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# Design of public open space: Site features, playing, and physical activity

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ABSTRACT

Not enough studies have examined how specific design features of public open space, such as movable site features, are associated with people's physical activity level or playfulness. To fill this gap, this study uses deep learning-based methods to extract visitors' movement trajectories (n = 18,592) from a time-lapse video of a promenade in Hong Kong. The trajectories are classified into different groups based on a set of movement indicators. Multinomial logistic regression is used to examine the relationship between trajectory types and the level of interaction with different site features. A one-way analysis of variance (ANOVA) is also used to compare the average amount of physical activity among different trajectory types. The results show that interaction with semi-fixed or movable site features is associated with higher odds of people having "playful" trajectories than other types of trajectories. People with "sporty" trajectories and "playful" trajectories on average have the highest amount of physical activity.

## 1. Introduction

The importance of physical activity for people's overall health and well-being has been increasingly recognized in recent years (Anderson and Durstine, 2019; Warburton and Bredin, 2017), partly because obesity has become a global problem (Inoue et al., 2018; Jaacks et al., 2019). Yet, little progress has been made in increasing people's physical activity in countries around the world (World Health Organization, 2019). At the same time, opportunities for children and adolescents to play in public spaces are also diminishing (Gray, 2011; Lee et al., 2021; Pyyry and Tani, 2015; Vanderbeck et al., 2000; Veitch et al., 2006), with urbanization (Lee et al., 2021), the popularity of televisions and the Internet (Gray, 2011), and increased parental concerns about children's safety (Veitch et al., 2006). Active play is essential for people's well-being, especially for children's overall development (Brockman et al., 2011; Tonkin and Whitaker, 2019; Quinn and Russo, 2022). Against this background, there is an urgent need to investigate ways that limited public space resources in cities can be (re-)designed to facilitate more physical and playful activities to make cities more liveable and sustainable (Edwards et al., 2015; Kaczynski et al., 2014; Slater et al., 2016).

Currently, studies that examine the relationship between public open space and physical activity mostly focus on the availability of or accessibility to public open space (Koohsari et al., 2015; Lackey and Kaczynski, 2009). There are also studies that examine whether the size, density, or the presence of some features in public open space are associated with the level of physical activity (Edwards et al., 2015; Kaczynski et al., 2014; Koohsari et al., 2015; Van Hecke et al., 2018). Despite extensive research efforts, there are research gaps that need to be addressed. In particular, whether and to what extent that specific design features of public open space influence physical activity at the microscale are not well examined (Baek et al., 2015; Veitch et al., 2021). Regarding play, the Dutch historian Johan Huizinga considered it necessary for the generation of culture. In his book, *Homo Ludens*, he defines play as irrational, non-serious, and voluntary, as opposed to the rationality, purpose, and seriousness of ordinary life (Huizinga, 1998). Play in public space benefits people's well-being in multiple ways. For children, outdoor play contributes to their momentary well-being (Leung and Loo, 2017), helps them develop social and cognitive capabilities (Holloway and Pimlott-Wilson, 2014; Tonkin and Whitaker, 2019), and increases their levels of physical activity (Farley et al., 2007). For adults, play offers an opportunity to escape the cycle of production and consumption in urban life (Stevens, 2007), fulfils their psychological needs of self-actualization and social interaction, promotes creativity, and helps them better cope with stress (Tonkin and Whitaker, 2019). In addition, play activities in public space can connect people of different generations and cultivate mutual understanding (Biggs and Carr, 2015).

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In comparison with physical activity, few studies have been conducted to measure play, possibly because it is not easy to distinguish playing from other behaviours. In this regard, people's movement trajectories in public open space can provide valuable information for detecting playful activities. The trajectory of a person can be understood as a sequence of spatial coordinates that describe his/her walking route across space (Gray, 2011). The shape of the trajectory can thus show the characteristics of the movement and provide hints on what kind of behaviour the person is conducting. For instance, Yan and Forsyth (2005) used people's trajectories to study their "wandering" behaviour in public spaces and their spatial relationship with the surrounding landscape features, such as the water fountain. Similarly, Okamoto et al. (2011) used movement trajectories to classify behaviours into "going straight", "finding the way", and "walking around". In a more recent study, the complexity and diversity of human trajectories are used to measure the vitality of public spaces (Niu et al., 2022).

Based on our initial site observations and hand drawing of people's trajectories, we found that the observed trajectories can actually distinguish people who move through space with a sense of seriousness and those who wander in the public space with a sense of spontaneity. Therefore, we believe there is great potential to use people's trajectories in public spaces to identify their play behaviour. A related objective is to investigate how microscale features in public spaces may facilitate more play and physical activity.

To our knowledge, no existing studies have used people's movement trajectory to examine active play behaviour in public space. Our research thus serves as a pilot study to test this methodology. Firstly, we develop a method to classify people's trajectories. Secondly, the role of different site features in supporting play in public open spaces is examined. Finally, the link between play and physical activity is investigated. To guide the analysis, there are three research hypotheses.

**Hypothesis 1**. People in public open space can be grouped by characteristics of their trajectories;

**Hypothesis 2**. People of different trajectory groups have different levels of interaction with features in public open space;

**Hypothesis 3**. People of different trajectory groups have different physical activity levels.

## 2. Methods

Fig. 1 presents a schematic diagram of our methodology. Based on anonymized video data of a harbourfront public space (described below), we first generate pedestrian trajectories by detecting and tracking people across video frames. Then, the trajectories are divided into different groups based on a set of indicators about their trajectories detected from the video (H1). Next, the relationship between trajectory types and the interaction with site features is examined using multinomial logistic regression model (H2). Finally, the physical activity level is estimated for each trajectory group and comparisons are made (H3).

### *2.1. Study area and video data*

The Belcher's Bay Promenade is located in the north-western part of the Hong Kong Island, along the Victoria Harbour. Previously a public cargo working area, it is now a harbourfront public open space. The site was designed in a way that allows the public to utilize the space in a flexible manner and to conduct activities according to their imagination through the provision of an unprogrammed open space and interactive site features (The Government of the Hong Kong Special Administrative Region, 2020). The size of the site is about 0.59 ha. The public space mainly consists of a multipurpose open space located at the centre, a harbourfront walking path, a dog park, as well as a community garden

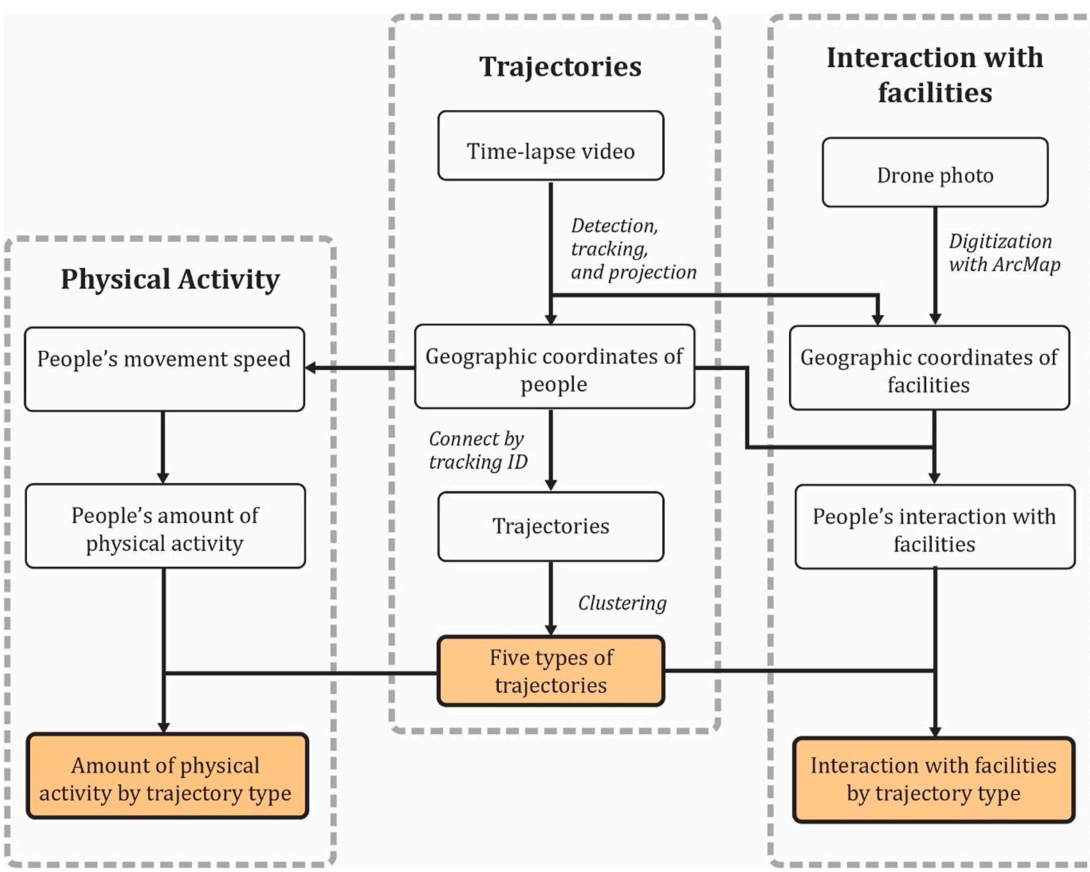



**Fig. 1.** A flow chart of methodology.

that was under construction during the study period. Video recordings of the site were obtained on February 14 of 2021 (Valentine's Day & Sunday) from 9:00 a.m. to 6:00 p.m. The data were provided by the Harbourfront Commission of Hong Kong and was limited to one day only. No other videos are available for analysis. The site layout at the time of the survey is shown in Fig. 2. Although the types of users and activities may be different on other days, we believe the data used are enough to test the aforementioned hypotheses as a pilot study. Research ethics approval was obtained from the authors' university.

### 2.2. Extraction and grouping of trajectories

To detect and track pedestrians, we apply a state-of-the-art multi-object tracking (MOT) algorithm named ByteTrack to track each person with the same ID across video frames (Zhang et al., 2022). Frame interpolation is also conducted before applying the MOT algorithm to improve the accuracy of tracking (Huang et al., 2022). Next, a homography matrix is calculated to project the coordinates on video frames into real-world geographic coordinates (Gocer et al., 2018).

After deriving the spatial locations of people in each video frame, the movement speed of each individual is calculated based on consecutive video frames. Noisy data, such as "jumping" IDs that result in unreasonable speed exceeding 10 m/s, are filtered out. Trajectories are then formed by connecting the geographic coordinates of the same person across video frames. Since some visitors were only tracked momentarily because of issues such as occlusion, only people who were tracked for 25 s or more were selected to form trajectories. We derive the 25-s threshold via trials of different thresholds and consideration of the dimension of the video scope. We have tested different threshold values of tracking period by visualizing the tracking results in videos and decided that 25 s is a reasonable threshold. The longest Euclidean distance between two points within the video scope is about 75m while the walking speed for most people detected are under 3 m/s. Thus, it would take about 25 s for a person walking very fast to pass through longest distance within video scope, making 25 s a reasonable threshold value.

Once the trajectories are formed, a set of indicators are used to divide individual trajectories into groups according to the typology of trajectories we observed from the video. Based on the concept of "playfulness", trajectories involving more play activities will make more detours in public open space compared to other trajectories. Therefore, an indicator named detour ratio ($R_D$) is calculated as the ratio of the total length of the trajectory ($L_T$) to the distance between the first location and the farthest location (from the first location) of the trajectory ($D_{FF}$):

$$R_D = \frac{L_T}{D_{FF}}$$

Next, in order to differentiate people who are passing through or moving back and forth with those who move more freely during play, the ratio of the long to short edge ($R_{LTS}$) of the minimum bounding rectangle is calculated for each trajectory, using the following formula:

$$R_{LTS} = \frac{L_L}{L_S}$$

Then, to separate trajectories that only cover small areas with those that explore a larger area in the open space during play, the area of the minimum bounding rectangle is also used. Finally, the total length and


**Fig. 2.** Site map of the study area.

duration for each of the trajectory are considered. This distinguishes people who move longer distances and dwell a longer time on the site from those who move shorter distances and spend less time in the public open space.

Based on our direct observation from the video, four primary trajectory types are identified with reference to the observation guidelines listed in the literature review. As shown in Table 1, they are "playful", "sporty", "strolling", and "passive". "Playful" trajectories are those associated with spontaneous movements which often involve a lot of detours and explorations of different parts of the public space. "Sporty" trajectories belong to those who move back and forth in a more-or-less opposite directions, such as people who are skateboarding on the site. "Strolling" trajectories are associated with people who are continuously moving towards the same direction, such as walking through the public space. "Passive" trajectories are associated with people who are mostly staying in a small area, such as people who are merely standing and talking to each other. Other trajectories that do not exhibit a strong association with any of the above are considered as "mixed" trajectories.

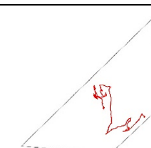
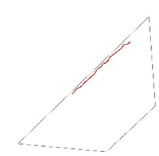
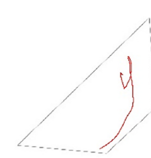
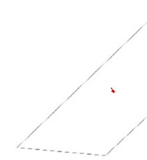
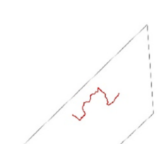
### 2.3. *Relating trajectories to features*

With reference to the existing literature, features in the public space can be categorized as fixed, semifixed, and movable (Mehta, 2014). One of the unique design features of the study area is that some movable and semi-fixed features are provided in addition to fixed features. The fixed features include benches, a pavilion and some heart-shaped seating (Fig. 2). The semi-fixed feature is a carousel; and the moveable features consist of about 80 blue cargo pallets. People on the site can move the blue cargo pallets around to form interesting structures such as a "maze" or a "fortress". They can also rotate the carousel. All of these behaviours induce play and physical activity. Photos for the carousel and blue cargo pallets can be found in Appendix 1. The locations of fixed or semi-fixed features are directly derived using the drone photo of the site and ArcMap.

To derive the spatial locations of movable features (blue cargo pallets) over time, the computer vision library OpenCV is used to extract the blue colour with pre-defined range of hue and saturation in the video frames (Loo and Fan, 2023). The same homography matrix calculated in the last step is also used to project the pixel coordinates into geographical coordinates.

In order to find out whether different movement trajectories are associated with the usage of different features in space, a multinomial logistic regression is used. Specifically, the type of trajectory is considered as the dependent variable. For independent variables, the total duration within 0.5m distance to different types of features is used to indicate the level of interaction between people and features. People with passive trajectories are used as the reference group.

**Table 1**
Thresholds for different trajectory types.

| Trajectory type | Detour Ratio | Area | Long to short edge ratio | Length of trajectory | Duration | Example of trajectory |
|---|---|---|---|---|---|---|
| Playful | > Median | >25th Percentile | <=Median | – | – |  |
| Strolling | <=Median | – | – | ≤75th Percentile | ≤25th Percentile |  |
| Sporty | – | – | > Median | >75th Percentile | >25th Percentile |  |
| Passive | – | ≤25th Percentile | – | ≤75th Percentile | >25th Percentile |  |
| Mixed | – | – | – | – | – |  |

### 2.4. Trajectories and physical activity

In this study, we also estimate the intensity of physical activity in the unit of metabolic equivalent of task (MET) (Maher and Conroy, 2015) using people's movement speed (Silva et al., 2015). Upon manually checking the videos, this approach is appropriate for this study as few people were found to be conducting stationary exercises, such as yoga or Tai Chi, during the survey period. Generally, the total energy expenditure of a person is calculated by multiplying the duration (minutes) of a specific activity and the estimated MET to derive the total amount of MET-minutes (Maher and Conroy, 2015).

Based on the *Physical Activity Guidelines for Americans* (U.S. Department of Health and Human Services, 2018), light-intensity activity refers to behaviours that require less than 3 METs, moderate-intensity activity requires 3–6 METs, while vigorous-intensity activity requires 6 or more METs. At the same time, sitting quietly (with some fidgeting) corresponds to 1.5 METs while the most intensive walking behaviour on a flat surface corresponds to 9.5 METs (Ainsworth et al., 2011). As the minimum walking speeds for moderate-intensity activity and vigorous-intensity activity are 1.118 m/s and 2.012 m/s, respectively (U.S. Department of Health and Human Services, 2018), we consider people with a speed slower than 1.118 m/s as conducting light-intensity activity with 1.5–3 METs; people with speeds between 1.118 m/s and 2.012 m/s are considered to be conducting moderate-intensity activity with 3–6 METs; those moving at 2.012 m/s or faster are considered to be conducting vigorous-intensity activity with 6–9.5 METs. Hence, the corresponding mean METs are 2.25, 4.5, and 7.75 respectively.

In order to calculate the total amount of physical activity (in MET-minutes), the duration of stay should also be considered. It is important to note that there is always a systematic underestimation for the duration of stay due to the tracking issue in occluded scenes, which is common in current pedestrian tracking algorithms (Stadler and Beyerer, 2021; Zhang et al., 2022). The corresponding physical activity intensity levels (light, moderate, vigorous) and mean METs (2.25, 4.5, 7.75) are derived based on each individual's movement speed. Next, the total MET-minutes for a trajectory are calculated by summing up the amount of physical activity involved. The average amount of physical activity can also be calculated for each trajectory group. Then, a one-way analysis of variance (ANOVA) is conducted to examine whether there are significant differences in the amount of physical activity among different trajectory groups.

Finally, to show the dynamics of physical activity for different trajectory groups, we divide the survey period (9:00 a.m. to 6:00 p.m.) into 15-min time slots. The number of visitors, percentage of different type of trajectories, total amount of physical activity, and the average amount of physical activity for each trajectory are calculated for each time slot. In rare cases that a trajectory straddles through multiple time slots, it will be counted in all related time slots.

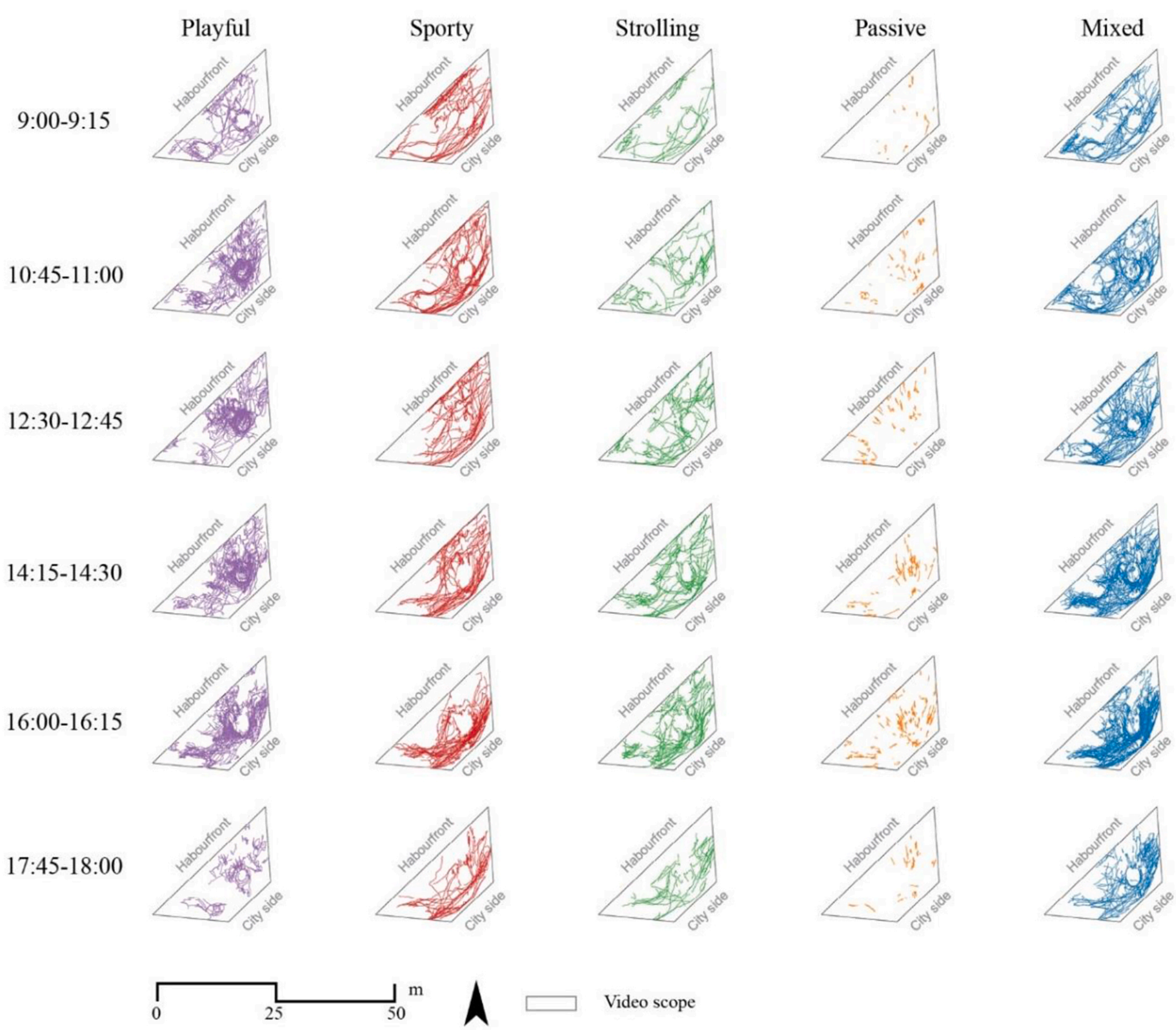



**Fig. 3.** Spatial and temporal patterns of different trajectory types.

## 3. Results

The Belcher Bay Promenade is a vibrant place where people conduct various types of leisure activities. In total, there were 18592 people observed, with each people having one corresponding trajectory. Based on the criteria listed in the methodology, the trajectories are further classified as "playful" (4240), "strolling" (2725), "sporty" (2119), "passive" (3050) and "mixed" (6458). It can be seen that the harbourfront open space is an inclusive space that caters for a mix of users with different activities. Fig. 3 shows the spatial and temporal patterns of different trajectory types. It can be observed that there are more trajectories during the afternoon of the survey day. More trajectories along the harbourfront are identified during early morning time (9:00–9:15) compared to late afternoon after the sun goes down (17:45–18:00). In addition, most playful trajectories are located near the semi-fixed carousel at the centre of the public space. On the contrary, sporty trajectories are more likely to be located at the harbourfront side or city side, potentially because people doing sports avoided the semi-fixed carousel near the centre of the site.

In order to examine whether people of different trajectory groups have different levels of interaction with site features (H2), a set of box plots are created to show the total time spent within 0.5m from the blue cargo pallets (moveable feature) for people with different trajectory types (Fig. 4). It can be observed that people with "playful" or "sporty" trajectory types have higher levels of interaction with the blue cargo pallets. Table 2 shows a summary of the average duration of interaction with different site features of the different trajectory types. The maximum value of the average duration of interaction ranges from less than 1 min (0.708 for strolling) to nearly 10 min (9.087 for playful). People with "playful" and "sporty" trajectories on average stayed much longer within the 0.5m distance to the blue cargo pallets.

Furthermore, a multinomial logistic regression is conducted. The results are shown in Table 3. With the "passive" trajectories as the reference group, we see that people have 10.2% and 138.7% greater odds to have "playful" trajectories per 1 min increase of the duration within 0.5m from blue cargo pallets (Odds ratio (OR) = 1.102) and the carousel (OR = 2.387), respectively. In other words, people with a "playful" trajectory tend to have a higher level of interaction with the movable or semi-fixed site features, especially the carousel. Similarly, spending more time near the blue cargo pallets is associated with 13.9% higher odds for people to have "sporty" trajectories (OR = 1.139). Different from people with "playful" trajectories, interaction with the carousel is associated with 99.6% lower odds of people having "sporty" trajectories (OR = 0.004). On the other hand, interaction with site features (whether fixed or semi-fixed) is associated with significant lower odds of people having "strolling" or "mixed" trajectory types, compared to the "passive" group. The results here suggest that moveable features, such as the blue cargo pallets, is significantly associated with more play and physical activity among visitors at the public open space. In addition, the semi-fixed and interactive carousel can facilitate more playing, but may also block other active use of space such as skateboarding, running or biking back and forth, as it is placed in the centre of the site.

**Table 2**
Descriptive statistics of interaction with the blue cargo pallets by trajectory type (total duration within 0.5m distance to blue cargo pallets in minutes).

| Trajectory type | Mean (minutes) | Median (minutes) | Max (minutes) | Std. (minutes) |
|---|---|---|---|---|
| Playful | 0.241 | 0.034 | 9.087 | 0.549 |
| Sporty | 0.285 | 0.034 | 8.312 | 0.770 |
| Strolling | 0.057 | 0.000 | 0.708 | 0.102 |
| Passive | 0.229 | 0.017 | 5.243 | 0.413 |
| Mixed | 0.128 | 0.017 | 4.619 | 0.271 |

Fig. 5 shows the amount and intensity of physical activity for each trajectory group. To recap, people having speeds under 1.118 m/s are considered conducting light-intensity physical activity (with 2.25 METs on average). Those with speeds between 1.118 and 2.012 m/s are conducting moderate-intensity physical activity (with 4.5 METs on average). And those with speeds over 2.012 m/s are conducting vigorous-intensity physical activity (with 7.75 METs on average). From Fig. 5, we can see that people with "sporty" trajectories, such as those skateboarding, have the highest amount of physical activity in general (mean = 4.663, s.d. = 3.576). Those with "playful" trajectories on average have the second-highest amount of physical activity. In comparison, people with "strolling", "passive", or "mixed" trajectory types on average have relatively lower amount of MET-minutes. It can also be

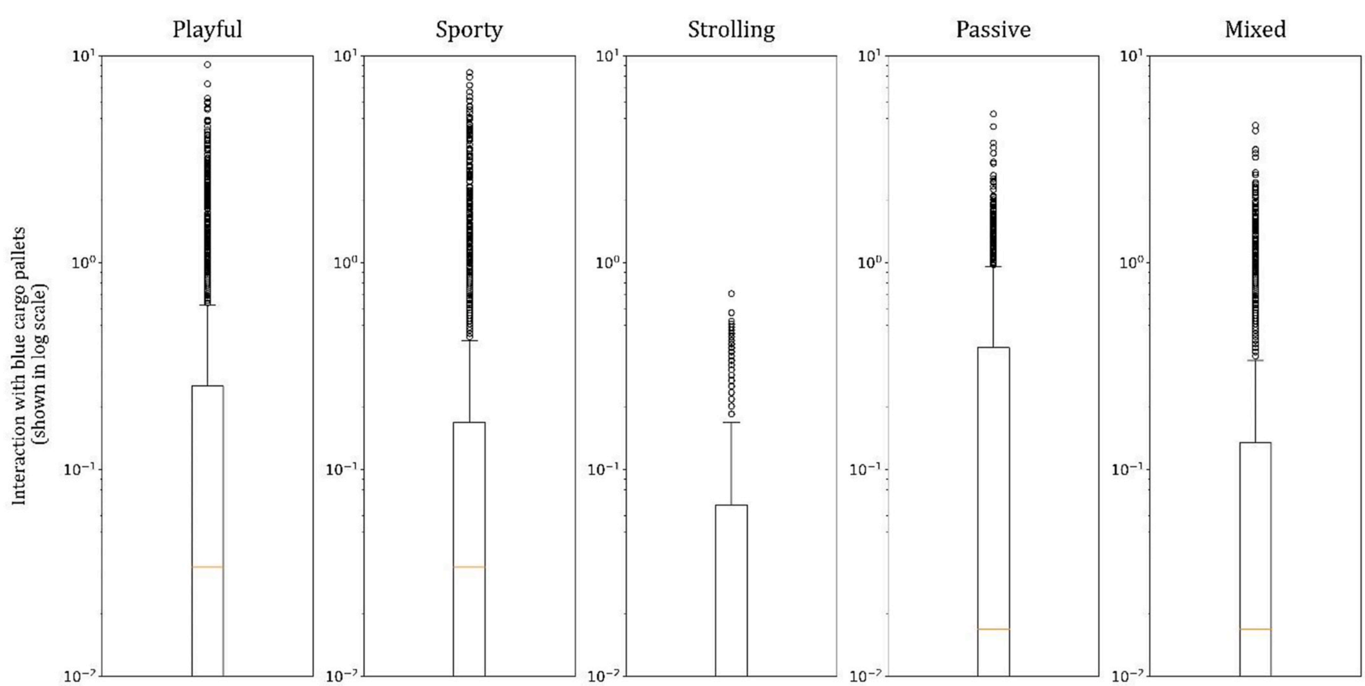



**Fig. 4.** Level of interaction between people with different trajectory types and the blue cargo pallets (total duration spent within 0.5m to blue cargo pallets).

**Table 3**
Multinomial logistic regression (MNL) results for different trajectory types (n = 18592).

| | Playful (n = 4240) | | Sporty (n = 2119) | | Strolling (n = 2725) | | Mixed (n = 6458) | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | Odds ratio (95% CI) | Coef. | Odds ratio (95% CI) | Coef. | Odds ratio (95% CI) | Coef. | Odds ratio (95% CI) |
| Intercept | 0.281 | | −0.313 | | 0.523 | | 1.040 | |
| Interaction with blue cargo pallets | 0.097 | 1.102 (1.008–1.204)* | 0.130 | 1.139 (1.034–1.255)** | −3.241 | 0.039 (0.028–0.055)*** | −0.814 | 0.443 (0.39–0.503)*** |
| Interaction with carousel | 0.870 | 2.387 (1.843–3.092)*** | −3.114 | 0.044 (0.022–0.090)*** | −2.952 | 0.052 (0.031–0.088)*** | −1.956 | 0.141 (0.100–0.201)*** |
| Interaction with heart-shaped seating | −0.116 | 0.891 (0.827–0.96)** | 0.020 | 1.02 (0.959–1.085) | −4.720 | 0.009 (0.004–0.019)*** | −0.680 | 0.507 (0.447–0.575)*** |
| Interaction with bench | −0.610 | 0.543 (0.281–1.051) | 0.312 | 1.367 (0.742–2.517) | −9.987 | 0.0 (0.0–0.001)*** | −2.589 | 0.075 (0.033–0.172)*** |
| Interaction with pavilion | −0.261 | 0.77 (0.621–0.956)* | −0.914 | 0.401 (0.222–0.723)** | −2.428 | 0.088 (0.03–0.26)*** | −0.587 | 0.556 (0.411–0.754)*** |
| Interaction with waterfront | −2.329 | 0.097 (0.006–1.465) | −1.332 | 0.264 (0.022–3.236) | −1.490 | 0.225 (0.023–2.181) | −0.392 | 0.676 (0.181–2.518) |

Reference group: Passive (n = 3050).
Interaction with certain site features is measured as the total duration (minutes) spent within 0.5m distance to the site feature.
Coefficient and odds ratio are significant at * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

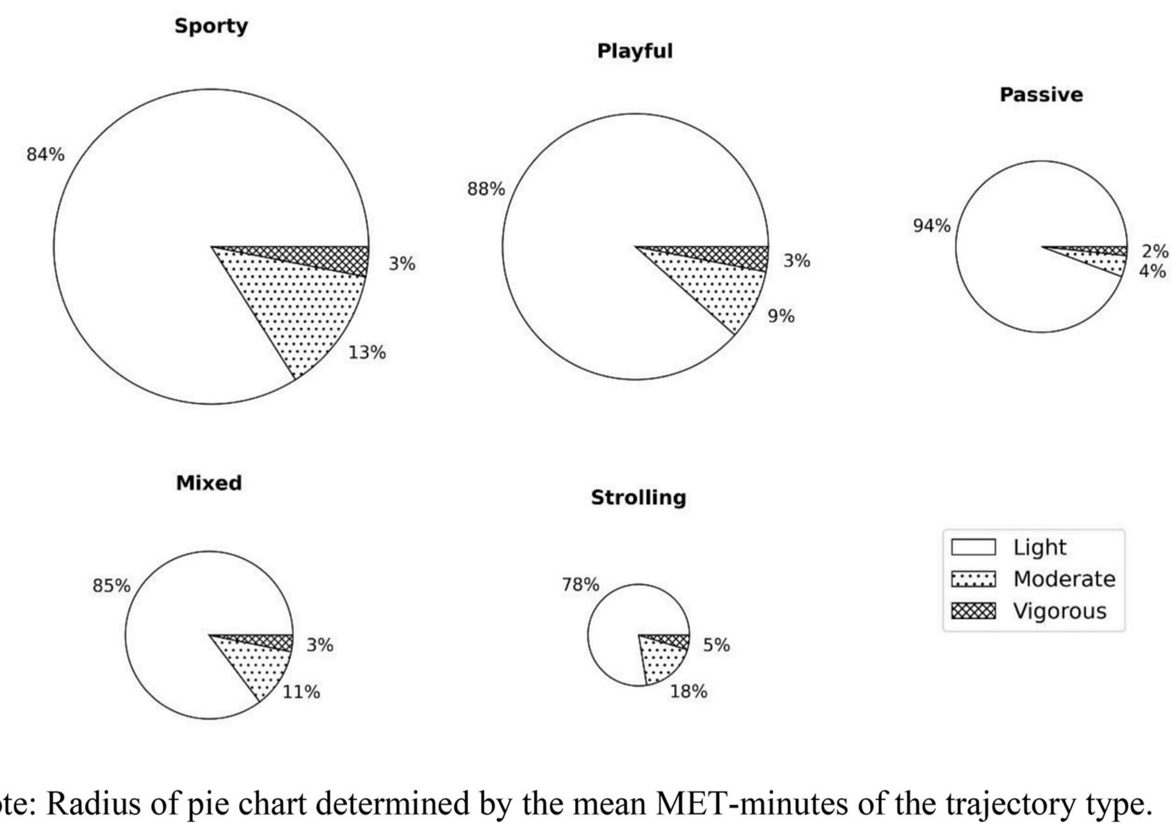



**Fig. 5.** Amount and intensity of physical activity by trajectory type.
Note: Radius of pie chart determined by the mean MET-minutes of the trajectory type.

observed that people on the site were mainly conducting light-intensity activity most of the time, with the passive group having only 6% of moderate (4%) or vigorous (2%) activity. The findings suggest that, from the perspective of encouraging more physical activity, design features associated with sporty or playful trajectories should be encouraged. For the one-way ANOVA test, since the assumption of the homogeneity is violated, the Welch's Test is conducted instead. The results suggest that significant differences exist among the groups ($p < 0.001$). The Post Hoc analysis is also conducted with the Games-Howell test to evaluate pairwise differences among the amount of physical activity for different trajectory groups. Results show that significant differences exist among each pair of the trajectory groups ($p < 0.001$), except for between the "passive" group and the "mixed" group ($p = 0.802$). Thus, Hypothesis 3 is supported.

Fig. 6 shows the total amount of MET-minutes, as well as the percentages of different trajectory types throughout the day. Generally, the total number of visitors and total amount of MET-minutes increases in the morning, drops around noon, and peaks around 3:00–5:00 p.m. The trend can be partly explained by the thermal comfort level throughout the day and the rhymes of daily life (e.g. lunch time). In comparison, the percentages of different trajectory types are generally stable throughout the day, though a slightly higher percentage of "playful" trajectories can be observed in the morning. It is possible that as the public open space became more crowded in the afternoon, it became more difficult for people to play freely on the site.

Fig. 7 provides an overview of the average MET-minutes by

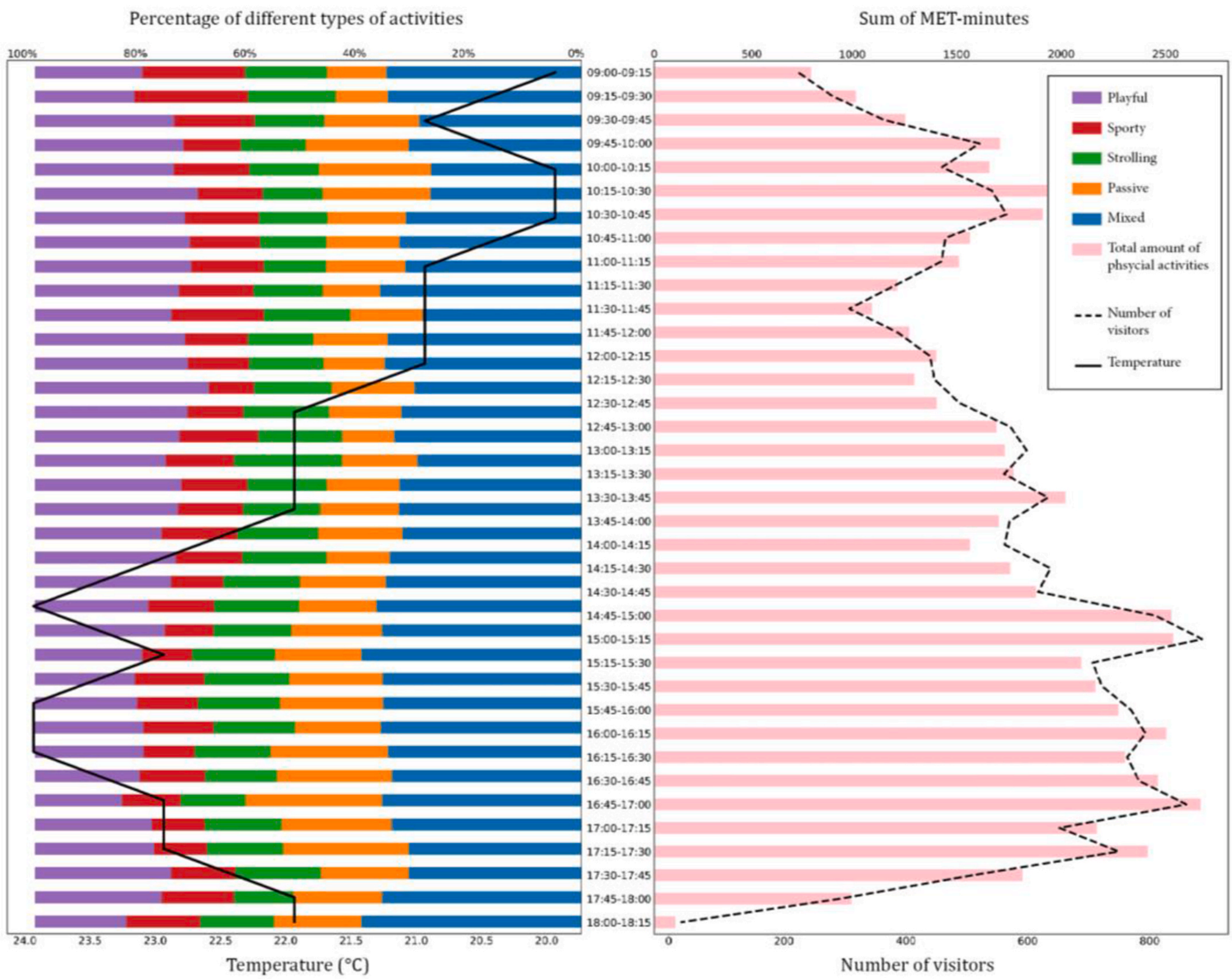



**Fig. 6.** Total amount of MET-minutes and trajectory distribution across the day.

trajectory type. It can be seen that there are three major groups. Firstly, the strolling group has been having consistently low average MET-minutes throughout the day. Then, the passive and mixed trajectory groups are having middle-range average MET-minutes. The final group consists of the playful and sporty trajectory groups. They are having the highest average MET-minutes and are very active users of the public open space. While the playful group has been enjoying more physical activity during the early morning and towards the evening, the sporty group has also been active during the early afternoon from 1 to 2 PM.

## 4. Discussion

### *4.1. Strengths*

To our knowledge, this is the first study using people's movement patterns to identify the playful use of a public space and the associated physical activity level. Compared to traditional methods such as direct observation and questionnaire surveys, we are able to identify playful behaviours in the public space with a large sample size in a much less labour-intensive way and for a continuous period throughout the day. The method has the potential to be applied to other contexts for studying play and physical activity in public open space so that the generalizability of the study results can be increased.

The association between site features and the engaging use of the public open space identified in this study conforms to existing studies that find site features to facilitate playful and active use of the space (Baek et al., 2015; Jones, 2013). In comparison to the current literature, this study makes unique contributions by identifying that the interaction with semi-fixed/movable features in public space has a stronger association with play behaviour, when compared to fixed site features. It is reasonable as semi-fixed/movable features open up more possibilities for people to play in the public space according to their imagination with more autonomy, thereby allowing more spontaneous actions (Deci and Ryan, 2012; Lynch, 1995; Staempfli, 2009). In addition, the finding about the higher average amount of MET-Minutes associated with "playful" trajectories add more empirical evidence to research that draws a linkage between playing and physical activity (Brockman et al., 2011; Reimers and Knapp, 2017; Smith et al., 2014; Sugiyama et al., 2012).

The findings of study are relevant to urban design projects around the world. It is especially related to the growing trend of Tactical Urbanism, which aims to create temporary changes using low-cost and moveable features in under-utilized public spaces that leads to long-term impacts (Jiang et al., 2019; Lydon and Garcia, 2015; Rossini, 2019; Stevens et al., 2021). For instance, the Seating for Socializing (SOS) project in Hong Kong placed 27 32 cm × 32 cm movable meta cubes in a public space. People can decide where to place and how to use the cubes, which help foster the playful use of space and social interaction (Rossini,

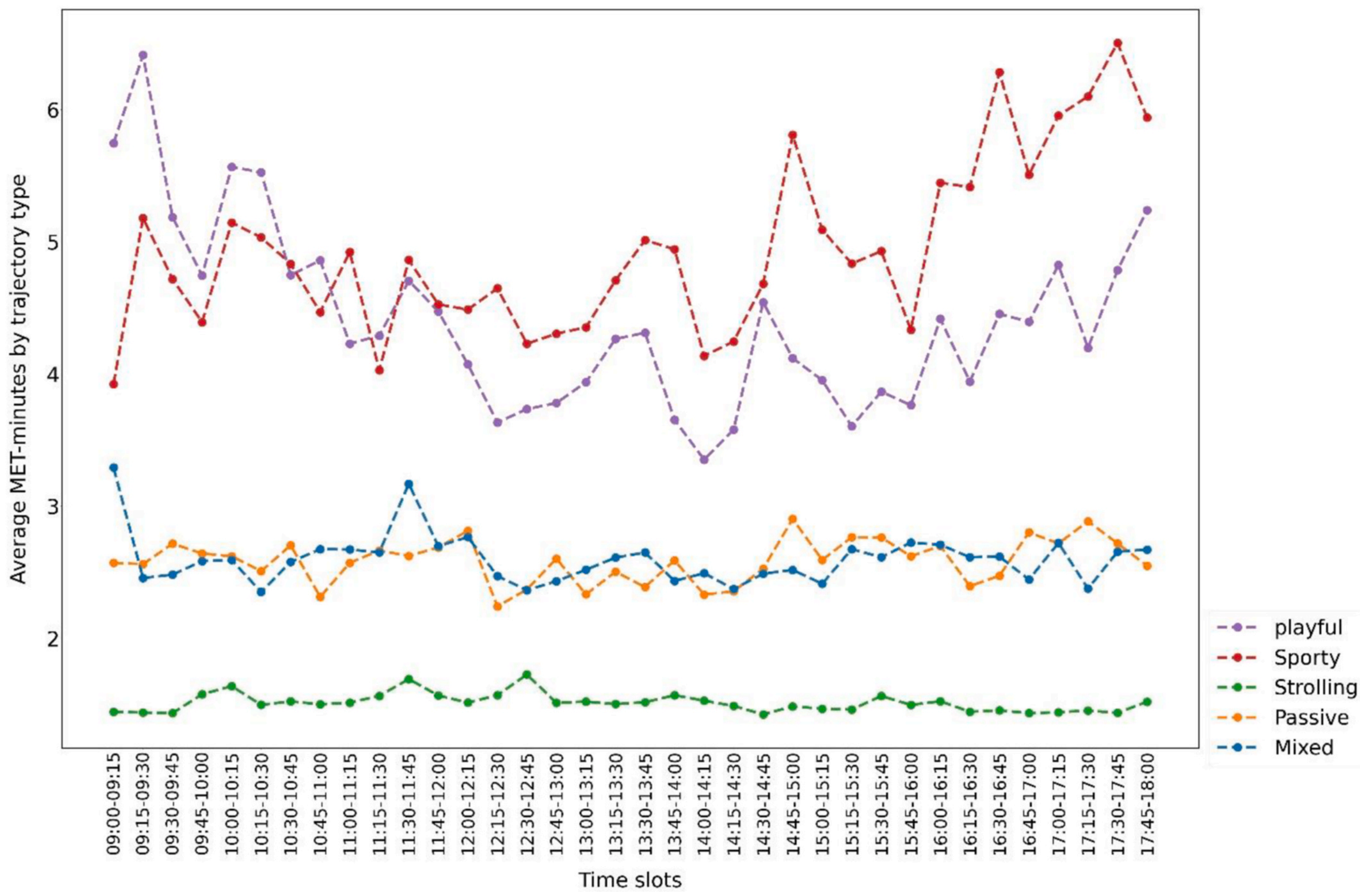



**Fig. 7.** Average MET-minutes by trajectory type across the day.

2019). Our study provides further scientific evidence for such urban interventions.

Moreover, there is also another trend of bringing adventurous experience back to children's playground by including "loose parts" (i.e. movable and manipulatable items) in the play space (Almon and Keeler, 2018; Houser et al., 2016; Staempfli, 2009). These "loose parts" can allow children to direct their own play in a creative and imaginative way (Woolley and Lowe, 2013), For instance, the city of Calgary in Canada offers materials such as "boards, tires, tap, cardboard" in parks during the play day so that children can "build, demolish, assemble and change their environments as they desire" (Almon and Keeler, 2018, p.70). In this regard, findings of this study also support the provision of such movable and manipulatable materials/features in children's play spaces or via the programming of public spaces.

### *4.2. Limitations*

This study also has several limitations. Firstly, this study only uses the time-lapse video of a small site on one day. The usage of the site may be different on other days of the year. Ideally, repeated observational study using the same method can be conducted, but it was not possible as video-recording requires special permissions and the original study (conducted by a consultancy firm not related to this research team and commissioned by the Harbourfront Commission) has been completed. More importantly, the site settings have changed since then. We acknowledge that there are daily, monthly, and seasonally differences in the usage of the site. Specifically, there may be fewer visitors during the weekdays compared to weekends. The monthly or seasonable difference will be affected by weather conditions. During hot and rainy summer days (June to August), people may prefer to stay in an air-conditioned and sheltered environment. In comparison, there are more outdoor activities during Autumn and early Spring when the weather is nice. To test these hypotheses, future studies may consider using video data that covers multiple dates in different months, including weekdays, weekends, and public holidays, to examine the differences in behavioural patterns at different times. Moreover, future studies may examine public spaces of larger sizes, and compare multiple public spaces using the methods described in this study.

Secondly, the proposed study only focuses on physically active play. Less active forms of play, such as playing card/chess and yoga, are not captured in this study. Similarly, the play behaviour of people with disabilities or reduced physical capabilities may also be overlooked. Future research can combine this method and traditional survey methods to account for less active forms of play and people with reduced physical capabilities.

Thirdly, accuracy issue can arise when applying deep-learning based methods to detect and track people across multiple video frames, especially when the public space is crowded. Though frame interpolation is done before applying the MOT algorithm of ByteTrack, the issue of "jumping ID" remains, especially during crowded periods. To illustrate, a visitor may be assigned an ID of 1 (with trajectory ID 1) when entering the site. However, he or she will be assigned another ID of 2 (with trajectory ID 2) after he or she walked "behind" a group of visitors or a big site feature in the video. As a result, there will be an over-estimation of the number of visitors and an under-estimation of the stay duration. These technical issues have been partially addressed by weighting the trajectories with time duration, but will need to be tackled in future research.

Fourthly, there can be some ambiguity between different trajectory types. For example, a trajectory can be classified as "playful" or "mixed" depending on the specific thresholds set. Future studies may explore alternative ways of clustering people's movement patterns, such as using deep learning-based image classification model trained by expert ratings. For instance, we may invite a group of experts to label individual trajectories first to prepare the training data. Then, the training data can be applied to train an image classification model that distinguishes different trajectory types. In this way, we can further break down the "mixed" trajectories.

Finally, it is difficult to acquire the demographic information of the visitors, such as age, gender, income, residential location, etc., based on deep learning methods. Further research may consider combining traditional surveys and deep learning-based video analytics to include demographic variables or even people's lifestyle into the analysis. For instance, people's age is an important variable to consider since children may exhibit different behavioural patterns in public spaces when compared to adults.

## 5. Conclusion

This paper uses deep-learning based video analytics to capture playful activities and the associated physical activity levels of people in public open space. The results suggest that people in public open space can be grouped by their movement trajectories. Moreover, different trajectory groups have different levels of interaction with various site features. Specifically, semi-fixed or movable site features can facilitate more playful use of the public space. People with "sporty" trajectories (such as those skateboarding) or "playful" trajectories (such as those playing on carousel) have a higher amount of MET-minutes than other groups. When (re-)designing future public spaces, it would be worthy to consider including some semi-fixed or movable elements in the design when appropriate, so that people's playful activities can be facilitated and a higher level of physical activity can be induced. It is also important to leave some unprogrammed space (without fixed or semi-fixed features) in the public open space so that people's spontaneous activities can be allowed.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A

A) Moveable blue cargo pallets

B) Semi-fixed carousel

**Fig. A1.** Moveable blue cargo pallets and semi-fixed carousel.

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