staff allocation and event scheduling.

However, it is important to approach these findings with caution, as frequent crowding fluctuations can complicate peak time identification. While our study provides insights into the timing and location of perceived crowding, it did not specifically assess the emotional impact or positive/negative impressions of crowding. Further research is needed to fully understand these effects and validate the findings across different conditions.

Additionally, caution is advised when conducting crowding surveys that rely solely on visual information. Our findings suggest that the perception of crowding might differ from perceptions based solely on visual input, which is consistent with previous studies[32–35]. This becomes relevant in virtual reality crowding surveys, where the absence of multi-sensory input might affect the accuracy of perceived crowding levels.

In addition, this study has limitations that should be noted. First, it is uncertain whether the trends observed apply to even more crowded situations or different populations and events, given that crowding perception is influenced by numerous individual factors. Second, societal attitudes and regulations regarding gatherings due to infection concerns have evolved; in 2022, gatherings were discouraged, whereas restrictions were relaxed in 2023. These changes could affect the generalizability of our findings. Future research should aim to validate these results across various conditions, including more diverse and densely crowded situations, different population groups, and various types of events. Additionally, incorporating spatiotemporal analysis could provide a more comprehensive understanding of crowding dynamics. Nevertheless, this study significantly contributes to our understanding of crowding perception, highlighting its quantitative aspects and inherent biases.

Methods

This study was approved by the Ethical Committee of The University of Tokyo and all methods were carried out in accordance with relevant guidelines and regulations. Written informed consent was obtained from all participants prior to the start of the study.

Tokyo Big Sight in Tokyo, Japan, served as the venue for our research, where a series of concurrent technology exhibitions took place. These combined events provided participants with the impression of a unified, expansive experience. Among these exhibitions was the "International Nanotechnology Exhibition & Conference," a comprehensive nanotechnology showcase held annually since 2002. We included observations from two sessions of this exhibition: January 26th–28th, 2022 and February 1st–3rd, 2023, from 10:00 a.m. to 5:00 p.m.

Within Tokyo Big Sight, the exhibitions took place in the East Exhibition Halls and Conference Tower (Fig. 7a,b). Upon entering the venue's main corridor, participants were greeted by a central passage flanked by the East Halls. From the main entrance of Tokyo Big Sight, the East Exhibition Hall 1 Atrium was the nearest. The layout arranged the East Exhibition Hall 1–3 Atrium on one side of the corridor and the East Exhibition Hall 4–6 Atrium on the opposite side. Notably, there were no walls separating the East Exhibition Hall 1–3

Atrium from Halls 4–6 Atrium, but each hall maintained its own distinct gate and exit. It is important to mention that only the East Exhibition Halls 2–3 Atrium from Halls 4–6 Atrium were utilized for the 2022 exhibition. Consequently, the venue area in 2022 and 2023 was approximately 27,000 and 34,000 sq. m, respectively, with the ratio of the booth area to the total area being 0.36 in both years. Staff members were positioned at these gates to ensure that only individuals with registration for participation are granted access to the event.

Beacon measurement

The primary purpose of the beacon survey was to evaluate crowding levels and track participants' movement trajectories within the venue. The participants were provided with beacon transmitters sized for easy attachment to bags or name tags upon entry to the venue. These transmitters emitted Bluetooth signals approximately every 0.5 s with a communication strength of 0 dBm. Participants were requested to carry a beacon with them during scheduled breaks and to return the beacon upon exiting the premises completely.

Receivers, which were strategically positioned throughout the venue including at gates as illustrated in Fig. 7a,b, scanned for beacon signals every 10 s. Each time a beacon was detected, the system documented the timestamp, beacon ID, and RSSI (Received Signal Strength Indicator) value.

To reconstruct the movement trajectories of participants, we first organized the receiver data by date and further subdivided it based on Beacon ID. We retained records with an RSSI value of -80 dBm or above. Then, for those records demonstrating an RSSI of -75 dBm or higher, we surmised that the beacon's location coincided with the coordinates of the detecting receiver. For records with an RSSI below -75 dBm, we estimated the beacon's position using the centroid of records immediately before, during, and after that specific timestamp, where the weight was calculated based on the RSSI value in relation to -80 dBm. In case of missing records for certain timestamps, we assumed a continuous linear path between the two nearest timestamps to deduce the beacon's trajectory.

Note that we hypothesize that the number of beacons with an RSSI value above -80 dBm, as detected by each receiver, correlates linearly with the local population density in the vicinity of the receiver, representing the approximated crowding size. While RSSI values are primarily influenced by distance, they can also be affected by various environmental factors. Nevertheless, for the purpose of our analysis, we assume that an RSSI threshold of -80 dBm effectively captures beacon signals within a reasonable range.

We ensured that our trajectory estimation method was accurate, with a 68% probability of any positional discrepancy being confined within an 18 m radius (see Supplementary Fig. S1). An in-depth exploration of this methodology is available in Supplementary Information.

For crowding density level analysis, we first counted the number of beacons with an RSSI value of -80 dBm or higher for each receiver for each 10 s, and subsequently calculated the minute-average counts. Then, we averaged the counts from receivers that were within the same divisions as specified in the questionnaire for comparison with the survey responses.

To identify the moment of the maximum approximated crowding size experienced by each participant, we divided their trajectory data into one-minute segments and computed the centroid of positions within each segment. By matching this centroid to the closest receiver, we ascertained the corresponding area division and employed the approximated crowding size for that division as the approximated crowding size the participant experienced at that time. By comparing the crowding levels across a participant's trajectory, we discerned the specific time and location where the maximum approximated crowding size was encountered. The crowding gauged through this approach was termed as "measured crowding."

Questionnaire design

The questionnaire survey was aimed at individuals who had concluded their visit to the exhibition and was conducted between 10:00 a.m. and 5:00 p.m. We arranged chairs and tables onsite to facilitate participants' completion of the survey without needing to leave the venue. In both 2022 and 2023, the survey engaged 500 participants at the event. The survey was exclusively administered to those who returned the beacons and expressed their willingness to participate further.

Our primary objective was to analyze the congruence between participants' perceived crowding and the actual conditions quantified by the beacon system. Consequently, our questions were tailored to probe crowding from the perspectives of time, location, and density level. The crowding discerned from the respondents' input was labeled as "perceived crowding." In relation to location, the respondents were guided to mark all zones where they experienced most crowding. The venue was demarcated into 12 and 14 distinct zones in 2022 and 2023, respectively, as delineated in Fig. 7a,b. The respondents were encouraged to provide an estimated timeframe when they experienced most crowding in the areas pinpointed in the preceding question, which is an open-ended response. To gauge the perceived density level of crowding, we presented respondents with a visual aid. To illustrate diverse crowd sizes, five distinct photographs featuring varying numbers of individuals were created using Photoshop. These photographs vividly portrayed groups comprising 7, 11, 16, 21, and 25 people, as shown in Fig. 7c. The range of group sizes was appropriate for this event; at the most crowded time (11:00 a.m. on February 3rd, 2023, see Fig. 2), the density, assuming uniform distribution, was approximately 0.12 persons per sq. m. Estimating that the area in each photograph is about 100 sq. m, this would correspond to 12 people per photograph, which fits within the range of the prepared images. Participants were asked to select one photograph from this set of five photographs that most represented the crowd density in the zone where they experienced crowding. If participants felt no sense of crowding during their visit, they were instructed to bypass these specific questions.

Data availability
The datasets generated and analyzed during the current study are not publicly available due to the involvement of private companies in the study but are available from the corresponding author on reasonable request.

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Author contributions
S.T., H.K., C.F., X.J., A.T., and T.A. conducted the experiments, with S.T. leading the analysis of the results. S.T., H.K., C.F., and X.J. were involved in interpreting the data. H.K. and T.A. designed the work, while T.A. and K.N. developed the initial concept. All authors contributed to the review of the manuscript.

Additional information
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