# JUXTAPOSED ANALYSIS OF
# INDIVIDUAL AND GROUP MOVEMENTS
# FROM WIFI SIGNATURES

Thesis Submitted in Partial Fulfilment of the Requirements for the Degree of

Master of Science in Applied Geographic Information Systems

by

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# ABSTRACT

Having a good grasp of human movements is considered conducive to enriching the common good. Mobile apparatuses to trace the ubieties of individuals have been developed accordingly. GPS was commonly utilised at first, while the ubiquity of WiFi functionality is now becoming more and more conspicuous, at a reduced cost. That is to say, WiFi has become a more sustainable alternative to conventional practices to study the inclination of individual trips. However, many existing studies have only investigated individual trips even though some research suggested group trips contain unique characteristics, and they have not mentioned the multidimensionality by user attribute. As such, this study introduces a juxtaposed framework tested on a university campus, big enough to provide various exemplary movements of humans. First, this study delves into individual trips through apposite data wrangling, labelling, stay generation and doppelgänger elimination. Then, this study formulates group trips according to the coincidence of their journeys. Lastly, this study probes the differentiation in terms of peak analysis, spatial distributions, night activities, transition patterns and network topologies. The present study reveals distinct disparities between individuality and group solidarity, and heterogeneities amongst users with different attributes, only from WiFi signatures. The framework introduced in this study also opens up the possibility for more scholarly research and, thus, paves the way for better public infrastructure construction in the future.



Keywords: WiFi, computational social science, societal behaviours, human trajectories, semantics

# TABLE OF CONTENTS

# TABLE OF FIGURES

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*I hope this study turns difficulty into opportunity.*

*Kohei Yamamoto*

# Chapter 1. INTRODUCTION

With the rapid development of digital technologies, many social entities in the public and private sectors are gradually coming to appreciate the smart city concept. Smart cities utilise a variety of stages such as the deployments of edge hardware and data science to make the most out of them for the improvement of public health, transportation, energy, and more (Nuaimi et al. 2015). One of the most potent techniques in this evolution is the big data application (Lv et al. 2015, Hashem et al. 2016), which, by offering advice and insights, plays a critical role in stakeholders' decision-making.

In parallel with this growing recognition, mobile apparatuses, which track moving objects from freight (Prasanna and Hemalatha 2012, Tang et al. 2015) to people (Zhang et al. 2019), have also been gaining attention. The main feature of these digital accessories is the ability to trace an entity from the beginning to the end of a trip – even personalised to the individual level – in the case of human tracking. The mechanisms behind these digital accessories, like GPS, have been adopted in a wide variety of fields, such as monitoring the patterns in the movements of athletes (Petersen et al. 2009) and building a system which automatically learns significant locations through clustering GPS data (Ashbrook and Starner 2003). Accordingly, many institutions have started mining large datasets of real users' trajectories with the support of massive computational capability (Zhang et al. 2019) to break through the research frontiers.

Furthermore, owing to the evolvement of Internet of Things (IoT) and progress in wireless networking technologies, the ubiquity of WiFi functionality has become conspicuous in the past decade. Besides the extension of Internet coverage, WiFi has paved the way for location-based services. Though the accuracy and resolution of WiFi are less rich compared to GPS, the energy consumption, for example, is low when a mobile device is connected to WiFi in comparison with GPS. Also, while GPS becomes the best approach to studying outdoor trails, GPS struggles to perform within doors since the signals from GPS satellites hardly reach indoor space (Zirari et al. 2010), and this feature, therefore, limits spatially detailed analysis. There are also studies sniffing cellular information to trace human movements (Calabrese et al. 2013, Jiang et al. 2016), however, capturing only users of a specific network provider cannot well represent the population (Traunmuellera et al. 2018).

On top of the fact that the granularity of WiFi facilities is high enough to have a nice grasp of human flows, at a reduced cost, WiFi is now a more sustainable path to the future of human movements analysis, as it can be used as the proxy of the loci of users. Several studies have attempted to understand the flows of people, taking advantage of the wide use of WiFi signatures, for example, to detect the congestion points of subway stations (Ding et al. 2019), to monitor the flows on a smart university campus (Alvarez-Campana et al. 2017) and so on.

However, many existing studies have only investigated individual trips even though some studies suggested group trips contain unique characteristics (Conradt and Roper 2010). For example, the timing, directions and destinations of group movements usually differ as social animals routinely make collective decisions to move cohesively (Conradt et al. 2019). Social entities, on the other hand, have to plan the orchestration and optimisation of infrastructure resource concerning this variation. Besides, in the case of a global pandemic, group activities are also a risk factor for rapid transmission of respiratory viruses such as SARS-CoV[1] (Mat et al. 2020), and hence uncovering group movements must not be underestimated even from the viewpoint of public health.

At the same time, theoretical studies on the mechanisms behind group activities have been somewhat investigated thus far, and they found some elements such as influencing factors and the costs for making a group consensus (Conradt et al. 2019). Recent studies have also proposed platforms to augment the aforesaid factors and reduce the costs in group trips (Sigala 2012). Yet, they have rarely examined their studies on the group movements in the real-world application and the multidimensionality by user attribute.

Thus, this study presents a framework to contrast individual trips against group trips through elaborate data processing and illuminate the heterogeneities among users with different attributes, from WiFi signatures. The identity and differentiation of the results are scrutinised, which will infer the potential implication and contexts.

[1] SARS-CoV: Severe Acute Respiratory Syndrome coronavirus. Available at: https://www.who.int/ith/diseases/sars/en/ (accessed 15 Jul 2020).

# Chapter 2. RELATED WORK AND MOTIVATION

This chapter is a brief overview of the existing studies tackling group trips and flow analysis with localisation. There are several types of network devices utilised for human tracking, especially, WiFi is a popular approach where GPS is inadequate. At the same time, research on the mechanisms and theories behind group activities and studies on the collaboration in group trips have been developed. Each of those is explained in the following sections, respectively, and the research gaps between the present study and conventional studies are given at the end.

## 2.1. Flow analysis with conventional localisation techniques

With the advancement in the localisation techniques using radio waves such as GPS (Shaw and Gopalan 2014, Zhang et al. 2019), Bluetooth Low Energy (BLE) (Pu and You 2018), Indoor Messaging System (IMES) (Sakamoto et al. 2014) and Call Detail Records (CDRs) (Jiang et al. 2016), the movements of objects have been thoroughly anatomised, and wireless devices have become the proxy of their owners' loci.

Zhang et al. (2019) recorded GPS trajectory data and proposed a system with a probabilistic generative model to extract the semantics. After they pre-processed the raw data, the model was built up to annotate the semantic information of the trajectories by comparing with Point of Interests (POI) data. Then they verified their system successfully provided the meaningful patterns over five years of the experiment. In many cases or instances, GPS can become one of the best solutions to study outdoor trails and spatial patterns as described above, however, GPS has to struggle to perform within doors. This is because the signals from GPS satellites are not strong enough to reach indoor space (Zirari et al. 2010), and this characteristic brings a limitation into spatially detailed analysis.

On the other hand, some studies sniffing cellular information, what is called CDRs, have been also implemented (Calabrese et al. 2013, Jiang et al. 2016). Jiang et al. (2016) introduced a modelling framework which analysed the sparse CDRs to uncover urban mobilities. The framework detected the stay duration, the number of significant locations and mobility networks for each individual, and they measured the geographical interaction between land use and the generation of individual trips. These flow analysis on CDRs are practical for the purpose of human-tracing, however, capturing only users of a specific mobile network provider is not suitable to represent the population (Traunmuellera et al. 2018).

In the meantime, WiFi localisation is becoming increasingly conspicuous in the IoT market due to the ubiquity of wireless network facilities. This growing trend solidifies location-based computing with WiFi signatures, which outweigh other localisation types. The energy consumption, for example, is low in comparison with GPS, and WiFi localisation does not require any additional equipment or instalments in a test bench, unlike BLE or IMES. Consequently, tracking with WiFi is now becoming a more sustainable approach to unobtrusively identifying the ubiety of an entity, at a reduced cost.

### 2.2. Flow analysis with WiFi localisation techniques

Abundant studies have been carried out to understand the flows of humans taking advantage of the wider use of WiFi, for instance, the evaluation of facility usage in a hospital complex (Prentow et al. 2015), inference of activity episodes (Danalet et al. 2014), the establishment of smart city concept (Alvarez-Campana et al. 2017) and detection of the congestion points of subway stations (Ding et al. 2019).

Chilipirea et al. (2018) partitioned each trajectory into fundamental periods of stops and moves to answer the complex questions about significant locations or social behaviours. They studied three different algorithms for stay point detections and then examined the accuracy comparatively with GPS instances. As a result, they have shown that at least one of their algorithms could achieve an expected performance to juice the knowledge from spatio-temporarily coarse WiFi signals.

On one hand, Traunmueller et al. (2018) developed a method to model the trajectories patterns in New York City, one of the densest urban environments in the world. They consecutively collected probe request data (a special frame sent from a client device requesting information of WiFi stations) from 54 public WiFi stations and analysed more than 30 million records of 800,000 individuals. Then they used the data to estimate the population along with edge frequencies and directions of journeys in the mobility network.

These studies have established new ways to well understand urban mobilities at a reduced cost, however, quite a few analytics have only explored individual trips even though some research advised group trips have unique traits (Conradt and Roper 2010). For example, the timing, directions and destinations of group movements usually differ as social animals make collective decisions in daily lives (Conradt et al. 2019), and these group features shall be discussed in depth in the following sections. Social entities, on one hand, should optimise infrastructure resources concerning the variation between individuality and group solidarity. Besides, when it comes to a worldwide pandemic, group activities are also a risk factor for the transmission of viruses (Mat et al. 2020), and hence group movements also need to be scrutinised to enrich public health.

## 2.3. Theories and mechanisms behind group activities

Over the past decades, research on mechanisms and theories behind group activities have been made. To begin with, living in a group is one of the most fundamental traits in all human and non-human societies as individuals coordinate their activities to benefit from each other (Kerth 2010). Even though, the cohesion of individuals within their group is of great concern, which takes a high cost to form a group consensus (Jacobs 2010). In an extreme instance, where the cost becomes too high, a group can temporarily split (Ruckstuhl 1999).

Group tripping is a typical example of group cohesion (Conradt et al. 2019). Generally, a group trip is an aggregation of individual trips with the same timing and common trails, and incidentally, Boinski's study in 2000 (cited in Jacobs 2010) mentioned an operational definition of cohesive group as 'an aggregation of individuals that in most circumstances remain in visual or vocal contact with most other group members and travel together as a concerted unit'.

Usually, group trips can be implemented once group members reach a consensus about the timing and spatial destinations of the collective movements (Conradt and Roper 2010), however, spatial cohesion in group decision-making tends to be highly variable (Sueur et al. 2011). The latest study by Conradt et al. (2019) found that the interests of outcomes and environmental information (e.g. travelling routes) are two major factors influencing the consensus decision of group trips, and they concluded these factors are critical for advantageous decisions.

### 2.4. Studies on influencing factors and costs in group trips

In the meanwhile, several studies have been developed to foster group collaboration through augmenting the two factors above and reducing the aforementioned costs (Ewert 1993, Sigala 2012, Hashem et al. 2013, Ahmadi and Nascimento 2015). Giving regard to the influencing factors, studies on group collaboration can be traced back to the last century, when Ewert (1993) found the causality in the motive importance between trip success and group membership. A recent and more extensive study, by Sigala (2012), developed a framework, which evaluated the impact of geo-collaborative platforms on group decision-making in trip planning with individual perception measurements. The work fused several group support systems with Web 2.0 and geo-collaborative features. The framework was tested with students, and the author validated the geo-collaborative framework effectively facilitated the teamwork while enriching the aforesaid factors.

Other researchers, on one hand, presented platforms to suggest the best travelling route in a group (Hashem et al. 2013, Ahmadi and Nascimento 2015). Ahmadi and Nascimento (2015) focused on location-based social networks which individuals can interact with each other from anywhere and introduced the possibility to help them spontaneously meet at certain points while minimising the total travel distance for all members. They called this type of query as a group trip planning query, and they have shown an algorithm to handle these queries to reduce the costs of group trips.

Those studies on the mechanisms and collaboration of group activities suggested new findings. They, however, have hardly reported the distinction between individual trips and group trips in the real-world application, besides, they have not elucidated the multidimensionality by user attribute, which can potentially bring further variations into results.

## 2.5. Research gaps and contribution

As stated so far, analysing mobility patterns upon WiFi technologies has come into reality and demonstrated the capabilities in many industrial and academic disciplines. However, they have nonetheless only investigated individual trips, while understanding group trips can help achieve higher living standards. Meanwhile, many studies have been conducted to comprehend the underlying mechanisms behind group movements and collaboration, however, they have not mentioned the displacements between individual movements and group movements in the real-world practice, and they have not scrutinised the variations by user attribute, which can be factors influencing results.

Hence, this study introduces a juxtaposed framework to illuminate the heterogeneities between individual trips and group trips in the real-word application, and the identity and differentiation of the results by user attribute are also examined.

Once the study is carried out, the results will help stakeholders make smarter decisions to enrich the common good (i.e. the optimisation of infrastructure resources, the improvement of public health), so that they could reach the required level of sustainability.

# Chapter 3. DATA REQUIREMENTS

This chapter explains a test bed which the present framework is applied to, the spatio-temporal resolution of WiFi data and the details of the collected WiFi observations, and the terminologies unique to this study are described at the end.

## 3.1. Study area

This study chose the Kent Ridge Campus, National University of Singapore (NUS) which covers an area of 1.5km$^2$ for the test bench as shown in Figure 3.1, and it provides three different private WiFi networks (students, staff and guests).

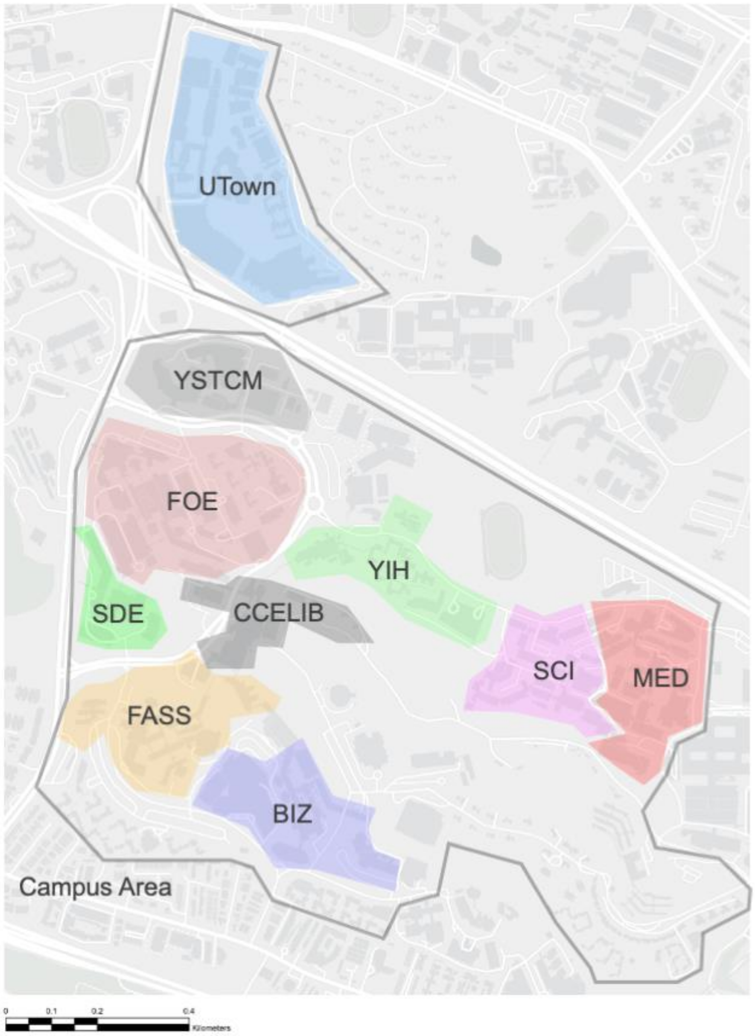



Figure 3.1 Test bench in this study.

According to Figure 3.1, the whole campus is divided into several zones: Faculty of Arts and Social Sciences (FASS), Faculty of Engineering (FOE), NUS Business School (BIZ), Yusof Ishak House (YIH), School of Design and Environment (SDE), CCELIB, Yong Siew Toh Conservatory of Music (YSTCM), Faculty of Science (SCI), School of Medicine (MED) and University Town (UTown). First, YIH houses facilities for events, training and discussions with the office of student unions, a university health care centre and a university hall. Second, YSTCM is Singapore's first conservatory of music, and it offers full-time studies and hosts a performance calendar of 200 concerts yearly. Third, UTown is a recreational amenity space where it allows people to gather around and has canteens, dining halls, cafes, dorms and shops. Last, CCELIB is a zone mainly consisting of a library (the central library) and a computer centre (a technical service).

### 3.2. Study Data

This study examines one week (03 September 2018 00:00:00 – 09 September 2018 23:59:59), as the registrations to three different user networks were settled in this period. The data contains 3,052 files with 0.1 billion (105,068,677) records, and the volume is around 35 gigabytes in total.

As for the temporal resolution, each WiFi record is added to the central database (in NUS IT[2]) every minute from 8 am to 12 am and every five minutes from 12 am to 8 am. By contrast, in terms of the spatial resolution, the WiFi facilities are deployed across the campus area, and each WiFi facility detects a connected device by floor basis of the buildings in the target faculties (e.g. FASS-AS1-4th).

[2] NUS IT: NUS Information Technology. Available at https://nusit.nus.edu.sg/ (accessed 18 July 2020).

Each record is comprised of around 20 attributes. Among these values, the time, user ID, MAC address[3] and location are mainly used to analyse movement patterns. The time shows the time which the record was added to the database, the user ID represents a hashed username used to join the networks, the MAC address indicates a hashed identifier unique to a device and the location denotes a floor-wise location where the device was detected.

### 3.3. Terminologies

There are some unique terms to the present study: a trip, stay and journey. A trip refers to a trajectory of a certain individual and consists of two different time-series sequences, namely, stays and journeys (referred to as stops and moves, respectively in the study by Chilipirea et al. (2018)). A stay denotes a status where an individual dwells at a certain place for 30 minutes or longer (Zhao et al. 2018), while a journey indicates a status of travelling from a certain locus to some other locations, which can be derived from the difference of stays.

[3] MAC address: media access control address

# Chapter 4. METHODOLOGY

This chapter illustrates an overview of the juxtaposed framework to estimate human movements on a test bed and elucidates how the framework builds upon several data processing. Following which, it describes the details of each data handling procedure step by step.

## 4.1. Juxtaposed framework

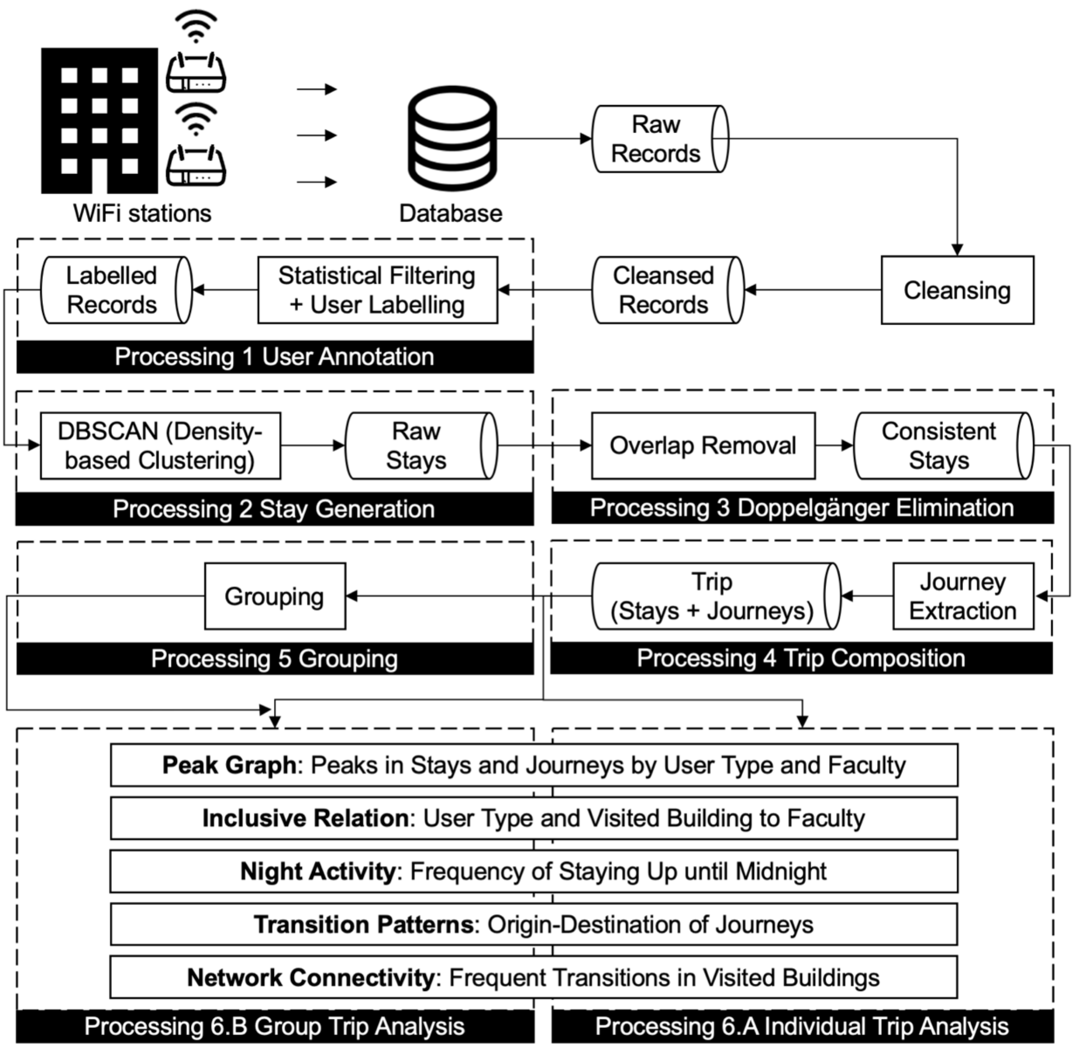



Figure 4.1 Overview of proposed framework

As depicted in Figure 4.1, the framework is comprised of several steps of data processing; first, all the WiFi records are curated into the central database from each station, which is deployed on each floor of each complex. After the raw records are retrieved from the database, they go through data cleansing (e.g. the removal of duplication records) and then the first data processing; user annotation to annotate a user type attribute to each individual.

After the annotation, by employing a density-based clustering method, the stays statuses are generated from the trips (i.e. trajectories) for each individual. At this point, many users can be located at different places in parallel because they may carry around multiple devices, thus the following data processing takes place; doppelgänger elimination is applied to the string of raw stays. This processing looks into the density of each overlap of parallel stays and the stay whose density is higher than the others is preceded, and journeys are extracted from the difference of stays over time. Through these procedures, the sequence of stays and journeys are obtained without any chronological paradox. Incidentally, these procedures are implemented using Python 3.7[4], and the source codes are managed by GitHub[5].

In advance of the comparative analysis of individual trips and group trips, the grouping has to be implemented and it outputs the certain combinations of individuals in accordance with the coincidence of their journeys. After that, the juxtaposed analysis is performed with respect to the peak analysis of stays and journeys, inclusive relations, night activities, transitions patterns over faculties and the network connectivity of visited places.

[4] Python. What's New In Python 3.7. Available at https://docs.python.org/3/whatsnew/3.7.html (accessed at 18 July 2020)
[5] GitHub. nus-wifi Available at https://github.com/KoheiYamamoto/nus-wifi (Classified for now in the view of information security. Instead, an archive is attached to the thesis). (accessed at 18 July 2020)

### 4.2. User annotation

Generally, large organisations with the rich multifariousness in their members tend to separate their wireless networks by category. Even in such case, unintended access to an unassigned network can happen because of the network users who have permission to join multiple networks. Thus, it is not reasonable to simply assume that the accessed network is representative of the user attribute, and accordingly, the necessity of labelling each user and filtering noise arise at this point. The frequencies of network access for each user $\mathrm{U_i}$ out of all users $\mathbf{U}$ are referenced as follows, where $\mathrm{N_j}$ indicates the accessed network and $\mathrm{c(N_j)}$ represents the frequency of $\mathrm{N_j}$:

$$\mathrm{U_i} = [\mathrm{c(N_1)}, \mathrm{c(N_2)}, \ldots, \mathrm{c(N_n)}]$$

Then $\mathrm{U_i}$ is labelled either as noise or a specific user type as follows, where $\mathrm{threshold}$ is a constant and σ indicates the standard deviation of the frequency of the accessed network that is used as a threshold to detect the most frequent network usage:

$$\sigma = \sqrt{\frac{1}{\mathrm{n}} \sum_{\mathrm{j=1}}^{\mathrm{n}} \left(\mathrm{c(N_j)} - \overline{\mathrm{c(N)}}\right)^2}$$

$$\mathrm{U_i} = \begin{cases} \mathrm{noise}, & \sigma < \mathrm{threshold} \\ \mathrm{N_j}, & \sigma \geq \mathrm{threshold}, \max\left(\mathrm{c}\left(\mathrm{N_j}\right)\right) \end{cases}$$

### 4.3. Stay generation

After the user labelling, to knit the whole trip which consists of stays and journeys statuses for each user, stay points are detected using density-based clustering as a first step. As each WiFi record r typically represents a single row in the database with the unique user ID, time attribute $\mathrm{t}$ when his/her presence is observed in the proximity of a station and location attribute, a raw trajectory $\mathrm{R_i}$ of each user $\mathrm{U_i}$ is comprised of a sequence of discrete records in the following chronological order:

$$\mathrm{R_i} = [\mathrm{r_1}, \mathrm{r_2}, \ldots, \mathrm{r_m}], \qquad (\mathrm{r_{m-1}.t} < \mathrm{r_m.t})$$

To extract stay points, a density-based spatial clustering of applications with noise, the so-called DBSCAN algorithm introduced by Ester et al. (1996) is employed. DBSCAN is one of the most commonly used algorithms to find spatial clusters in the field of data mining, which classifies point datasets into clusters and noise points by searching with a circle of radius epsilon ε. Usually, this method is applied to two-dimensional data; in this study, it is modified to one-dimension to fit the chronological sequence per locus. Figure 4.2 shown below is the pseudocode of the customised DBSCAN used to detect stays in this study. As Zhao et al. (2018) suggested, a presence at one place for 30 consecutive minutes or more is defined as a stay with a meaningful context. If the chronological duration of a cluster is more than or equal to 30 minutes, with a limit up to 24 hours, then it is regarded as a stay in this study.

```
dataset - R
distance - ε
begin
    stays S ← 0
    for each point r in R do
        if r is visited then
            continue to next r
        end
        else
            mark r as visited
            neighborhood_points ← points in ε-neighborhood of r
            if sizeof(neighborhood_points) < 2 then
                mark r as noise
            end
            else
                if new cluster ≥ 30 minutes then
                    S ← new cluster (stay)
                end
                call function recursively
            end
        end
    end
end
```

Figure 4.2 Pseudocode of customised DBSCAN used to fit the present study.

### 4.4. Doppelgänger elimination

After the stay generation, a sequence of stays for $U_i$ is still a string of raw stays as it contains overlaps among their stays over time, which is referred to as a doppelgänger hereafter. The reasons could be multiple, but mostly they are observed by two main cases: by a device receiving WiFi radio waves on and off from multiple WiFi stations and by a user carrying around multiple devices using the same user ID for the user authentication. The former case will often happen when a user is positioned somewhere in the middle between a close WiFi station and another station which is at a little distance, and his/her device can perceive multiple WiFi on and off. However, in light of the facts that the strongest WiFi according to signal strength indication (RSSI) is commonly prioritised in the operating system layer[6] and that the strength of RSSI is a function of distance (Koo and Cha 2011), the identical device is trying to connect to the closer WiFi more frequently. As such, the former case will be handled by calculating the density of records $r_m$ contained in the overlap, and the stay with the higher density is prioritised, as in Figure 4.3, where a and c indicate the adjunct stays and b represents the overlap between the presence of X and Y.

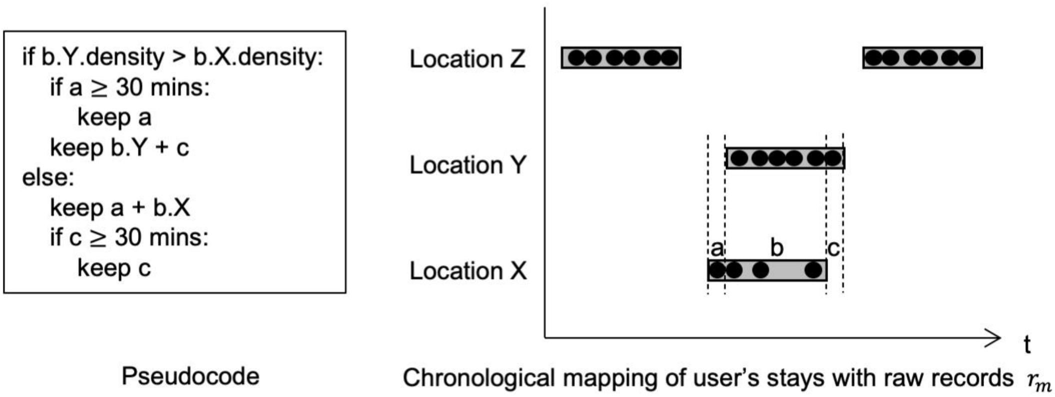



Figure 4.3 Handling when a doppelgänger happens with a single device.

[6] Apple (2019) About wireless roaming for enterprise. Available at https://support.apple.com/en-sg/HT203068 (accessed 12 Apr 2020).

The latter case is caused when a user leaves a device somewhere and uses other devices somewhere else. In this case, two main cases can frequently occur, as depicted in Figure 4.4, and are handled in consideration of the chronological consistency or logic.

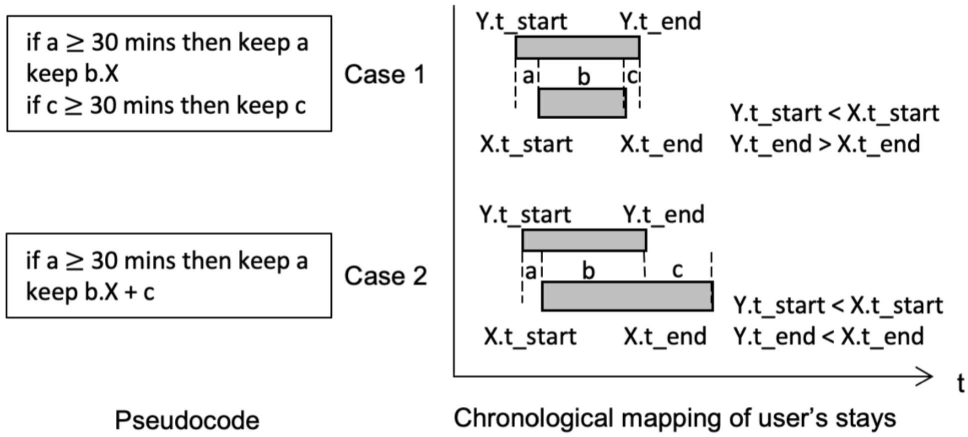



Figure 4.4 Handling when a doppelgänger happens among multiple devices.

After all the doppelgängers are removed, the sequence of stays without any over-time paradox is output for each user $U_i$. Then the differences of stays are extracted as journeys with a maximum duration threshold of two hours, as it is highly likely to take an intermediate stay which is not recorded in the database (Goulding 2014). Hence, stays $S_i$ and journeys $J_i$ constitute a trip $T_i$ of the user $U_i$ described as follows:

$$T_i = \begin{cases} S_i = [s_1, s_2, \dots, s_k], & (30 \text{ mins} \leq s_k.t'_{end} - s_k.t'_{start} < 24 \text{ hrs}) \\ J_i = \quad [j_1, j_2, \dots, j_l], & (j_l.t'_{end} - j_l.t'_{start} < 2 \text{ hrs}) \end{cases}$$

A stay $s_k$ has the start and end time with the location, while a journey $j_l$ has the origin and destination aside from the time attribute.

## 4.5. Grouping

Prior to the juxtaposed analysis, the combinations of users who have strong dependency need to be identified so that a series of group trips, which are comprised of group stays and group journeys can be extracted accordingly. This process, called grouping, which needs certain parameters, an offset and coincidence value, is implemented on the basis of the coincidence of journeys.

The offset is the number of minutes used to measure the coincidence value. When the difference of the start time between two journeys of different users and that of the end time are within the offset, respectively, the coincidence value is incremented. The coincidence value, in other words, denotes how many common journeys are implemented per day by a certain combination of users; the more frequent, the closer they are to each other. Then this process is computed for each set of users, and the user combination is registered as a group if the coincidence value becomes higher or equal to a given threshold with varying the offset. For the present study, the offset is slid from five minutes to ten minutes by one minute, as the longest interval of WiFi curation is five minutes, and the constituents of each group are not necessarily identical user types, but mixed.

### 4.6. Juxtaposed analysis

This study examines the patterns of human dynamics based on the following concepts:

- Peak graph: Peaks in stays and journeys by user type and faculty
- Inclusive relation: User type and visited buildings to faculty
- Night activity: Frequency of staying up until midnight
- Transition patterns: Origin-Destination of journeys
- Network connectivity: Frequent transitions in visited buildings

We then look into the contrast between individual trips and group trips, and also check if they exhibit any differentiation by user type.

# Chapter 5. RESULTS

This chapter reports all the results of the proposed framework tested on a huge test bed, and in the following, each section reviews the findings and the contrasts between individual trips and group trips in light of each aforementioned concept, with the help of visualisation.

## 5.1. Statistics

The number of users on campus tracked during the examined period was 46,212 individuals in total. Of 46,212, 34,932 were students, 8,437 were staff and 2,843 were guests, respectively. In light of the official numbers of students (37,047) and staff (12,176) (NUS OCR 2019 as at February 2019), the estimate of students was slightly more than the registered number as it is assumable that the number could contain external constituents such as exchange students. On the other hand, the number of staff was estimated lower than the actual number, and it can be presumed that there was a certain amount of staff who did not appear on campus in the study period, for instance, lecturers who conducted remote classes, faculty members absent due to business trips or those committed as visiting scholars in other countries at that time. This study, therefore, reckoned the numbers detected were reasonable.

Related to the grouping process, Figure 5.1 is a summary of the variations of the total stays and journeys involved in group trips where the number of group members $n$ is aggregated ($n \geq 2$). In Figure 5.1, solid and dotted lines represent stays and journeys, respectively, and the two aforesaid parameters are varied. As shown, the trends in stays and journeys are similarly depicted, and there is a considerable dip before bottoming out, varying one to two at coincidence value.

As the result became limited when the coincidence value was set to three, this study thus specified a set of two parameters for the following analysis as follows: the strictest offset of 300 (i.e. five minutes) and the coincidence value of two.

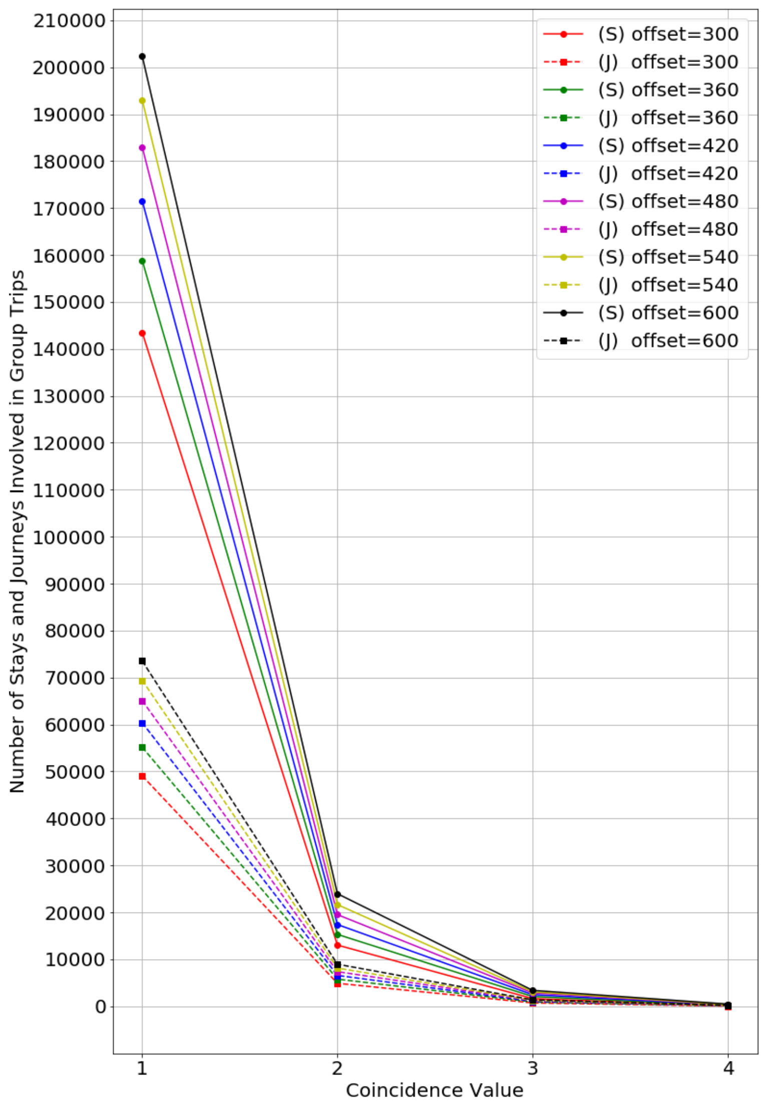



Figure 5.1 Total stays (solid) and journeys (dotted) involved in group trips with two parameters: offset and coincidence value.

Figure 5.2 is a box plot of individual stays and group stays by user type. From both charts, it can be seen that the mean of staff stays was the highest of all user types, and that of students was second, followed by guests in Figure 5.2 (a) and this is reversed in Figure 5.2 (b). As to the variation, individual students and guests demonstrated similar inclinations but staff had more outliers, meanwhile that in group trips illustrated similarity in all user types.

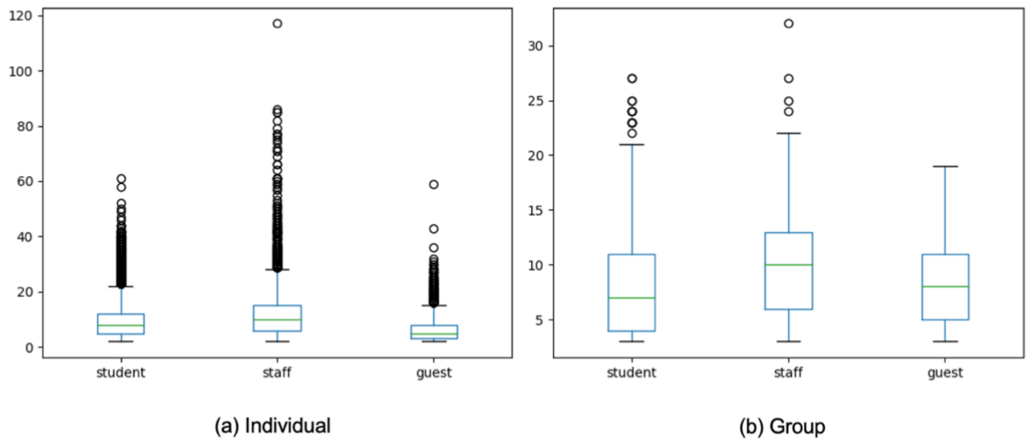
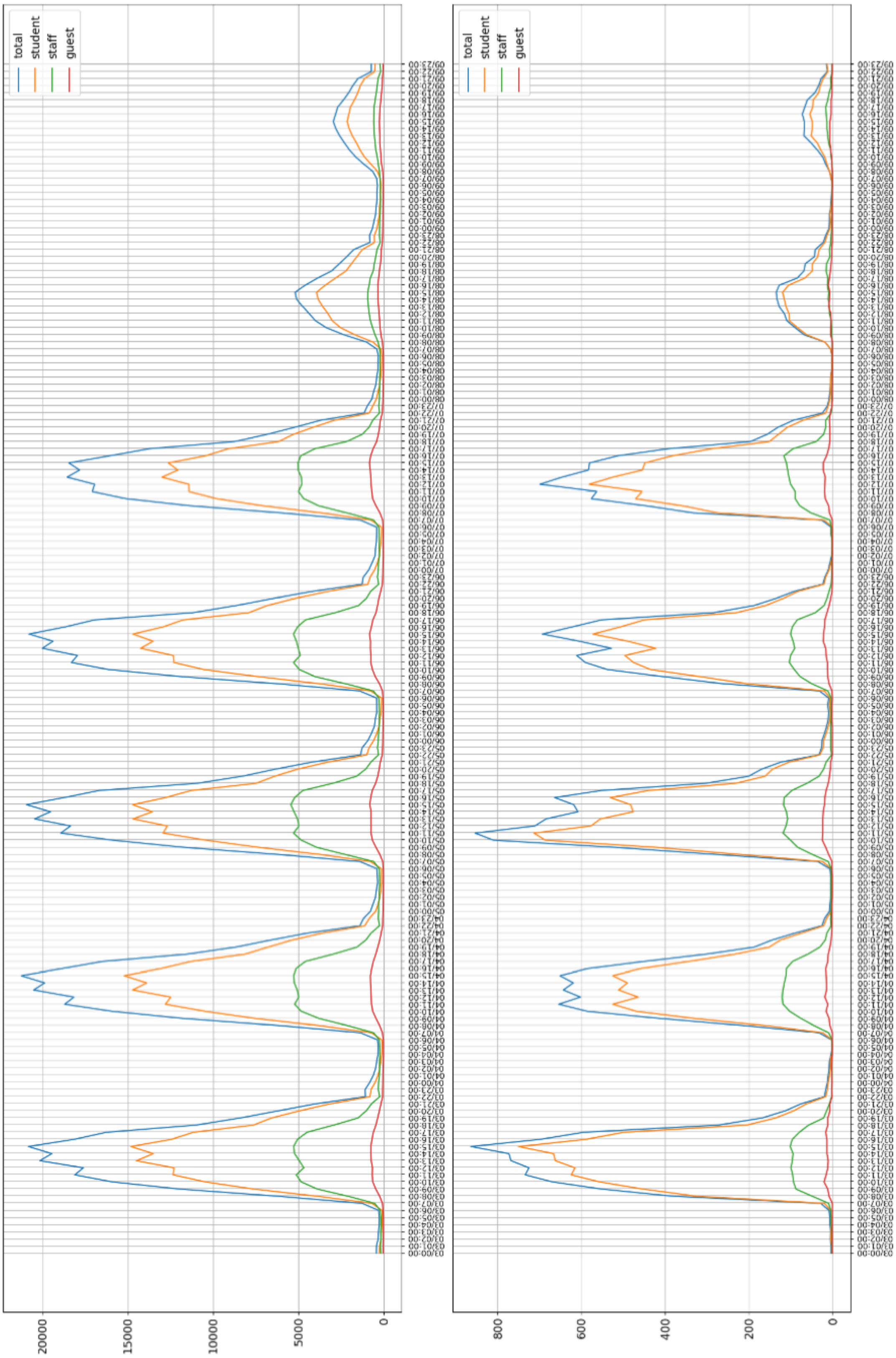



Figure 5.2 Box plots of individual stays and group stays by user type. Note: (a) and (b) represents individual trips and group trips, hereafter.

## 5.2. Peak graph

Figure 5.3 shows the peak charts of individual stays and group stays by user type. In both graphs, each line denotes the quantity of the stays; a blue line describes the total, yellow is students, green is staff and red is guests. Looking at the total in Figure 5.2 (a), shows a periodic trend from Monday to Friday but a little drop on Friday and a dramatic fall on the weekend. Also, the stays of students had three distinct peaks at 11:00, 13:00 and 15:00 on weekdays, with a single peak at 15:00 on the weekend, whereas the stays of staff and guests illustrated a gentle curve both on weekdays and on the weekend.

On the other hand, paying attention to Figure 5.3 (b), the number of peaks in all types appears identical to the former, however, what stands out here is an absence of the regularity - the waveforms do not show any recurrent patterns but random peaks.




(a) Individual

(b) Group

Figure 5.3 Peak charts of individual stays and group stays by user type.

Figure 5.4 shows the peak charts of individual stays and group stays by faculty. According to Figure 5.4 (a), FASS, FOE, MED and SCI seem to be the top faculties in terms of the concentration of stays. As for peaks, stays at YSTCM and YIH showed a smooth curve, while other faculties had some cyclical peaks on weekdays and fewer on the weekend. Among all faculties, UTown was the only faculty which retained stays volume even on the weekend, whereas others showed a sharp decline.

On one hand, Figure 5.4 (b) loses the cyclicity in all faculties, and in particular, it illuminates the divergence of MED with the notable traffic only on weekdays (the volume tripled others on average).

Figure 5.5 shows the peak charts of individual journeys and group journeys by user type. Just like the stays, both figures follow a similar pattern with a large number of journeys on weekdays and a heavy drop on the weekend, and all types commonly had peaks at 13:00 throughout the week. With a particular emphasis on the regularity, journeys in a group brought about a random trend and unveiled a more significant discrepancy than the results in the previous sections, regardless of user type.

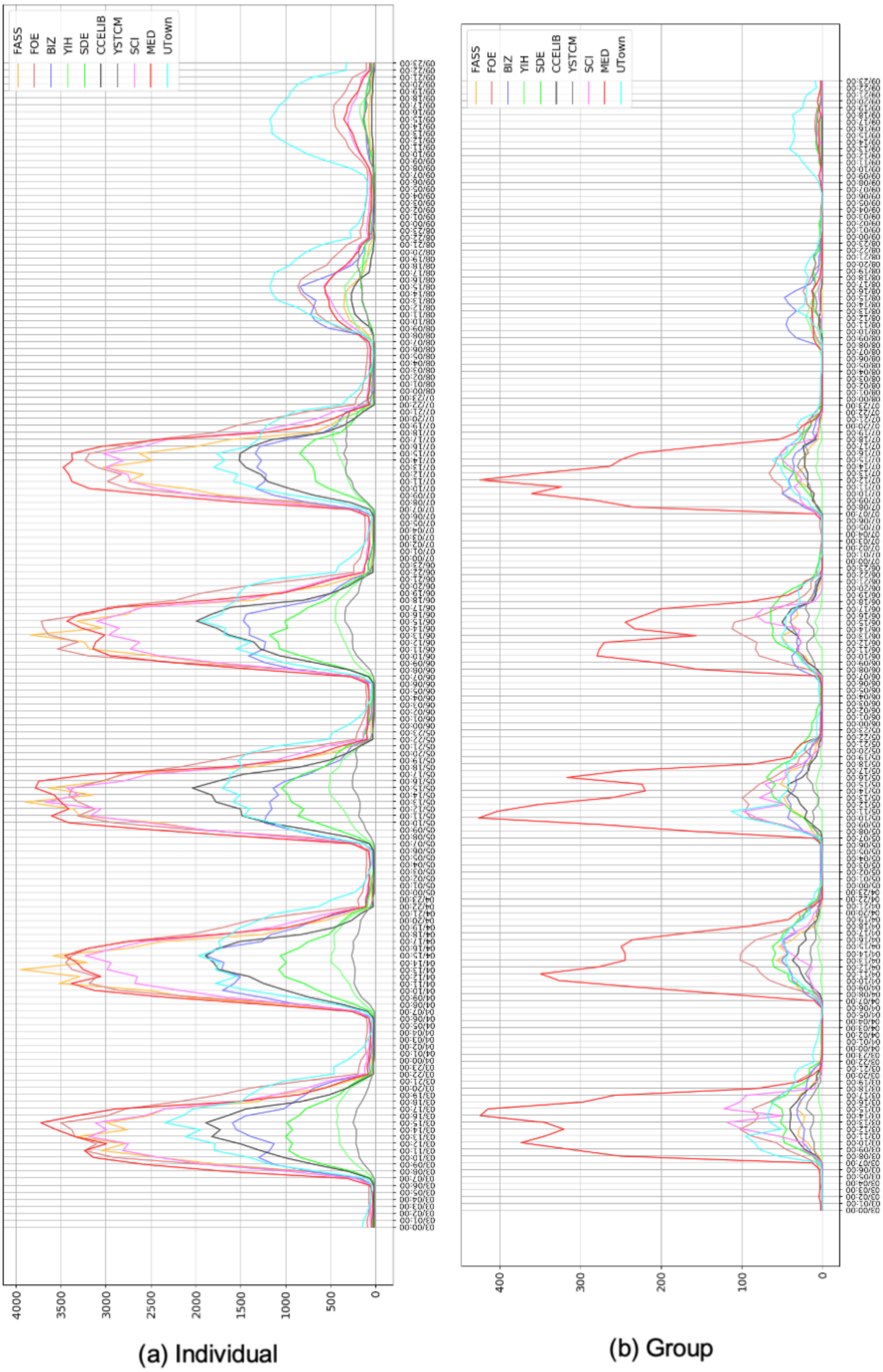
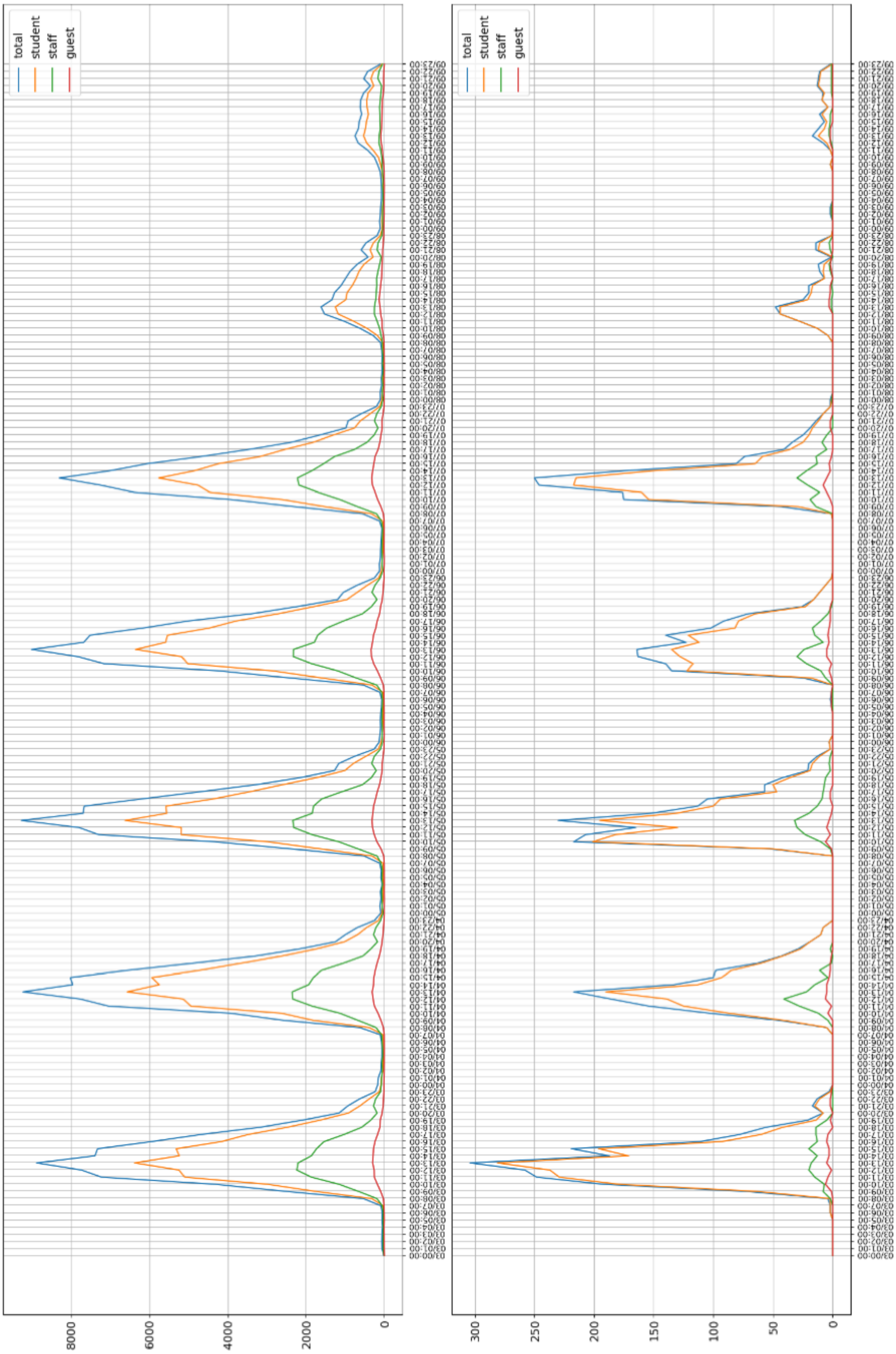



Figure 5.4 Peak charts of individual stays and group stays by faculty.




(a) Individual

(b) Group

Figure 5.5 Peak charts of individual journeys and group journeys by user type.

## 5.3. Inclusive relation

Figure 5.6 is visual representations of inclusive relations analysing user types and faculties for individual stays and group stays. The visualisation was implemented using HIGHCHARTS [7].

Figure 5.6 (a) suggests there was a tendency in students to dwell more at FASS, followed by UTown, MED and FOE, whereas staff were observed often at FOE and MED, followed by SCI, which are all faculties delivering STEM[8] subjects. Guests were inclined to have stays at UTown more frequently.

Figure 5.6 (b), by contrast, exhibits many visits to MED, which were dominated by students. Aside from MED, students tended to form groups at FOE and UTown, followed by SCI. UTown and YSTCM seemed relatively popular for guests, and all in all, staff were detected much less than students at most faculties.

Figure 5.7 is visual representations of inclusive relations analysing visited buildings and faculties for individual stays and group stays. Figure 5.7 (a) portrays frequently visited buildings by individuals, and there are some iconic facilities in each faculty: YIH and university healthcare centre (UHC) at YIH, YSTCM and a university culture centre at YSTCM, MochtarRiyardy (multi-purpose building) at BIZ, the central library and a culture centre (CC) at CCELIB, Education Resource Centre (ERC; recreational spaces with cafes), UTown Create (multi-purpose building including theatres), UTown 25 (dorm and residence hall), dining halls and colleges at UTown and many of the rest were academic facilities.

[7] HIGHCHARTS. Available at https://www.highcharts.com/ (accessed 5 July 2020).
[8] STEM: Science, Technology, Engineering and Mathematics.

On the flip side, Figure 5.7 (b) has a lot in common with the former result, nevertheless, the usage of canteens at FASS, the central library at CCELIB, ERC, UTown Create and UTown 25 at UTown is more highlighted.

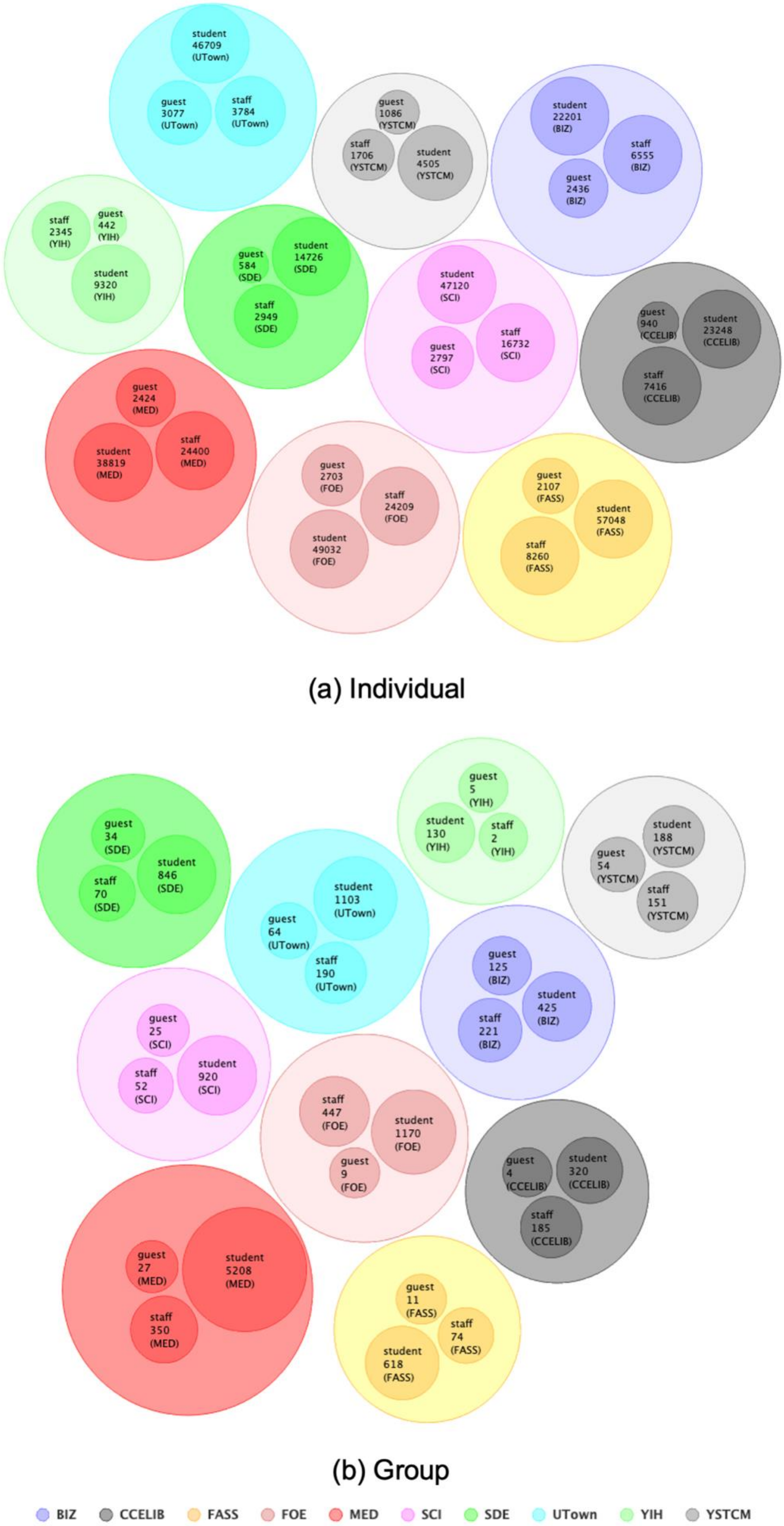



Figure 5.6 Visual representations of inclusive relations analysing user types and faculties for individual stays and group stays.

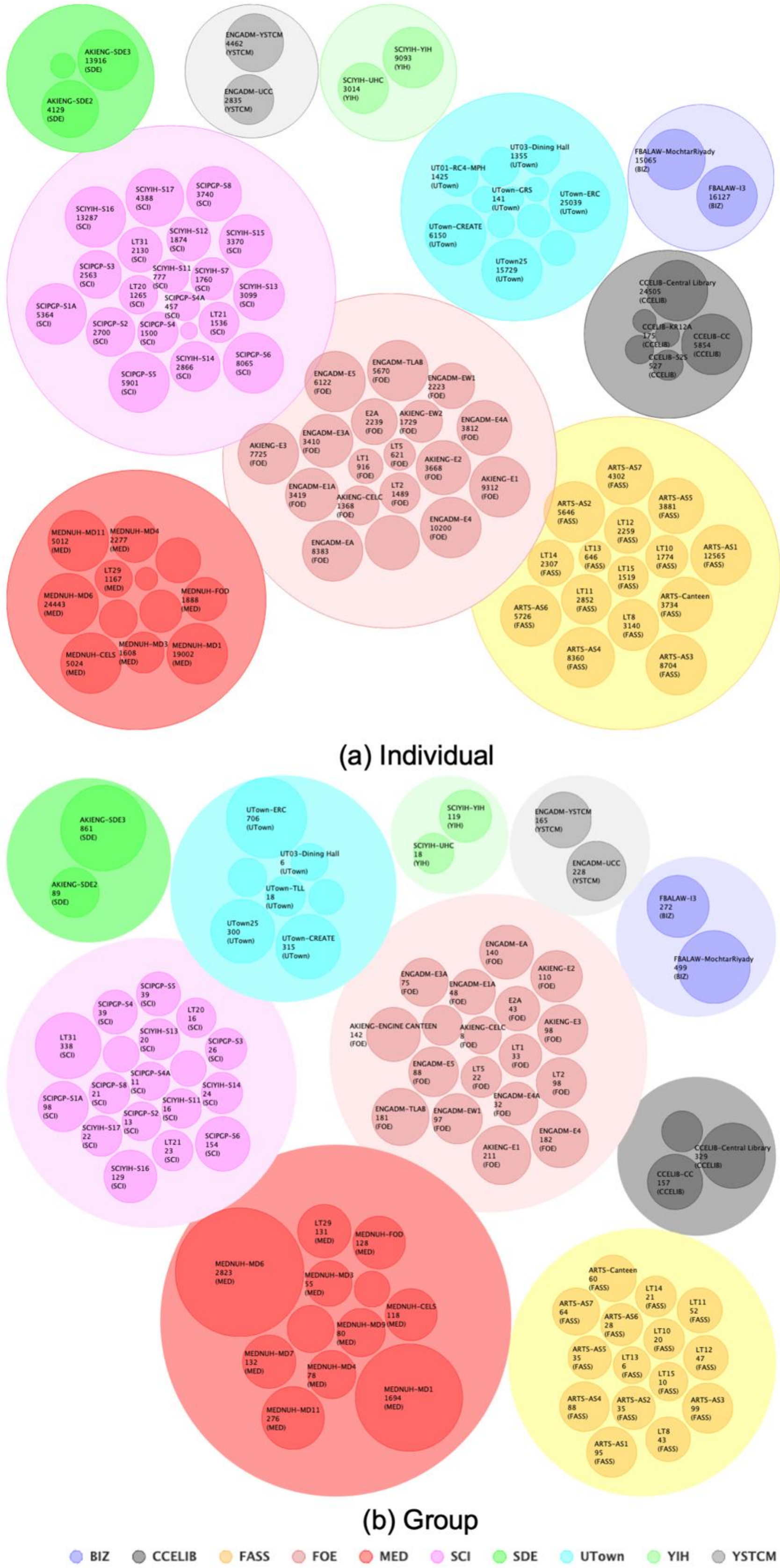



Figure 5.7 Visual representations of inclusive relations analysing visited buildings and faculties for individual stays and group stays.

## 5.4. Night activity

Figure 5.8 shows bar graphs of individual stay-up and group stay-up behaviours throughout the investigated period, and stay-up was defined as those who dwelled beyond 24:00 (twelve midnight) upon assuming 23:30-24:00 is the time for last buses available in the vicinity of the study area. From the graphs, it is clear that people tended to stay up most frequently from Wednesday to Thursday, individually, and in a group.

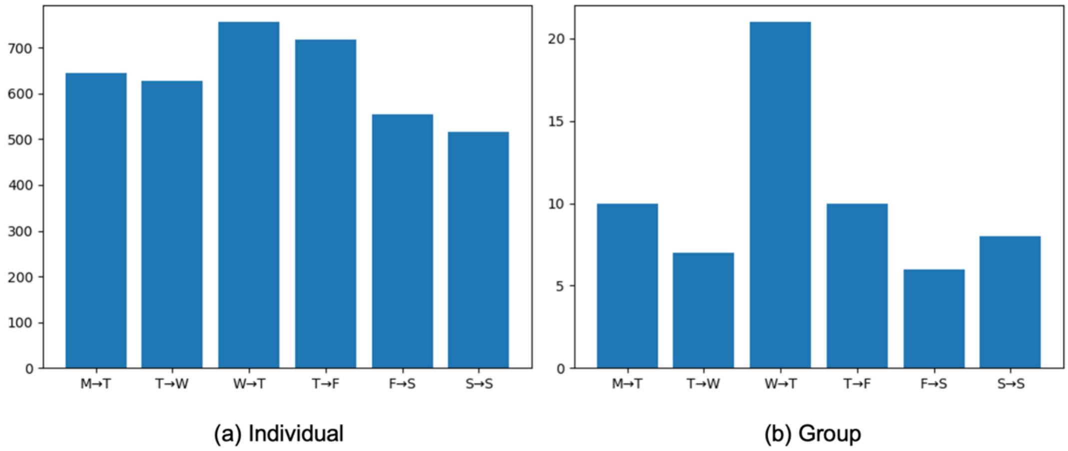



Figure 5.8 Bar graphs of individual stay-up and group stay-up behaviours throughout the investigated period. Note: M→T, for instance, represents a stay-up from Monday to Tuesday.

Figure 5.9 shows bar charts illustrating the frequency of stay-up behaviours in the week by user type.

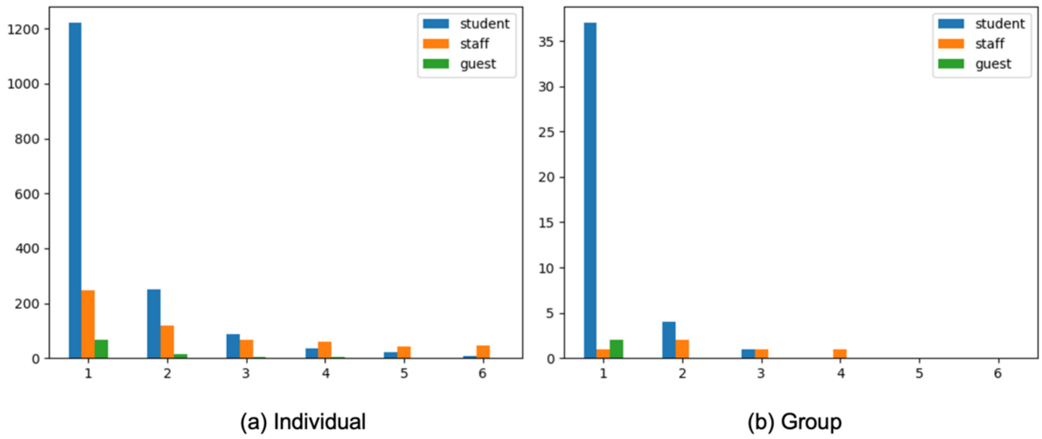



Figure 5.9 Bar charts manifesting the frequency of stay-up behaviours in the week by user type.

Giving regard to the difference in Figure 5.9 (a), guests stayed up once or twice, while students more often stayed up and some stayed up up to six times, and staff also frequently stayed up and showed the highest continuity of the three types. Figure 5.9 (b), indicates that guests stayed up once in a group, most students three times at most, and a smaller amount of staff up to four times.

Upon the assumption that there should have been the dissimilarity in the patterns by user types and utilised buildings depending on the continuity of stay-up behaviours, this study determined to dig into this phenomenon.

Figure 5.10 is visual depictions of inclusive relations displaying user types and faculties for individual stays and group stays varying the continuity of stay-up activities.

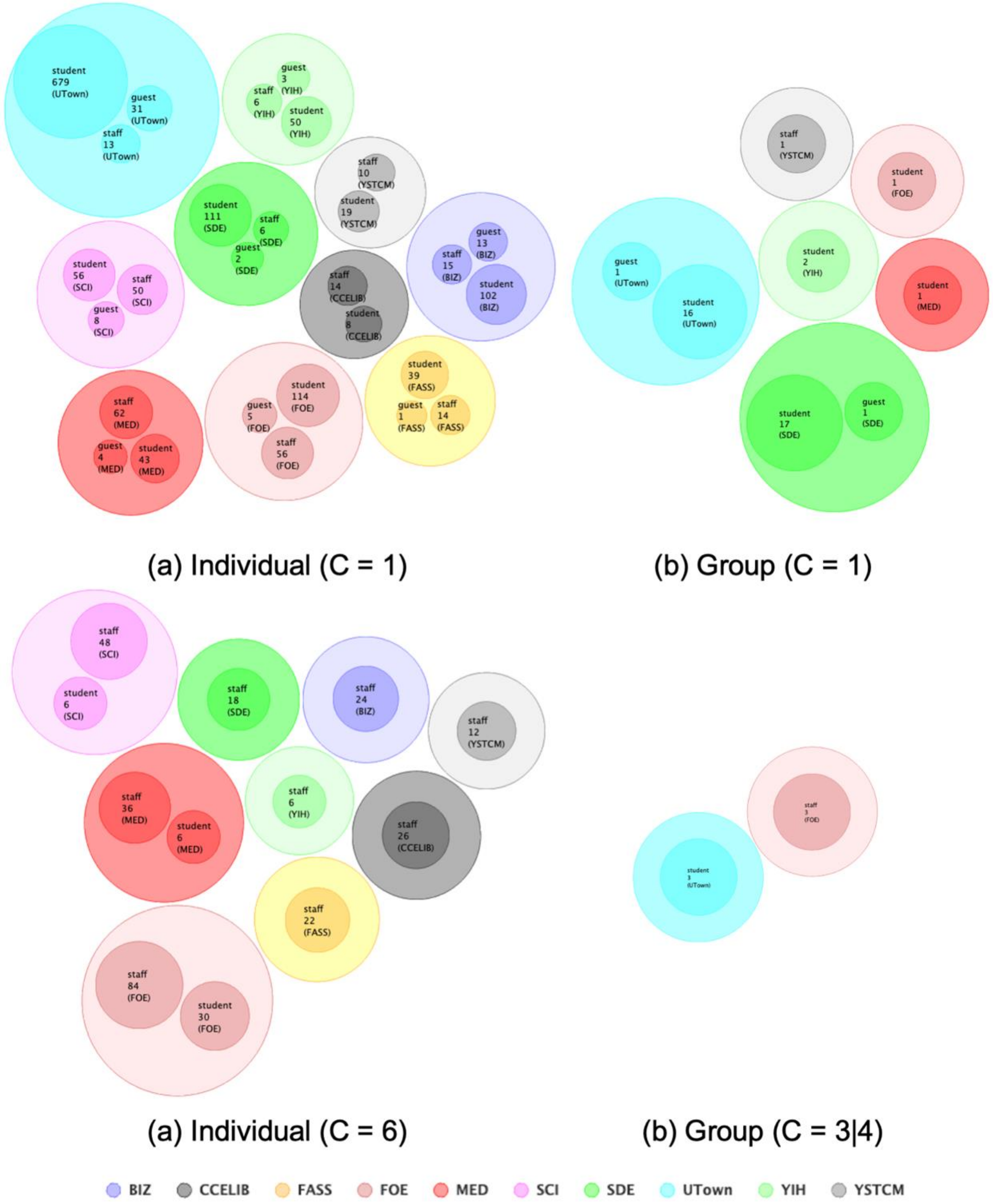



Figure 5.10 Visual depictions of inclusive relations displaying user types and faculties for individual stays and group stays varying the continuity of stay-up activities. Abbreviation: $C$: continuity.

From Figure 5.10 (a, $C$=1), it is clear that stay-ups were well-observed at UTown and FOE, and less at YSTCM, CCELIB and YIH. The top rate of stay-up activity for students was at UTown and that of staff was at FOE. When it comes to the more regular stay-ups, in light of Figure 5.10 (a, $C$=6), staff were present at most of the faculties, while a certain number of students could be seen at FOE, SCI and MED. Changing $C$ from one to six, UTown was no longer found in the chart, meanwhile, FOE became the most significant faculty where individuals sought to stay up regardless of user attributes.

In contrast with individual instances, Figure 5.10 (b, $C$=1) plots stay-ups of students in a group intensively at SDE and staff at FOE, followed by BIZ, while the general feature was undifferentiated. When $C$ was either three or four times, students chose UTown for their late-night activities, whereas staff were concentrated at FOE.

Figure 5.11 is visual depictions of inclusive relations expressing visited buildings and faculties for individual stays and group stays varying the continuity of stay-up activities. Overall, Figure 5.11 helps explain that most of the stay-up points were academic facilities. Taking particular note of some facilities which had a great number of stay-ups, Figure 5.11 (a, $C$=1) depicts that UTown-ERC was the most favoured location as it has a 24-hour café capable of accommodating many people, MochtarRiyardy at BIZ is a nine-storey complex providing a series of informal interaction zones to encourage discussion, the central library at CCELIB was also present, and UHC at YIH also housed a certain volume at midnight. In the case of $C$=6 in Figure 5.11 (a), MochtarRiyardy at BIZ is turned up this time too, meanwhile, the central library and UHC disappear, and a cultural centre at CCELIB, which it is equipped with lounges and function rooms, was also confirmed along with YSTCM (conservatory of Music).

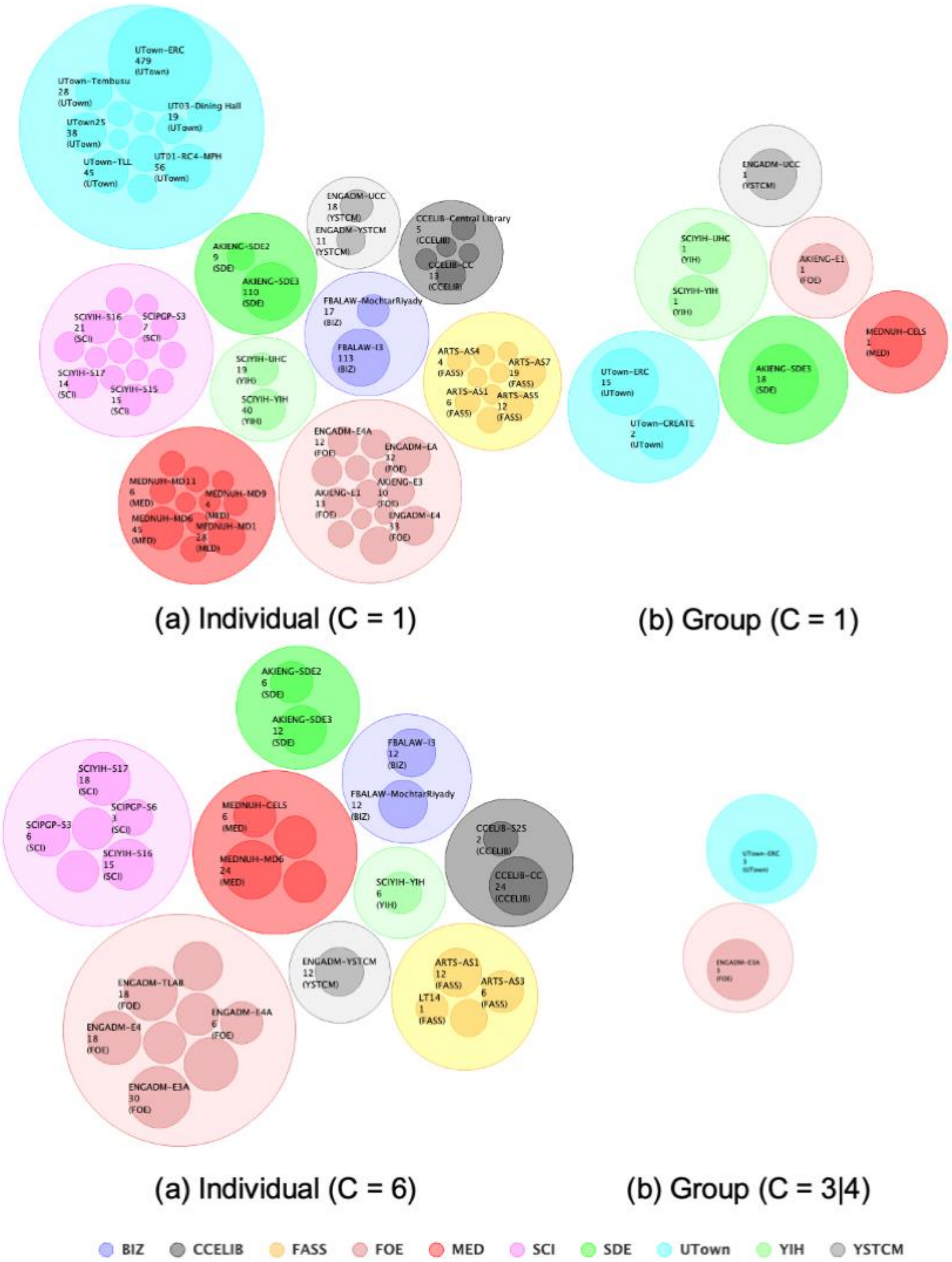



Figure 5.11 Visual depictions of inclusive relations expressing visited buildings and faculties for individual stays and group stays varying the continuity of stay-up activities.

Regarding stays in a group in Figure 5.11 (b, $C$=1), ERC at UTown maintained the popularity, whereas AKIENG-SDE3 (academic facility) was also one of the top tiers but it seemed a topical concentration. When it comes to $C$=3|4 in Figure 5.11 (b), in light of results in Figure 5.10 (b, $C$=3|4), it is indicated that three students chose ERC at UTown to stay up regularly, and three staff dwelled at midnight at ENGADM (academic facility).

## 5.5. Transition patterns

Figure 5.12 is graphic delineations of the transitions among all faculties for individual journeys and group journeys by user type, where the total number of involved journeys $n$ is 157,787 for (a, student), 56,802 for (a, staff), 8,926 for (a, guest), 4,242 for (b, student), 525 for (b, staff) and 119 for (b, guest).

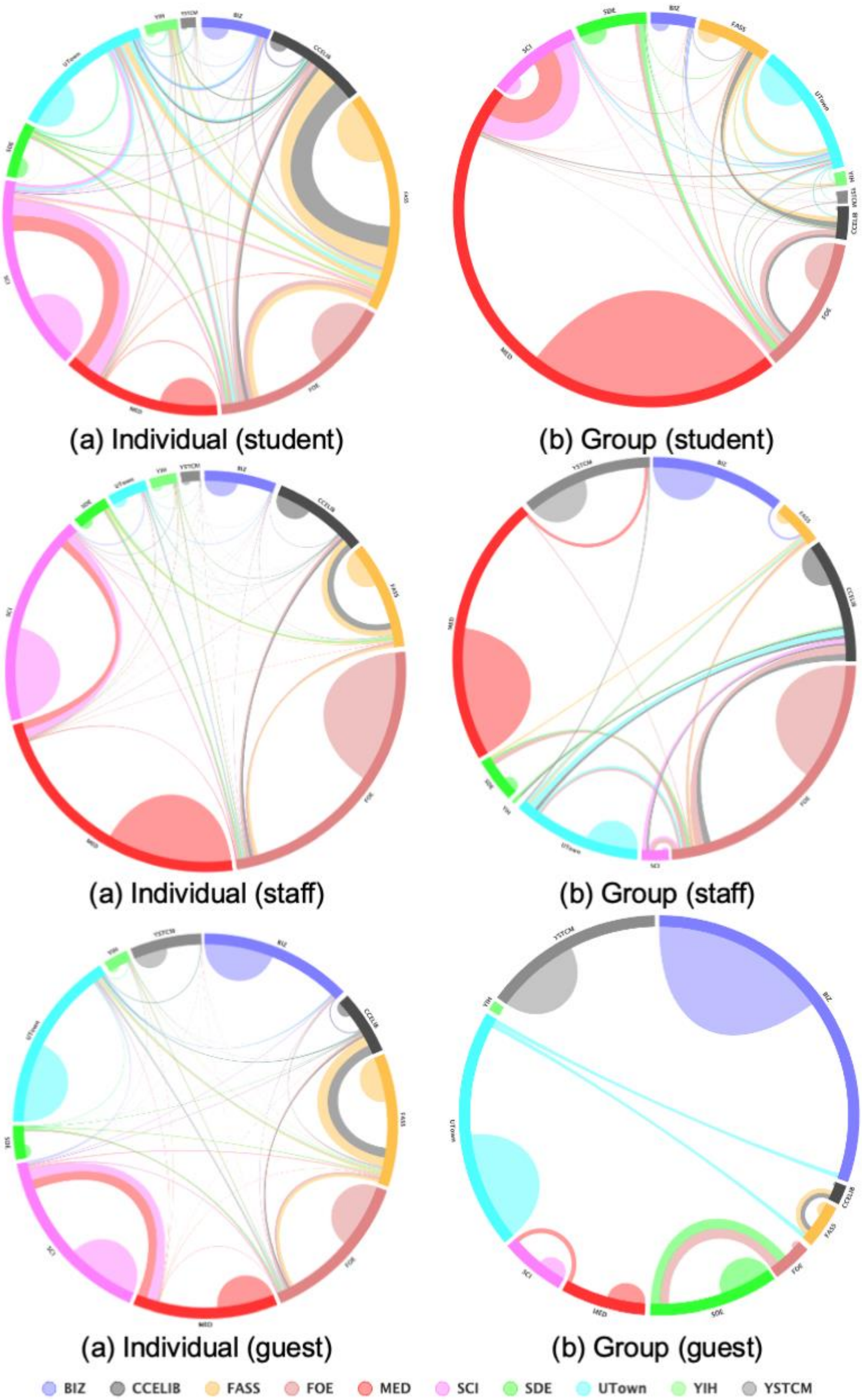



Figure 5.12 Graphic delineations of transitions among all faculties for individual journeys and group journeys by user type.

Figure 5.12 (a, student) delineates a large number of transitions in FASS-CCELIB and SCI-MED. Speaking of UTown, it had a certain amount of traffic with many other faculties, the movements from and to SCI, FASS and FOE were relatively higher than others. With regard to staff, self-transitions (a transition within the same faculty) were remarkable at MED, SCI and FASS in Figure 5.12 (a, staff). The traffic trend from and to UTown declined as well as YSTCM losing transitions with some faculties compared with that of students, while the volumes in CCELIB-FOE and CCELIB-FASS were still active. In terms of guests in Figure 5.12 (a, guest), lines denoting transition activities over faculties became generally thinner than other types, whereas self-transitions at UTown were prominent.

On the other hand, in Figure 5.12 (b, student), as with the individual tendency, huge transitions were discovered in MED-SCI strikingly, followed by FASS-CCELIB, CCELIB-FOE and FOE-SDE, plus, MED pronouncedly had transitions within itself. Concerning Figure 5.12 (b, staff), it experienced a radical decline between MED and SCI dissimilar to that of students. There were still some transitions over faculties among CCELIB, FOE and UTown, meanwhile, MED and FOE were dominated by huge self-transitions. As to Figure 5.12 (b, guest), it uncovers the high inclination of self-transitions at many faculties in lieu of over-faculty movements, yet, a small number of group journeys were seen at UTown.

## 5.6. Network connectivity

Figure 5.13 is network maps of visited buildings by students for individual journeys and group journeys, where the colourisation corresponds as follows: aqua when the node volume $n < 500$, purple when $500 \leq n < 1000$, orange when $1000 \leq n < 2000$ and black when $2000 \leq n$ in (a), whereas aqua when the node volume $n < 10$, purple when $10 \leq n < 50$, orange when $50 \leq n < 100$ and black when $100 \leq n$ in (b).

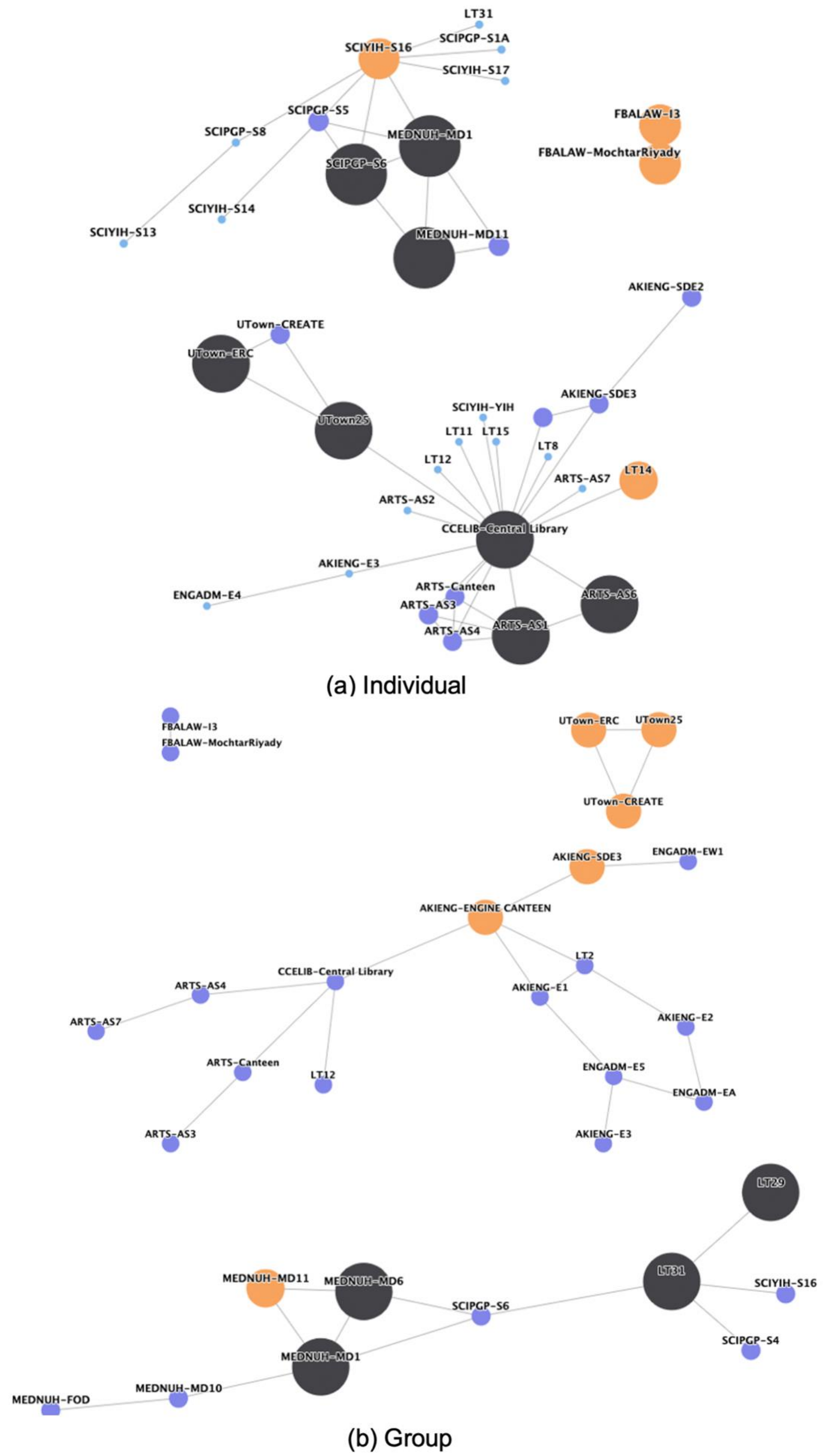



Figure 5.13 Network maps of visited buildings by students for individual journeys and group journeys.

Figure 5.13 (a) reveals the major connectivity among FASS, CCELIB, FOE and UTown, and between MED and SCI as MEDNUH-MD1, MEDNUH-6 and SCIPGP-S6 showed strong connectivity. It is also worth mentioning that the central library was projected as a centre of the network, which interconnected a variety of academic facilities, amenities at UTown and canteens. For example, UTown-ERC and UTown 25, which can accommodate on-campus students and staff, were found to be major nodes.

By contrast, Figure 5.13 (b) exemplifies a similar structure with that of the individual scenario, and in particular, the great connectivity was discerned between MEDNUH-MD6 and MEDNUH-MD1, between LT29 and LT31 and the strength between UTown-ERC and UTown 25 was still outstanding. Apart from that, canteens and the central library had high usage.

Figure 5.14 is network maps of visited buildings by staff for individual journeys and group journeys, where the colourisation corresponds as follows: aqua when the node volume $n < 150$, purple when $150 \leq n < 200$, orange when $200 \leq n < 300$ and black when $300 \leq n$ in (a), whereas aqua when the node volume $n < 1$, purple when $1 \leq n < 5$, orange when $5 \leq n < 10$ and black when $10 \leq n$ in (b).

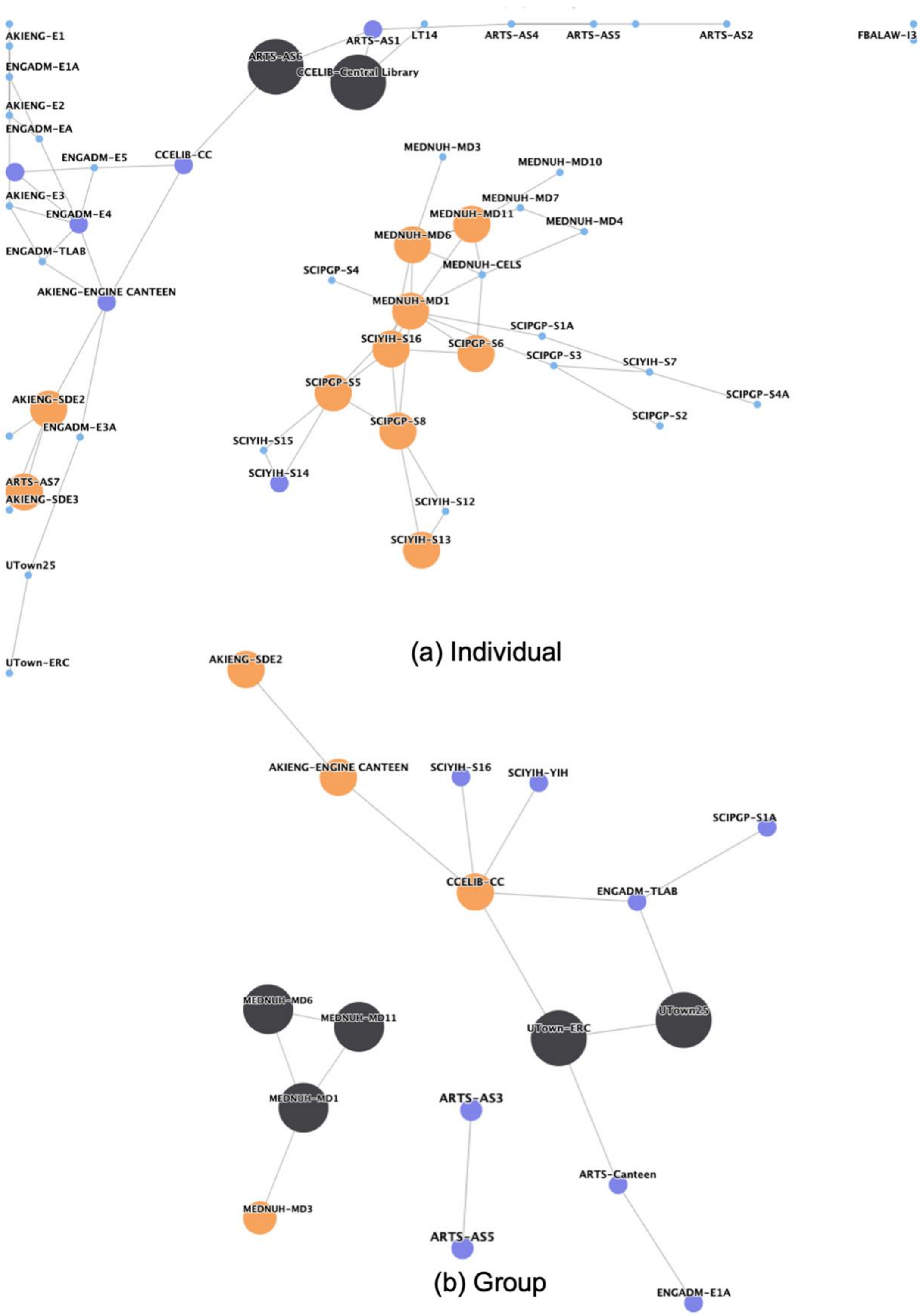



Figure 5.14 Network maps of visited buildings by staff for individual journeys and group journeys.

Figure 5.14 (a) contrasts with the results of students in that the frequency of amenities visited at UTown was saliently reduced, while the central library remained significant as a network hub. Meanwhile, Figure 5.14 (b) depicts the high transitions amongst MED-1, MED-6 and MED-11, whereas amenities at UTown seemed relatively active in the network.

Figure 5.15 is network maps of visited buildings by guests for individual journeys and group journeys, where the colourisation corresponds as follows: aqua when the node volume $n < 30$, purple when $30 \leq n < 50$, orange when $50 \leq n < 100$ and black when $100 \leq n$ in (a), whereas aqua when the node volume $n < 2$, purple when $2 \leq n < 4$, orange when $4 \leq n < 6$ and black when $6 \leq n$ in (b).

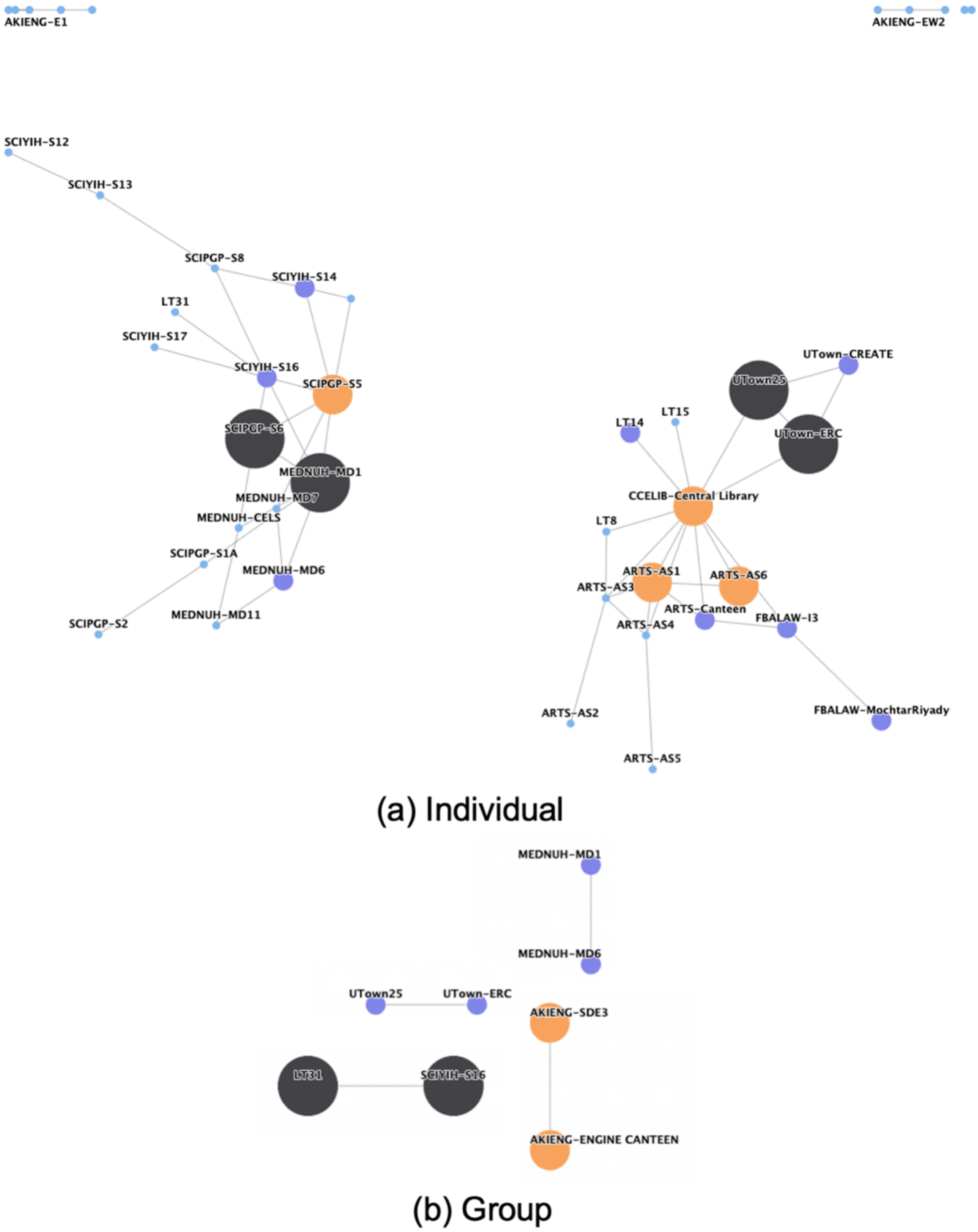



Figure 5.15 Network maps of visited buildings by guests for individual journeys and group journeys.

Figure 5.15 (a) illuminates the network partitioned and the connectivity became sparse. Amenities at UTown seemed popular for guests, while the central library bridged FASS and CCELIB. On one hand, although the whole volume for the network was small, there was a certain connection between LT31 and SCIYIH in Figure 5.15 (b).

# Chapter 6. DISCUSSION AND CONCLUSION

This chapter discusses the findings in the last chapter. It first sorts out the disparities in trip types and user attributes, and then reviews the implication behind the results, followed by the limitations of this study. A conclusion is given at the end.

## 6.1. Heterogeneities and implication

First, in regard to the peak trends, individual stays retained the cyclicity to some extent (i.e. three distinct peaks at 11:00, 13:00 and 15:00) on weekdays, while group stays came with the random periodicity, the same was true of the trends in journeys with a single peak at 13:00. Also, the frequency of group stays at the school of medicine showed the divergence, which over tripled other faculties' on average. In the former finding, the periodic peaks on weekdays should possibly resonate with the class schedules. On the other hand, group trips must have involved the decision-making process over multiple individuals and ended up with the irregularity which triggered the random waveforms in the peak charts. Speaking of the latter result, the school of medicine seems to encompass intensive hands-on classes compared to other faculties and could hence bring about the higher frequency of collective movements.

Second, with reference to the inclusive relation, the volume was inclined to reflect the registered number of students at each faculty in individual stays. Meanwhile, group stays did not seem to follow the same hallmark, with a huge decrease in the number of the group stays in every faculty. This point should be reasonable as group tripping could incur certain costs. At the same time, the inclusive relation described the fact that the volume of staff at STEM faculties retained high both individual stays and group stays, as well as the tendency in staff to act more individually than students.

Third, in terms of activities on campus at midnight, it is a bit eye-opening that individuals regardless of user attributes had an inclination to stay up frequently from Wednesday over Thursday, and the group instances highlighted the same trend more prominently. This is presumed in the way that there should have been piled-up tasks in the middle of the week. What is more, staff overall unveiled the higher continuity of stay-up behaviours than students, whereas visitors acted at midnight once or twice. This analysis also illuminated the pattern that amenity space was popularly utilised by student individuals temporarily and so as facilities such as a library and healthcare centre when it comes to group activities in the middle of the night, meanwhile academic facilities generally housed a certain volume of regular stay-up regardless of group-forming, especially, at the faculty of engineering.

For transition patterns, it revealed a homogeneity that traffic was strongly linked to the physical proximity of buildings, though self-transitions in a group at the school of medicine was striking. Respecting the difference by user attribute, the movements from and to the recreational site were conspicuous in students but staff, both in individual and group trips, whereas visitors tended to self-transit in a group. It can be assumed that they enjoyed sightseeing with the help of navigation.

Last, with respect to network mapping, it conveyed an insight that each network was partitioned into some sub-networks and was related to the physical vicinity, especially when buildings were physically adjunct over faculties, as confirmed by most user types. Also, the traffic between amenity space and the library was notably depicted in students' network. Furthermore, the position of a functional space (e.g. library) in the network varied with user attribute, as it functioned as a centre for students and visitors but only a hub for staff. This helped explain the displacement in the topology of the network people mainly utilised. To visitors, recreational and amenity space with open availability for sightseeing on campus attracted more attentions.

## 6.2. Limitations

Since the dataset is from 2018, the validation is hardly implemented; whereas the inference based on the aforesaid framework is summarised in the present study. Also, the highest resolution of the spatial attribute is a one-floor basis in the buildings, and WiFi stations are unevenly distributed at some places; thus, those points might be a limitation of this study as they can trigger the accuracy issues. In this perspective, fusing the framework with GPS can complement the uncaptured user movements in the spatial test bed.

## 6.3. Conclusion

The present study proposed a juxtaposed framework to illuminate the displacements between individual trips and group trips concerning trip types and user attributes. The framework was tested on the campus of a huge university in Singapore as a test bed. Through the full battery of data processing, this study presents obvious contrasts respecting the inclinations in peaks, distributions of stays, activities at midnight, patterns in transitions and network topologies, by individuality, group solidarity and user attributes. In terms of the forthcoming applications, this study opened the possibility to build a predictive model, which considers the distinction in trip types and user attributes. Furthermore, such a model is expected to induce benefits for the public welfare, for example, optimising infrastructure resources and detecting collective movements during a worldwide pandemic. Last but not least, I hope this study helps see the light at the end of the tunnel with the difficult Covid-19 era.

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