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Additional Information

Pokémon GO in Melbourne CBD: A Case Study of the Cyber-Physical Symbiotic Social Networks

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Abstract

The recent popular game, Pokémon GO, created two symbiotic social networks by location-based mobile augmented reality (LMAR) technique. One is in the physical world among players, and another one is in the cyber world among players' avatars. To date, there is no study that has explored the formation of each social network and their symbiosis. In this paper, we carried out a data-driven research on the Pokémon GO game to solve this problem. We accordingly organised the collection of two real datasets. For the first dataset, we designed a questionnaire to collect players' individual behaviours in Pokémon GO, and used maps of Melbourne (Australia) to track and record their usual playing areas. Based on the data that we collected, we modelled the formation of the symbiotic social networks in both physical world (*i.e.* for players) and cyber world (*i.e.* for avatars) as well as interactions between players and Pokémon GO elements (*i.e.* 'bridges' of the two worlds). By investigating the mechanism of network formation, we revealed the relatively weak correlation between the formation processes of the two networks. We further incorporated the real-world

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pedestrian dataset collected by sensors across Melbourne CBD into the study of their symbiosis. Based on the second dataset, we examined the changes of people's social behaviours in terms of most visited places. The results suggested that the existence of the cyber social network has reciprocally changed the structure of the symbiotic physical social network.

Keywords: Social network, Augmented reality, Pokémon GO.

1. Introduction

The movie 'The Matrix' showed us a scene with two connected worlds: physical world and cyber virtual world. Characters can shuttle back and forth between the two worlds and interact with others. Nowadays, this fancy movie scene comes into being due to the emerging Location-based Mobile Augmented Reality (LMAR) techniques [1]. LMAR is changing the form of social networking from multiple aspects. Unlike traditional online social media and offline community, LMAR based social media requires users to physically attend to certain locations for interacting with others. People who interact online using avatars can also derive interactions in the real world when they are physically brought together by LMAR application. Therefore, LMAR has complicated the boundary of social networks, and it also cultivates brand-new forms of social networks. Accordingly, the cyber (virtual) world relationships and the real world connections of people evolve into two symbiotic social networks.

As one part of the symbiotic networks, the cyber social network states the relationships among the online avatars. At the same moment, an offline, location-sensitive physical social network rises among the corresponding users through face-to-face communication, greeting, or more generally, staying in a same area. The emerging mobile game Pokémon GO released by Niantic is a catalyst for symbiotic network formation. The game requires a player to arrive at certain places in order to interact with virtual game content. Players can also battle each other at the in-game facilities called gyms, which are usually pinned on landmark buildings of the real world. The battles between players in the cyber

space form a cyber social network. On the other hand, since players need to
25 stay in certain areas for playing, their interactions with other players in the real
world form an offline physical social network. Hence, the cyber social network
and the physical social network symbiotically affect each other.

Previous works about social network mainly focus on studying homogeneous
social networks, including the structures, robustness, and user behaviours. The
30 formation and effect of symbiotic social networks has not been deeply examined.
Meanwhile, the study of symbiotic network formation can be of great importance
to government decision making and society safety. Moreover, the formation of
symbiotic social network can be used as a reference and tool in psychological
research which studies the formation of social connection and the cognition of
35 human relationship. Potentially, since Pokémon GO and alike applications have
great capability to increase physical activity of individuals, this research may
assist the analysis of the impact of LMAR on user health.

We carried out a data-driven research to study the symbiotic networks
formed by the offline interactions of users and the online connections of the
40 avatars. We studied the properties, user behaviour, and formation of such
novel social networks. Accordingly, we used two real datasets in our research.
First, we designed a questionnaire to collect Pokémon GO players' individual
behaviours in Pokémon GO. Maps of Melbourne were then introduced to track
and record players' usual playing areas. Second, we employed pedestrian count
45 data imported from sensors distributed across Melbourne CBD to reflect social
behaviours that differ from that of players. Based on the Pokémon dataset,
we first built a symbiotic social network of Pokémon GO players. The build-
ing process models and simulates the formation of social interaction among the
players. Second, we analysed the relationship between the formation of the vir-
50 tual network and the physical network. Next, we investigated how the social
behaviours changed after the symbiotic network emerged. According to our ex-
periment, the popular socialising locations of people have drastically changed
after the interference of Pokémon GO. Our work is essential for modelling the
information diffusion, the user behaviours, or the impact of AR/VR on human

55 interaction in symbiosis social networks.

In this paper, we study the formation, symbiosis and impact of two networks, which are the virtual social network of in-game characters, and the social network of players in the physical world. The paper is organised as follows: methods for collecting and analysing data are presented in Section 2 and 3. Outcomes
60 of data analysis are exhibited in Section 4. Related works are introduced in Section 5. Finally, this paper is concluded in Section 6.

2. Dataset 1: Pokémon GO Data ⁵

To investigate the formation of the symbiotic social networks of Pokémon GO player and the symbiosis of the networks, we designed a survey including
65 the related questions.

2.1. Questionnaire

We distributed questionnaires to players to collect their playing information (see the details of our questionnaire in Appendix Appendix A). According to the content, the questions can be broadly classified as follows:

70 **Demographics:** We asked respondents for their age, title, pokémon master level, pokémon team and interaction preference with other players as the demographics of players. This information was mainly developed to justify the consistency of our survey with existing statistics.

Temporal Information: These kinds of questions are related to time arrangement of players. We recorded the approximate frequency and time that
75 players spent on the game. In addition, we also asked them about their working

⁵ We submitted and received Deakin's approval for our survey. To protect the privacy of respondents, we avoided asking the personal sensitive details such as name and contact information. In addition, we claimed that all confidential information in the questionnaires would be strictly protected and would not be released. Throughout the survey, we introduced our research team and provided contact information of ours in Deakin University. We also explained our research purpose to participants, some of whom showed interest in our work and expressed strong encouragement.

or studying time. By these questions, we can conclude the approximate physical social network construction of players. According to the survey results and location data (see details in Subsection 2.2), we can infer the construction of
80 physical and cyber social network for players.

Travelling Distance and Means: To catch more pokémons and challenge gyms, players usually need to travel afar. Therefore, travelling distance and means were investigated as well. This kind of data is expected to extract some preliminary information such as the behaviour comparison among respondents
85 in terms of travelling style.

2.2. Location Data

We used printed maps containing annotations of street name, pokéstop and gym to collect areas of playing from participants. The playing location is the key point for deriving the symbiosis of cyber/physical social networks. Considering
90 the fact that asking players to recall the places they travelled to could be difficult to implement online, we decided to use printed map to collect data on street.

We attached two maps with the questionnaire to collect the location information from the Pokémon GO players. The first map is of Melbourne CBD (i.e. small map), and the second map is the zoomed out great Melbourne area (i.e.
95 big map). The big map is 10× larger than the small map in size. We annotated part of the gyms, pokéstops and pokémons according to the Pokémon GO map application from Google map.

Annotations of virtual content are transposed to the two maps. The distribution of pokéstops on the big map is over-dense, so we excluded pokéstops
100 from the big map. As another fact, gyms are distributed more sparsely and have more significant inner differences than pokéstops. For this reason, compared to the small map, we mainly consider the impact of gyms on the big map. Consequently, the positions of gyms and pokéstops are annotated on the small map, while pokéstops are excluded from the big map 1.

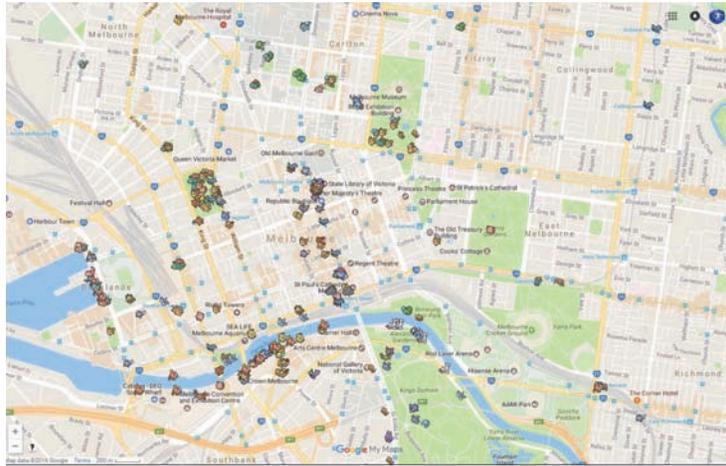


Figure 1: The Melbourne CBD map with pokémon annotated on. Pokémon is an important virtual element in the game. The link between virtual world and physical world is reflected by pokémon-master association.

105 2.3. Questionnaire Justification

In this section, we analyse the information extracted from the questionnaire outcome and compare the result to two Pokémon GO reports.

Preliminarily, we make a statistical study on the responses of the questions. Statistically, the travelling distance for catching pokémon is less than the travelling distance for challenging gym(3). Compared to catching pokémon, players are more likely to challenge gym nearby. From Table 4, we can see that only 37.26% players had no interaction experience with others while playing games. This presents great opportunities to construct physical social networks among players.

115 The frequency distribution histograms for players in terms of four aspects are shown in Fig. 4. Since there exists null values in the results, we applied the ratio representation instead of the sum in the frequency distribution histogram. If a player had more than one option such as on travelling means, we assumed that the probability of each option obeys uniform distribution. Fig. 4 (A) shows the result of how possible a player would challenge gyms in different time periods. We can see that most players prefer to challenge gyms in the evening,

Table 1: Comparison between Existing Statistics and Our Survey Result

	Age	Team			Gender	
	18~34	Yellow	Blue	Red	Male	Female
Existing	78%	25%	43%	32%	60%	40%
Ours	93%	25%	40%	35%	62%	38%
Difference	15%	0%	3%	3%	2%	2%

which is out of business time. The occupation is just under 40% among five breaks. It can be found that less gym challengers are active in the afternoon and night, the percentages of them are no more than half of the ratio towards evening. However, there are just over 10% players playing in the morning or noon.

We then compared the frequency of travels means selection by players between catching pokémon and challenging gym in Fig. 4 (B). It can be concluded that compared to catching pok'emons, players were more likely to use transport vehicles (i.e. car, train, tram and bus) in challenging gyms. In addition, most people preferred to drive their own vehicles to challenge gyms, while they chose not to travel faraway places to catch pokémons.

We also analysed the demographics of Pokémon GO players in Fig. 4 (C) and (D) in terms of age and master level, separately. We can see that the players were mainly from 20 to 30 years old, which accounted for around 80% of all ages. As for master levels, they were randomly distributed from 5 to 35. Significantly, the number of players at level 22 took a dominant place, the percentage of which were at least twice as any other level. There are rare players whose levels reached to more than 29, with only a few at 35.

We further compared our survey result with two existing Pokémon GO statistic analysis reports [2, 3] to justify the rationality of our questionnaire design. It was found that the distribution of our data was corresponding to current statistics in terms of age, team and gender as shown in Table 1. In the table, we removed the null values when each proportion was calculated, so the sum

145 of ratios in each category (e.g. Gender) was 100%. Except age, the value difference was not higher than one tenth of the values for comparison. The ratios of players aged from 18 to 34 differed with less than one fifth difference. In general, our questionnaire was proved to be reasonable since it followed historic distribution rules.

150 2.4. Implementation of the Survey

In this subsection, we describe how our experiment was carried out.

Geographic Location We conducted the survey in the Melbourne CBD. We walked there and randomly surveyed the players who were playing Pokémon GO at that time. In total, we have collected questionnaires of 104 players.

155 **Time** The investigation lasted for four days, from 18th to 21st August, 2016. We distributed questionnaires mainly during evening and night (around 6-10 pm), which was considered as spare time. And also, we observed that the number of players during that period was higher than other time of a day.

2.5. Data Storage and Preprocessing

160 We preprocessed the collected data for storage and analysis.

Questionnaire preprocessing The answers of collected questionnaires were translated into one-hot encoded answer vectors for computer processing. The vectors and the unchanged demographic information were entered into a database.

165 **Location Data Preprocessing** We preprocessed the collected location data. First, we gridded the small map by a 33×21 mesh grid, each grid equals a $160m \times 160m$ area. Similarly, the big map is gridded by a 30×20 mesh grid in which each grid covers a $1,600m \times 1,600m$ area. Second, we translated the locations marked by participants into coordinates of the grids which touch the
170 marked location areas. The example of the big map and small map with grid are presented in Fig. 2. The coordinates of players were stored in the database. On the other hand, we recorded the density of pokémon, pokéstop and gyms in each grid. The density data were also stored in database.

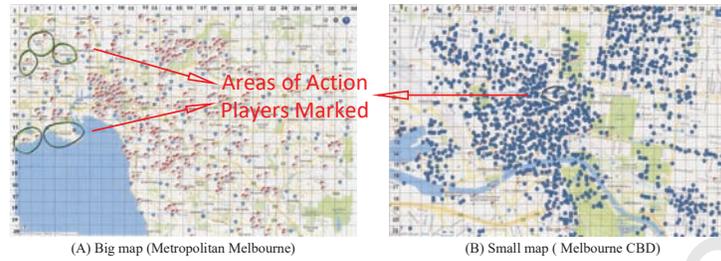


Figure 2: The example of the gridded big map and small map. Within the black circle is the playing area marked by the participant. Blue round dots are pokéstops and the red-white triangles are the gyms.

3. Dataset 2: Pedestrian Data ⁶

175 We use the pedestrian dataset to study the impact of the cyber social network to the structure of the physical world in terms of population distribution in the city area. The data is collected by 43 sensors distributed across Melbourne city. These sensors return pedestrian counts of the previous hour monthly. The data has been collected from year 2009 to date. The dataset includes 1,000 sensor
 180 records totally, each of which contains the latitude and longitude of the sensor, collecting date/time, the name of the street, and the counted hourly pedestrian number.

3.1. Computing Pedestrian Density in Grid

185 We adopted the pedestrian count value as the hourly density of pedestrian according to the nature of the data. We then computed the pedestrian density in each grid. We transformed the latitude and longitude of each sensor to the position in the mesh grid on the small map. We used Google map API (<https://developers.google.com/maps/web-services>) to find the latitudes and the longitudes of the mesh grid boundaries. The range of latitude and longitude

⁶ The pedestrian count data was imported by APIs from Melbourne City Government database (<https://data.melbourne.vic.gov.au>). The sensors used to collect pedestrian count data were deployed in most popular roads and streets over Melbourne CBD, by government approved agencies. The data was retrieved by sensor logs periodically.

Table 2: Temporal Statistics: Part I of Questionnaires

Time or Frequency	Respondents	
Time spent on playing Pokémon GO per week		
< 0.5 hour	10	9.62%
0.5 hour ~ 1 hour	14	13.46%
1 hour ~ 2 hours	12	11.54%
> 2 hours	68	65.38%
Frequency of playing Pokémon GO		
Every hour	23	22.12%
Every day	55	52.88%
One or two days in a week	17	16.35%
Almost forgot it	9	8.65%
Time spent on working or studying per week		
< 5 hours	16	15.38%
5 hours ~ 15 hours	22	21.15%
15 hours ~ 30 hours	20	19.23%
30 hours ~ 50 hours	40	38.46%
> 50 hours	4	3.85%
<i>No record</i>	2	1.92%
Frequency of challenging gym		
Every day	16	15.38%
Few times per week	45	43.27%
Few times per month	17	16.35%
Never	25	24.04%
<i>No record</i>	1	0.96%

190 of the mesh grid are $[-37.829725, -37.797483]$ and $[144.937239, 145.001183]$, respectively. The size of the used mesh grid on the small map is 33×21 . Therefore, we computed the ranges of latitude and longitude of each grid. Given a sensor's location, the sensor will be assigned in the grid whose latitude and longitude

Table 3: Travelling Distance Statistics: Part II of Questionnaires

Distance	Respondents			
	Catching pokémon		Challenging gym	
< 1 km	17	16.35%	44	42.31%
1 km ~ 5 km	36	34.62%	36	34.62%
5 km ~ 10 km	24	23.08%	14	13.46%
10 km ~ 20 km	13	12.50%	2	1.92%
> 20 km	14	13.46%	5	4.81%
<i>No record</i>	0	0.00%	3	2.88%

range covers the sensor’s location. We could therefore get the positions of the
 195 sensors in the mesh grid. The pedestrian density in a grid thus equals the pedestrian
 count in the grid. For a grid containing multiple sensors, the density is set
 as the average pedestrian number from all sensors in the grid.

3.2. Completing Pedestrian Density

Since the pedestrian density of the grid in which there is no sensor was
 200 unknown, we first completed the pedestrian density in this section. We inferred
 the density of pedestrian in each grid based on a regression model. We compared
 three regression models, namely radial basis kernel support vector regression
 (SVR) [4], kernel ridge regression (KR) [5], and linear regression (LR) [6].

Initially, we extracted features for the regression models. Suppose we have
 205 a set of grids G_{all} . $G_S \subseteq G_{all}$ are the set of grids in which there are sensors.
 The set of grids in which the pedestrian density will be estimated therefore is
 $G_E = G_{all} - G_S$. We compared three different metrics and adopted one as the
 feature for regression. Since the distribution of people highly related to spatial
 information, the three evaluated metrics utilise spatial distance and pedestrian
 210 count value.

As the first metric, for each grid $g_k \in G_{all}$, we computed the average

Table 4: Demographics Statistics: Part III of Questionnaires

Demographics	Respondents	
Title		
Mr	63	60.58%
Mrs	6	5.77%
Miss	33	31.73%
Dr	0	0.00%
Other	0	0.00%
<i>No record</i>	2	1.92%
Team		
Blue	40	38.46%
Red	35	33.65%
Yellow	25	24.04%
No team	3	2.88%
<i>No record</i>	1	0.96%
Interaction preference		
Greeting	37.75	36.30%
Grouping	6.25	6.01%
Friending	19.25	18.51%
No interaction	38.75	37.26%
<i>No record</i>	2	1.92%

Note: No record: the player failed to answer the question. When asked about interaction preference, some players had more than one choices. Therefore, for those players, we divided 1 by the number of choices, and added each division to the cumulative value of respondents.

distance-weighted density coefficient C :

$$C(g_k) = \frac{\sum_{g_j \in G_S} \frac{n_{g_j}}{Dist(g_k, g_j)^2}}{N}$$

wherein n_{g_j} is the pedestrian count in grid g_j . N is the number of grids in G_S .

$Dist(g_k, g_j)$ is the Euclidean distance between grid g_k and g_j . Second, for each $g_k \in G_{all}$, we recorded the pedestrian count $NC(g_k)$ in the nearest grid of g_k in G_S :

$$NC(g_k) = n_{g_j}, * \arg \min_{g_j} Dist(g_k, g_j)$$

Finally, we used the distance from g_k to g_j , $\arg \max_{g_j \in G_S} n_{g_j}$ as the third metric, $D(g_k)$. We built a training sample set based on the features. There are 37 grids in G_S . For each $g_j \in G_S$, we computed $C(g_j)$, $NC(g_j)$ and $D(g_j)$ as features, which is labelled by the pedestrian count n_{g_j} in g_j . Thus 37 training samples
 215 were built in this manner.

To achieve better performance, we employed cross validation to evaluate regression performance and chose the best model. We split 30% of the total training samples as testing samples in cross validation. Then, we evaluated regression performance in terms of mean average error (MAE), mean average percentage
 220 error (MAPE), explained variance score (EVS), and R^2 score. We also tuned the features used in regression to improve the regression performance. By solely using $C(g_k)$, the regression models gained the best performance. Among the regression models, SVR using radial basis kernel performed as the best regression model on all metrics (Fig.3). Thus we adopted SVR using radial basis kernel
 225 to infer pedestrian density for each $g_e \in G_E$. The inferred pedestrian density is utilised in Section IV C.

4. Results

4.1. Preliminary Analysis on Questionnaire and Location

Table 5: PCC between player and virtual content

Player/Gym	0.069
Player/Pokémon	0.385
Player/Pokéstop	0.480

In this section, we present the statistics of the survey participants and their
 230 playing behaviours according to the questionnaires. Participants are anonymised

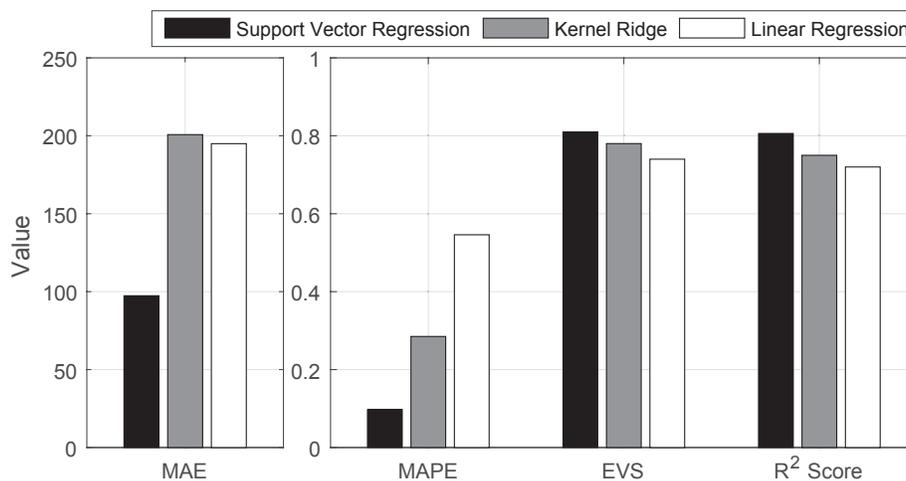


Figure 3: The performance comparison of SVR, Kernel Ridge, and Linear Regression. SVR achieves best performance in terms of MAE, MAPE, EVS and R^2 score.

for privacy considerations. As shown in Table 2, 75% of the 104 respondents played Pokémon GO every hour or every day, while there were only around 15.38% of the players challenged gym at the same frequency. It is deduced that players were much less frequent in challenging gym than catching pokémon.

235 Next, we analysed the characteristics of the obtained data in terms of player location distribution, gym distribution, pokéstop distribution, pokémon distribution on the big and small map. Based on the collected location data with the mesh grid, we plotted the heat map of distributions in Fig. 5. For each grid, we accumulated the number of player whose playing area includes the grid. The
 240 accumulated value is the number of player in this grid. In this manner, we got the relative density distribution of players on the whole mesh grid. The relative density of virtual content on the mesh grid is counted in the same way. It can be observed from Fig. 5 that players are mainly distributed in the CBD area on the map of greater Melbourne. As for the locations on the zoomed in small
 245 map, players are gathered in the city central and south bank areas. We then analysed the correlations of the distributions.

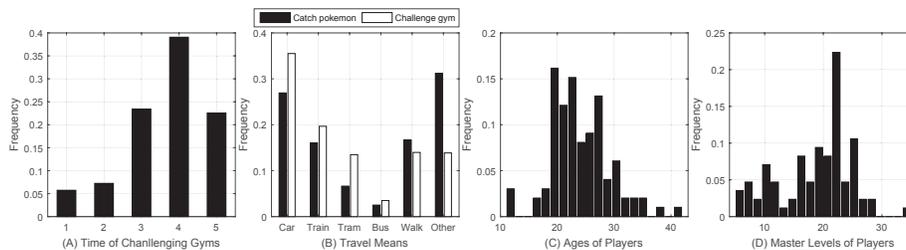


Figure 4: Our preliminary statistical analysis of the questionnaires are based on the followed frequency distributions: (A) Time of players challenging gyms (note: '1': Morning, '2': Noon, '3': Afternoon, '4': Evening, and '5': Night.), (B) Travel means selected in catching pokémon and challenging gyms (note: 'Other' represents the players who never travelled far away.), (C) Ages of players, and (D) Master levels of players.

4.2. Formation and Symbiosis of Symbiotic Social Networks

4.2.1. Physical Social Network: Human Interaction in Real World

The interactions among players are analysed in this section. We assume
 250 that two players staying in the same grid at the same time of a day have the potential to physically meet and interact with each other in the real world. We then estimate the probability of meeting, which indicates the likelihood that social activity occurs between the two players.

We first defined $P_{u,v}$ as the probability that two players u and v come across
 255 each other in the physical world. In other words, P stands for the formation likelihood of the interaction between a new player and other existing players. As an intuitive assumption, we assume that: 1) $P(u,v)$ decreases with increasing distance between u and v ; 2) $P(u,v)$ decreases with increasing time interval between the timing when u or v plays the game. Second, we define $P_{u,v}$ as 1
 260 when u and v stay in the same grid in the same hour of a day. According to the previous research, the timing of many human activities follows Poisson distribution [7]. Furthermore, as a statistical property of Poisson processes, the time intervals between consecutive events follow an exponential distribution, while distributions obeying power-law are also observed [8]. According to the property
 265 held by the time interval, in this research, we estimate the probability $P(u,v)$ using the following model. The model serves as a prompt for the utilisation of

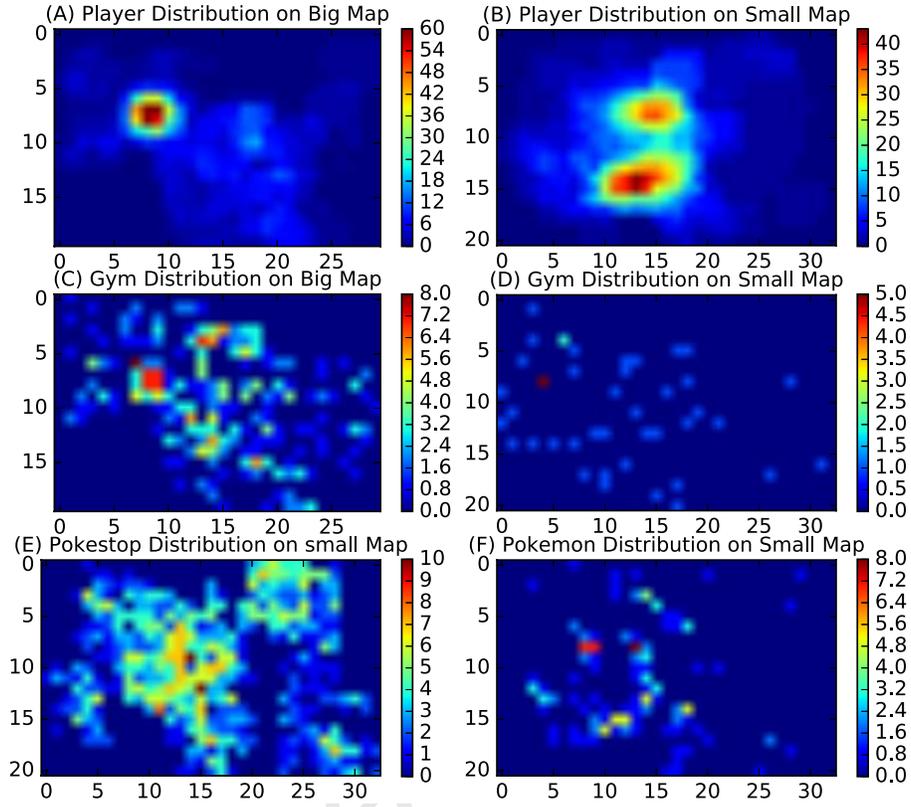


Figure 5: The distribution heat maps of player, gym, pokéstop, and pokémon in Melbourne.

this dataset. Extension and better model can be proposed in the future.

$$\left\{ \begin{array}{l} P(u, v) = \alpha \cdot e^{-\alpha \cdot \Delta t_{u,v}} \text{ or } P(u, v) = \alpha \cdot \Delta t_{u,v}^{-1-\alpha} \\ \alpha = \frac{1}{e^{\Delta S_{u,v}}} \end{array} \right.$$

wherein α is the penalty on the probability based on the distance between the locations of the players (Fig. 6(B)). $\Delta S_{u,v}$ denotes the average Euclidean distance between u and v . $\Delta S_{u,v}$ is computed as:

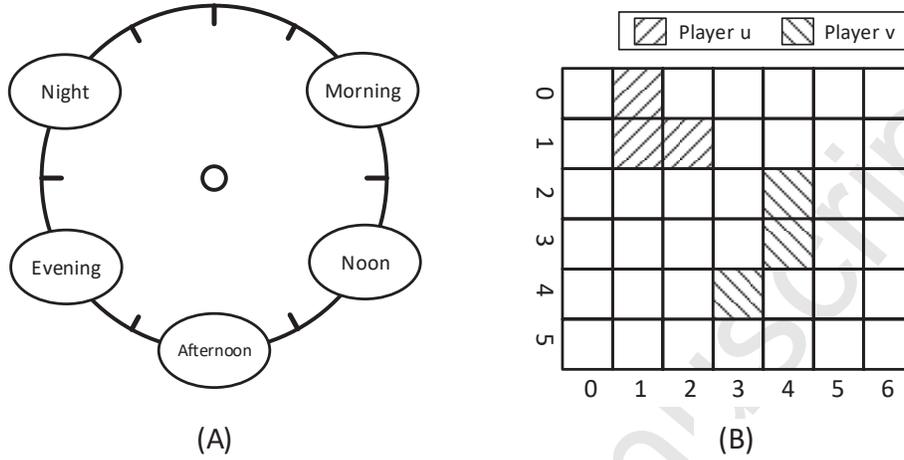


Figure 6: (A) The intervals between different time of a day. The interval between night and morning is 8 hours, and others are 4 hours. (B) The locations of user u and v in the mesh grid.

$$\Delta S_{u,v} = \sum_{i \in A(u), j \in A(v)} dist(i, j)$$

herein i, j are the coordinates of the grids that are from the active areas of player u and v , respectively. $dist(i, j)$ is the Euclidean distance between i and j . $\Delta t_{u,v}$ is the time interval (Fig. 6(A)). Specifically:

$$\Delta t_{u,v} = \begin{cases} 8 & \text{between night and morning} \\ 4 & \text{Otherwise} \end{cases}$$

We calculated the defined P of all the surveyed players. By setting a cutoff
 275 of P , the network in which P between any player pair exceeds the cutoff is selected. A physical social network conditioned by the cutoff selection is therefore built. We swept the cutoff from 0.1 to 0.9 in steps of 0.1. We considered the generated network as non-trivial for studying if the network has average node degree larger than 1. Therefore, we set the cutoff as 0.2 in this paper to obtain

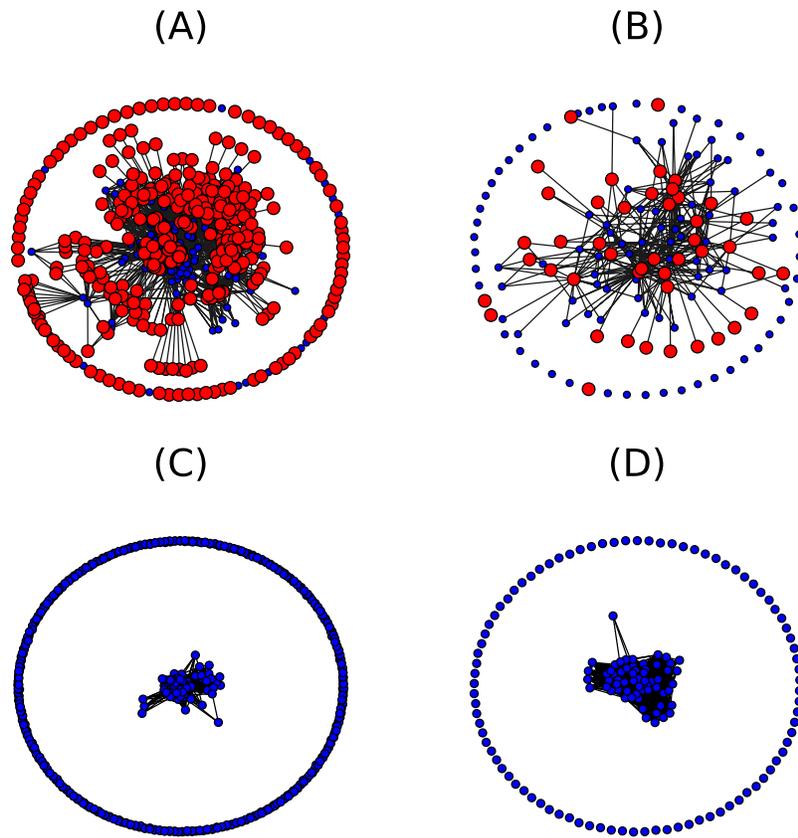


Figure 7: The interactions between the avatars of the 104 players and the gyms on the maps. (A) The virtual network of avatars, including gyms, on big map. (B) The virtual network of avatars, including gyms, on small map. Red nodes are gyms and blue nodes are avatars. The edge standing for the existence of interaction links the character and the gym if the gym is in the location of the player to whom the character belongs. (C) The joint network of avatars and players on big map. (D) The joint network of avatars and players on small map. There is an edge connecting two avatars if their players share the same gyms in their playing areas to form the virtual interaction. Isolated nodes are also plotted to show the avatars without interaction with others.

280 the non-trivial network. The value can be tuned to acquire network of different scales.

4.2.2. Virtual Social Network: Avatars in Virtual World

In this section, the analysis about the interactions among avatars (e.g. pokémon masters) is presented. The gym is the sole venue in the game for the avatars to interact. Once players win the gym battles, they become leaders of the gyms and their pokémons will be selected as gym guardians. Then other players' pokémons can interact with the defenders even when the gym leaders are not geographically close to the gym. From another perspective, avatars in the game derive interaction at the gyms. Therefore, the interaction activity through challenging gym constructs a virtual social network among pokémons.

Firstly, we obtain the virtual interaction network of gyms and avatars based on the assumption that once the playing area of a player has a gym in it, the interaction between the avatar of the player and the gym is existing. The virtual network is plotted in Fig.7 (A) and (B). In fact, the edge and gym nodes in the network are dynamic.

Then, we calculated the interaction probability of two arbitrary avatars in the pokémon world. In the world, each avatar was mapped as the pokémon belonging to each player. We assumed that a player challenges each gym in their area at the same probability. Given two avatars u_v and v_v which are corresponding to two players, their meeting probability in virtual world can be expressed as below:

$$P'(u_v, v_v) = n(u_v, v_v) / (n(u_v) * n(v_v))$$

wherein $n(u_v)$ and $n(v_v)$ represent the number of gyms in the area of u and v respectively, and $n(u_v, v_v)$ means the number of gyms in the common area of u and v . In the cyber social network, there is an edge connecting two avatars if their players share the same gyms in their playing areas to form the virtual interaction. Differing from the P of physical interaction probability, we used P' as the weights of edges in the network.

4.2.3. Symbiosis: Player and Virtual Content

305 The interaction between player and virtual content (e.g. pokémon ,pokéstop, and gym) is established when the player is hunting pokémons, visiting gym, or connected to pokéstop. In this section, we intended to shine a light on how the virtual content from the mobile AR application can affect players in the real world. First, we investigated which virtual content has the most significant impact on player distribution. Second, we presented the analysis on the gradients of distribution density of players and virtual content. And then we studied the relationship between the gradient directions of players and virtual content.

We adopted the Pearson correlation coefficient (PCC) to analyse the covariance of the density of players and the density of virtual content based on the data in distribution matrices from Section B. We compared the PCC between 315 players and three types of virtual contents (i.e. gym, pokémon ,and pokéstop) on the small map. The result is presented in Table 5. Gym density has very limited correlation with player while the distributions of pokémon and pokéstop have much higher correlation with players. Interestingly, players are mostly driven by pokémon or pokéstops rather than gyms.

We then analysed the relations between gradients of densities on maps. For grid (i, j) in a matrix M of the mentioned distributions (i.e. distributions of players, pokémon, pokéstop and gym), we computed the gradient of the density $d(i, j)$ along four directions. Specifically, we compute $\Delta d_N =$ 325 $d(i, j) - d(i - 1, j)$, $\Delta d_S = d(i, j) - d(i + 1, j)$, $\Delta d_W = d(i, j) - d(i, j - 1)$, and $\Delta d_E = d(i, j) - d(i, j + 1)$. A gradient vector $V_{i,j}^M$ consisting of the four variation values can be constructed. Next, for (i, j) in distribution matrix M' , we can have another vector $V_{i,j}^{M'}$. The Euclidean distance between $V_{i,j}^M$ and $V_{i,j}^{M'}$ is calculated. The distance reflects the difference of density variation in the vicinity of grid (i, j) (see details in Fig. 8). Comparing Fig. 5 and Fig8, 330 it can be observed that the density variations are significant within the areas in which more players gather. According to Fig. 8 and Fig. 5, we can observe that the density of players and the density of virtual content show positive cor-

relations. However, the gradients of the densities are highly distinguishing.

335

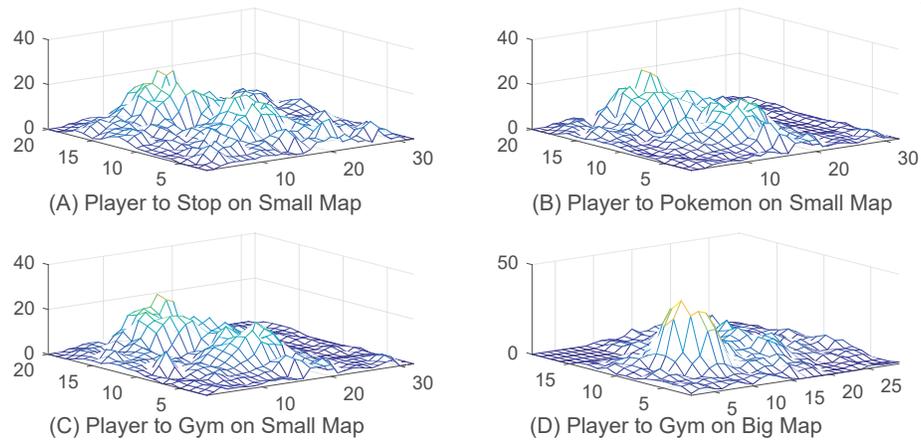


Figure 8: The height represents the the difference in the gradient of player distribution and the gradient of virtual world distributions of pokémons, pokéstops and gyms. Fig. A, B and C are based on distributions on small map, and Fig. D is based on distributions on big map.

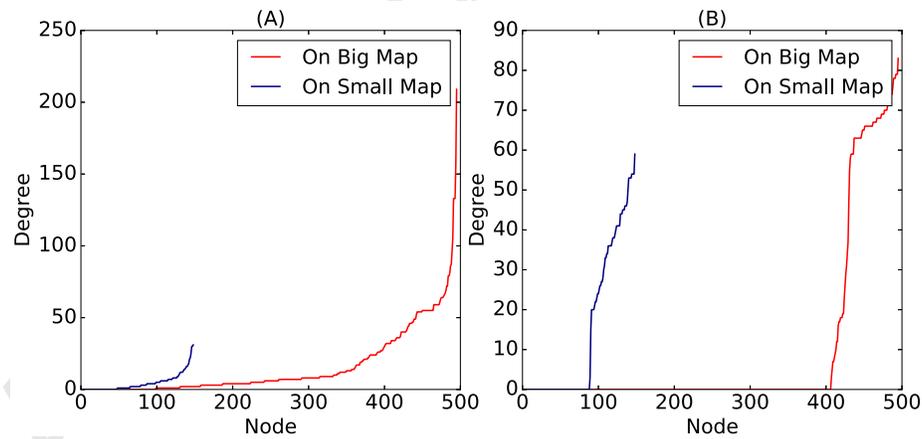


Figure 9: (A) The distribution of node degree in the cyber social network. The degrees demonstrate a power-law alike distribution. (B) The joint network of two symbiotic networks of avatars and players. The degree distribution differs from the power-law distribution.

4.3. Impact of Symbiotic Networks

We investigated the impact of the symbiosis on cyber social network and the physical activity network in this section.

4.3.1. Relationship between Formation Process

340 We investigated the correlation between the formation processes of two symbiotic networks, based on the condition that the formation processes of the networks are determined by probability. We adopted the Pearson correlation coefficient (PCC) to analyse the covariance of the interaction probability among physical players and avatars in terms of the big map and the small map. The result is presented in Table 6. It is indicated that while the interaction probability 345 shows positive correlation, the correlation in the big map is significantly higher than it in the small map. As explained in Subsection 4.2.1 and 4.2.2, time was considered as an impact factor of the meeting probability of players, while in the virtual world, characters interact without the restriction about time. Therefore, we then investigated the time effect on the meeting probability correlation between 350 physical and virtual world. We removed Δt (as mentioned in Subsection 4.2.1) to produce the results of the physical world without the time impact, and its correlation with virtual social networking is shown in the right column of Table 6. As both PCC values in big map and small map decreased with time, 355 time was proved to be a reduction factor of interaction consistency of players between the two worlds. However, Table 6 reveals that the virtual activity of players could not sufficiently reflect the physical behaviours conversely due to the low PCC value in both scenarios.

Table 6: PCC between interaction probability among physical players and avatars

	Time considered	Time eliminated
Big map	0.3046	0.3220
Small map	0.0784	0.0848

4.3.2. Change on Social Network and Social Behaviour

360 In this section, we first analysed the change on degree distribution of nodes in the social network. We then investigated how the location based mobile AR app can affect people's physical social behaviour. We compared the socialising hot-spot of Pokémon GO players and normal pedestrians in Melbourne CBD area.

365 We first analysed the topological characteristics of the cyber social network formed by the interactions among avatars. The degree distribution of the networks are illustrated in Fig. 9. It can be observed that the degrees of the network formed by gyms and avatars roughly obeys the power-law distribution, which is typical for online social networks. Secondly, we joined the cyber social network formed by avatars and the physical social network formed by people
370 on associated players and their avatars. The joint networks are plotted in Fig.7 (C) and (D). The degree distribution of the joint network demonstrates a non-power-law distribution. The degree changes more rapidly than the power-law curve.

375 Second, we looked into the change on the physical social behaviour of people, in particular, the popular socialising venue of people. We compared the pedestrian density inferred in Section II in Fig. 10. We considered the following 5 groups of sensor data: 1) *The average count value of all time*; 2) *The average count between 00:00 to 12:00 of all time*; 3) *The average count between 12:00 to 24:00 of all time*; 4) *The average count between Thursday to Sunday of all time*; 5) *The average count within every August since 2009*. Since we collected
380 player location data in August, from Thursday to Sunday in the evening/night, the setting of these rules helps us to unify the conditions for comparison. For each group of data, we correspondingly trained SVR and inferred the density of all grids without sensors.

385 We compared the social hot-spots of the non-player pedestrians and the players. The highly populated areas usually suggest the existence of more social activities. Therefore, by comparing the density of people, we intend to reflect

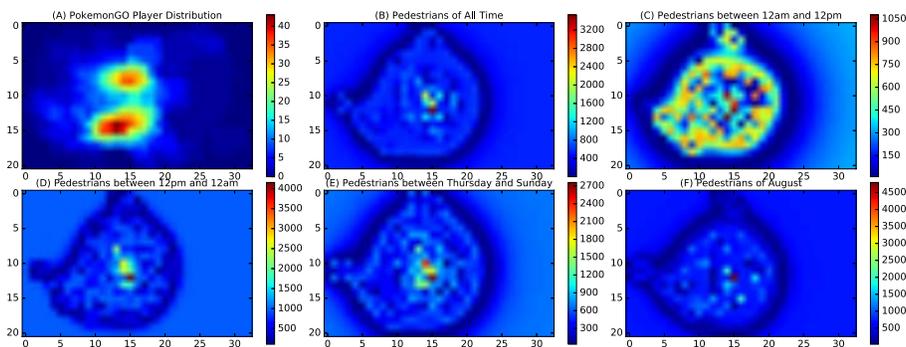


Figure 10: Comparison of the relative densities of Pokémon GO players and pedestrians on the small map. The colour bar at the right side of each plot indicates the density of people. The distributions show differences in the locations of player and non-player.

the area with more social activities. According to Fig. 10, the social hot-spot
 390 of pedestrians is around (15, 13) while the hot-spots of Pokémon GO players
 are located in grid (13, 15) and (15, 8), where have most of pokémons gathered.
 Players shift to the popular locations under the effect of the AR based app
 according to the aggregation of virtual content.

5. Related Work

395 The characteristics and interactions of traditional online/offline social net-
 works have been exclusively analysed. On the other hand, the perception re-
 garding location based mobile AR applications is evolving. It is of interest to
 understand how AR can affect social behaviour of users, and what the charac-
 teristics of the social network would then have. We provide a brief review of
 400 the research about social network characteristics and location based AR. As the
 latest phenomenal LMAR application, Pokémon GO has also been introduced
 in terms of the impact it brings and the perception it receives.

Analysis on Single Social Networks The topological structures of social
 networks and the user behaviours in the networks have been extensively studied.
 405 Social network could be broadly categorised into two kinds, namely static social
 network and dynamic social network. Currently, the social networks are mainly

dynamic. For example, the online social network (OSN) is one representative type of social networks. The studies around OSNs (e.g. Twitter, Facebook, Flickr, and Yahoo! 360 etc.) have revealed the features of impacting events diffusing in the network, and clues behind OSN user behaviours [9, 10]. A study conducted by Kumar et al. analysed the evolution and dynamics of the social network. Most of the studies address the topological feature (e.g. degree distribution, density, cluster coefficient, connectivity etc.) of the networks [11]. Second, studies on social networks from the socio-technical and user behavioural perspectives were conducted [12, 13, 14]. Also, the attributes of social network were also studied. For example, Heravi et al. studied the privacy calculus decision making processes in OSN [15], and David et al. found that a static network is more helpful in constructing stronger cooperation than traditional population distribution [16]. Apart from the single social network, there are also few studies about the symbiotic social network. Yagan et al. studied the information diffusion in conjoining social networks and revealed that information transmission speed and scale were remarkably larger in the conjoining online and physical social network than in the single social network [17]. However, though a few of the current works catch a glimpse of the symbiotic social network, the analysis on formation, feature, and user behaviour of LMAR based symbiotic social network was not provided.

Interconnected Networks To better understand the physical interactions for individuals, complex networking models are generally employed. In fact, there are many sub interconnected networks in the real-world scenarios. For instance, Dickison et al. and Wang et al. developed the epidemics effect through interconnected networks [18, 19]. In their studies, the impact on epidemic broadcasting was analysed according to different connection strength of two mutually interdependent networks. Likewise, Radicchi experimentally explored the spectral features in the networks with different dynamic and topological properties such as degree distributions and connection distinction between intra-connected networks and interconnected networks [20]. In addition, the attribute robustness was also studied by researchers. For example, Parhami proved that swapped

networks were significantly robust and they have relatively small degrees of nodes [21]. Radicchi and Arenas also proposed that although there were sufficient distinct attributes such as robustness for the interconnected networks, abrupt transition would also occur inwards [22]. By contrast, our study about Pokémon GO mainly focuses on the formation of the symbiotic networks, where each connection is weighted numerically.

Location based Augmented Reality Differing from previous studies that focused on the technical details of AR components [23], research on mobile AR usage concentrates on the acceptance, user experience, and perceptions of mobile AR functionality [24]. Alternatively, researchers conducted experiments to test how mobile AR applications can be useful for certain applications such as navigation [25]. Investigation on the usage of Layar, which is a widely installed mobile AR application, exhibits the formation of social practises around mobile AR, and how emerging media may complicate the practices, experiences, and relationships in the spatial landscape[26]. Similar to Pokémon GO, Layar can overlay points of interest, annotations, or pictures on camera input of the real-world scene based on global positioning system. The development of an LMAR application named CityViewAR was presented as well [27, 28]. The study mainly focused on the design and the implementation of the application. Though studies about mobile AR related applications are continuously presented, there is no research modelling the social behaviours of users under LMAR technology. There is also an absence of study that analyses the relations between physical social networks and virtual contents from the LMAR application.

Impact of Pokémon GO The impact of Pokémon GO on player's physical activity has recently been studied [29]. The results of the study suggest that Pokémon GO can significantly increase the daily physical activity of players. Likewise, it was found that social comparison in online social networks could effectively activate individuals to do physical activity [19, 30]. The impact brought by Pokémon GO on traffic, personal security and privacy has attracted attention from government in some countries [31, 32, 33]. Current studies or perceptions about Pokémon GO are mainly focusing on the pros and the cons of

Pokémon GO on health and psychology. There is neither comprehensive analysis
470 about how the AR application associates with or changes the real world social
behaviours, nor study from the social network perspective.

6. Conclusion

In this paper, we analysed the symbiosis and characteristics of symbiotic
social networks among users of a location based augmented reality application.
475 For studying symbiotic social network formation, we collected a Pokémon GO
player dataset which contains the player demographics, playing behaviours, and
playing locations. By incorporating real world pedestrian count data, we stud-
ied the change on social behaviour brought by symbiotic social network in terms
of spatial hot-spot deriving social activity. For the first time, this paper offers
480 a clue for the study of symbiotic social networks. This study provides a series
of results from real-world data, which will contribute to the future research on
large-scale symbiotic social networks. The research has its limit. Through sur-
vey, the accuracy of the collected player location data is varying. Even though
we required the respondents to mark their location as accurate as possible,
485 human caused error still exists. Second, the collected data contains no social
connection information due to the privacy preservation consideration. There-
fore the performance of the proposed model is unable to be validated. We will
develop better mechanism for collecting dataset that records social graphs of
participants in our future work to tackle these issues. Based on this paper, the
490 dynamics of the symbiotic social networks and the information diffusion in the
networks will also be modelled in our future work.

From an economic perspective, the study of cyber-physical symbiotic so-
cial network formation could provide insight into mechanisms of social capital
creation and social influence generation compared with purely physical or vir-
495 tual/cyber social networks - potentially allowing companies to more effectively
leverage LMAR technology to concurrently build both physical and virtual so-
cial capital and influence across traditional commerce, e-commerce, and social

commerce platforms. Social support and companionship deriving from social networks have also been shown to impact profoundly on mental health [34];
500 however, studies have predominately focused on the effects of either physical social networks (e.g. family, romantic relationships, friends) or virtual social networks (e.g. social media). A greater understanding of the formation and operation of cyber-physical symbiotic social networks could provide insight into the specific effects, whether positive or otherwise, of LMAR technology on mental
505 health. Further, cyber-physical symbiotic social networks may provide different levels or types of social support compared with purely physical or virtual/cyber social networks.

Appendix A. Questionnaire

This is the questionnaire that was handed to Pokémon GO players in the
510 Melbourne city.

Appendix A.1. Demographics

1. What is your title? [Mr, Mrs, Miss, Dr, Other]
2. What is your age?
3. What is your Pokémon master level?
- 515 4. Which Team did you select? [Blue, Red, Yellow, No team]
5. Do you interact with other players in the real world? [Greet them, Group with them, Friend them, No interaction]

Appendix A.2. Temporal

1. Approximately, how much time do you spend on playing Pokémon GO
520 per week? [Less than half an hour, Half an hour ~ 1 hour, 1 hour ~ 2 hours, More than 2 hours]
2. How frequent do you play Pokémon GO? [Check it every hour, Play it casually every day, Play it a day or two in a week, Almost forgot it]

3. How much time do you spend on working or studying per week? [Less
 525 than 5 hours, 5 hours ~ 15 hours, 15 hours ~ 30 hours, 30 hours ~ 50
 hours, More than 50 hours]
4. How frequent do you go to challenge gym? [Every day, Few times per
 week, Few times per month, Never]
5. What time in a day are you likely going to challenge gym? [Morning,
 530 Noon, Afternoon, Evening, Night]

Appendix A.3. Travel Distance and Means

1. What transport do you take when you travel to faraway places for catching
 rare pokémon? (You may choose multiple answers) [Private vehicle, Train,
 Tram, Bus, On foot, I don't travel to faraway places]
- 535 2. Within how long of travelling distance do you think is acceptable for catch-
 ing rare pok'emon? [Less than 1 km, 1 km ~ 5 km, 5 km ~ 10 km, 10 km
 ~ 20 km, More than 20 km]
3. What transport do you take when you travel to faraway places for challeng-
 ing gyms? (You may choose multiple answers) [Private vehicle (driving or
 540 passenging), Train, Tram, Bus, On foot, I don't travel to faraway places]
4. Within how long of travelling distance do you think is acceptable for catch-
 ing rare challenging gyms? [Less than 1 km, 1 km ~ 5 km, 5 km ~ 10
 km, 10 km ~ 20 km, More than 20 km]

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Highlights

In this paper, we study the formation, symbiosis and impact of two networks, which are the virtual social network of in-game characters, and the social network of players in the physical world.

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