Party on? Inferring campus parties from WiFi logging

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The quality of campus directly impacts student satisfaction and retention rates, making it crucial to understand how students interact with their campus environment. The traditional ways of analysing student behaviour (questionnaires and surveys) may produce biased results. Alternatively, collecting and analysing data, such as internet monitoring data and device connection logs, can provide valuable insights into student behaviour.

This research paper explores student behaviours on the University of Twente campus by analysing anonymised WiFi router connection data. Specifically, it focuses on students' partying behaviour in the residential areas of the campus. Analysing students' partying behaviour using WiFi connection data offers a data-driven approach to understanding student interactions with their campus environment. It provides insights for campus administrators, planners, and educators in developing targeted strategies to improve campus infrastructure, enhance resource allocation, and provide a better experience for students.

Additional Key Words and Phrases: WiFi log analysis, Student behaviour, University campus

1 INTRODUCTION

The quality of campus directly affects student satisfaction and student retention rate[5]. Understanding students' behaviour on campus, such as how students utilise campus spaces and navigate the university environment, can provide valuable insights for future campus planning, resource allocation, security measures and student experience enhancement. Analysing student behaviour using the traditional way of getting samples (questionnaires, surveys, and interviews), there are many possibilities for generating biased results [1]. An alternative is to collect other data that would address the goal and analyse these data instead.

With the growth in the number of WiFi-enabled devices, the internet monitoring data, such as device connection logs that the ICT department of the institute usually collects for network security and monitoring purposes, became valuable data for other purposes. During the Covid-19 pandemic, these data played a significant role in WiFi Trace technology used for contact tracing of infection[9]. These data were also used for monitoring the crowd level in each building[3].

For this paper, we will utilize a dataset supplied by the UT ICT department (LISA), which comprises the following data:

(1) Details on all access points under UT management, including their locations.
(2) Anonymized data on the devices connected to these access points and their respective owners.

The access points collect data every five minutes, and in each collection round, all the devices and users are re-assigned with a random identifier. So we can not identify who the users are, and we cannot track users across multiple collection rounds.

There are lots of interesting observations and analyses that can be done through these data. Our main research for this paper is: "Inferring campus parties from WiFi logging." As there are many analyses for student mobility behaviours on campus during teaching hours, we want to provide more insights for the ICT department about student behaviour during after-class hours. Therefore, we came up with the subquestions below:

(1) Where are the most attended student house gatherings or parties hosted around the University of Twente campus residence?
(2) Which month of the year are students most active with social gatherings or parties?
(3) Which day of the week are students most active with social gatherings or parties?
(4) How did the Covid-19 pandemic affect student mobility behaviour?

Investigating the above questions using the WiFi connection data will provide a data-driven approach to understanding how students interact with their campus environment. It will also offer valuable insights for campus administrators, planners, and educators in developing targeted strategies to improve campus infrastructure, enhance resource allocation, and provide a better experience for students.

The remainder of the paper will be organised as follows. In section 2, we will review the relevant literature on student behaviour analysis based on WiFi router connection data. Then we will briefly describe the data provided in section 3 and present the methodologies used in this study, including data preprocessing and data analysis techniques in section 4. Then, we will give our findings through data analysis, discussing the patterns and trends observed in the WiFi connection data in section 5. Finally, we will document ethical considerations in section 6, talk about future work in section 7 and conclude in the last section of this paper.

2 RELATED WORK

Many analyses are already done on human behaviour based on access points connection data. In this section, we will discuss two related work types: human presence detection and human mobility analysis.

L. Schaue et al. evaluated the accuracy of estimating crowd densities and pedestrian flows using Wi-Fi and Bluetooth in a naive way. Also, they presented three ways how to improve the estimation. [8] T. Huang et al. designed and implemented a WiFi-based real-time system for contactless human detection. [6] W. Li et al. proposed a novel system for non-invasive human presence detection by analysing the Doppler information contained in the WiFi signals. [7]

TScIT 39, July 7, 2023, Enschede, The Netherlands

Table 1. **ap_config** sample data

ap_config_id	ap_sys_mac	location
000001	ff:ff:ff:ff:ff:ff	Carre vl 3 nieuw
000002	ff:ff:ff:ff:ff:e0	Calslaan 13 vl 2

Table 2. **ap_location** sample data

ap_location_id	ap_sys_mac	location
000001	ff:ff:ff:ff:ff:ff	000000000A00000
000002	ff:ff:ff:ff:ff:e0	<null>

F. Chen et al. [2] have analysed student behaviour and designed a geospatial dashboard-based visualisation system based on students' characteristics and spatiotemporal patterns. C. Chilipirea et al. and L. Vu et al. analysed different techniques to identify movement in the building based on the WiFi connection data and also provided ways we can improve[4, 10] T. Xins et al. used a combination of Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT) and Dynamic Time Warping (DTW) techniques to recognise different movements based on the way how different personal movements influence WiFi signals [11]

In this study, we take a different view on behaviour through the analysis of WiFi connection data. We use the data to infer social gatherings and parties on a university campus. By analysing anonymized access points connection logs, we gain insights into student behaviours during after-class hours in residential areas of the campus. This provides another perspective on understanding student interactions with their campus environment.

By focusing specifically on student party behaviour, our study complements existing work by providing targeted insights into social dynamics and student engagement in campus residential areas. While previous studies have examined broader aspects of student behaviour, we narrow our scope to understand students' social gatherings and party behaviours on campus.

3 DATA DESCRIPTION

The dataset utilized in this study is generously provided by the Library, ICT Service & Archive (LISA) department at the University of Twente. It contains information from the WiFi access points located across the entire University. This includes access points in both educational buildings and student dorms across the whole campus of the University. This data provides the starting point of our study on student party behaviour in student dorms.

3.1 Data Information

Data collection was performed by the LISA department, which continuously monitors the university's WiFi access points. The dataset consists of data gathered at five-minute intervals spanning from 2019-07-12 to 2023-06-15. The dataset is organized into three tables within the PostgreSQL database:

(1) **ap_config:** This table has 277370 rows of data that contain detailed information about each access point, including its MAC address and other descriptive data, from which the physical location of the access point can be inferred. Table 1 shows sample data.

(2) **ap_location:** This table has 40692 rows of data which provide geo-location data associated with each access point's MAC address. Table 2 shows sample data.

(3) **client_assoc:** This table includes around 1.5 billion rows of data about each connection to the access points by the clients, such as a randomly assigned client identifier, the time of connection, and the associated user. For privacy reasons, the identifiers for devices and users are randomly reassigned in each collection round, thus preventing the identification or tracking of specific users or devices across multiple rounds. Table 3 shows sample data.

3.2 Limitation

Although the dataset provided by the Univeristy LISA department offered valuable insights into the university's WiFi usage, some limitations should be considered.

(1) **Lack of User Data:** A key limitation in the dataset is missing data in some of the **client_user_name_mapped** fields. Where we could identify the number of unique users connected to each access point within the 5 minutes time interval. Therefore, the analysis could only consider the number of devices connected to each WiFi access point, not the number of individual users. This limitation prevented us from gaining insights into user-level behaviours and restricted our understanding to device-level analysis. We believe, however, that the number of connected devices for each access point is a good proxy for the number of people present at each location.

(2) **Lack of User Continuity:** Due to privacy measures, identifiers for devices and users are randomly reassigned in each collection round, preventing tracking specific users or devices across multiple rounds. This means our study could not analyze longitudinal trends at the individual user or device level.

(3) **Location Inference:** The geo-location for some access points is not specified; therefore, the physical location of access points had to be inferred from the description in the **ap_config** table, which might not always be precise. Any inaccuracies in this inference could impact our understanding of the relationship between access point location and usage patterns.

These limitations should be considered when interpreting our study's findings.

4 METHODOLOGY

In this section, we will discuss the methodology used in our study to perform our analysis. This includes two steps; the first step is data preprocessing, where we preprocess the data in the way that best fits our analysis method, and the second step is the actual analysis based on the preprocessed data.

Table 3. **client_assoc** sample data

client_assoc_id	**ap_location_id**	**time_ingested**	**client_user_name_mapped**
00000001	104106	2022-01-21 13:01:31.961944 +00:00	abABABABa
00000002	104201	2022-01-21 13:01:31.961944 +00:00	<null>

4.1 Data Preprocessing

The preprocessing of data involved several key steps to ensure its readiness for analysis. These steps primarily focused on cleaning, reformatting, and labelling the data and mapping related elements between the different tables in the dataset.

(1) **Data Mapping:** One of the critical steps in the preprocessing was the integration of location data from the **ap_config** table into the **ap_location** table. Initially, the **ap_location** table lacked actual location information, which was provided as text descriptions in the **ap_config** table, associated with each access point's MAC address.
In the client_assoc table, each device connection was linked to an **ap_location_id**, but without the corresponding location information from the **ap_config** table, the insights that could be drawn from the **client_assoc** table were limited. Therefore, a mapping was established to link the MAC addresses in the **ap_config** table with their corresponding location descriptions. The location descriptions from the **ap_config** table were then integrated into the **ap_location** table using this mapping.
This data integration procedure effectively bridged the **client_assoc** and **ap_config** tables through the **ap_location** table, providing comprehensive information about each client connection's physical location.

(2) **Manual Labeling:** The detailed location descriptions were manually simplified and categorized for a more high-level analysis. For instance, specific location descriptors like "Calslaan 6 vloer 3" were re-categorized under broader labels such as "Calslaan 6".
Also, each location was further labelled as either an "educational" or "residential" building. This classification was based on the description of the location and supplemented with information from the campus map. This manual labelling was especially important for residential buildings. Most dormitories on campus share a common space for cooking and gathering. For our study, it was critical to consider each dormitory building as a whole rather than individual dorm rooms.

(3) **Data Filtering and Selection:** Once the manual labelling of locations was complete, we performed a selection process to keep only the data that was relevant to our research question. Given our interest in WiFi usage in residential buildings, we filtered our data only to include client connections where the location had been labelled as "residential".
This filtering step resulted in a subset of data that specifically represented WiFi usage in residential buildings, allowing for a more focused analysis that matches our study.

(4) **Data Aggregation:** After the cleaning, mapping, labelling, and filtering processes, the data were aggregated to form a more concise and meaningful dataset for analysis. For each round of the data collection, a row is generated for each client connected to an access point; it was necessary to group the data by location and timestamp to generate a count of clients at each location for each collection round.
To achieve this, we grouped the **client_assoc** table and created a new field, **client_count**, that represented the number of clients connected to a given location at a particular timestamp. This field was created by grouping the data by location and timestamp and counting the number of rows for each group.
This aggregation process transformed the data from a detailed log of individual connections into a time-series dataset representing the WiFi usage density at each location over time. This format was better suited for our objective of identifying periods of unusually high WiFi usage that might indicate a party.

(5) **Extra Feature Addition:** A weekday column was added to the data to prepare for our study. This column represented the day of the week for each timestamp.
By adding the weekday, we enabled an analysis of WiFi usage patterns that took into account the day of the week. This feature was useful in identifying potential variations in WiFi usage across different days, which could be insightful when inferring the occurrence of parties.
For example, one might expect WiFi usage in residential areas to be different on weekdays compared to weekends. By adding this feature, we were better equipped to explore such hypotheses.

Table 4 shows sample data after being processed and ready to be used for analysing

4.2 Data Analysis

We mostly focused on the **client_count** field, which shows how many clients are connected to each location at any given time. This section will explain the analysis steps we took to get to the final results.

(1) **Temporal Focus:** We first narrowed down the dataset to include data only from the hours of 18:00 to 6:00, considering that social gatherings or parties are more likely to occur during these hours. This step ensured that our analysis was targeted towards identifying significant deviations during these key time periods.

(2) **Computing Client Count Mean:** For this step, we aimed to establish a baseline or "normal" number of clients connected

Table 4. Preprocessed sample data

location	time_ingested	client_count	weekday
Calslaan x	2022-01-21 13:01:31.961944 +00:00	12	0
Witbreuksweg xxx	2022-01-21 13:01:31.961944 +00:00	32	3

to each access point during the designated hours (18:00 to 6:00). We calculated the average **client_count** for each location during the corresponding period over one month. This shorter interval was selected to make the baseline more responsive to changes and variations in WiFi usage, which would be more diluted in longer intervals. We can take calculating the three-month mean for July, August and September as an example; July and August are typically summer vacations when many students are away from campus, resulting in low WiFi usage in dorms. Whereas at the end of August and in September, students return to campus, leading to increased WiFi usage. If we were to calculate the mean client count for these three months, it would dilute the variations in WiFi usage due to the big difference between the number of connections during summer vacation and the start of the academic year resulting in the baseline calculated using this longer interval would not accurately reflect the average WiFi usage during September.

To do this, we extracted all data for each location within the one-month intervals and our designated hours. We then calculated the mean **client_count** for each of these subsets. This mean **client_count** represented the average level of WiFi usage for each location during these hours over the months. It served as a baseline by which we could compare individual timestamps to identify social gatherings or parties. Table 5 shows resulted sample mean data for a residential building located on Calslaan street.

(3) **Identifying Potential Gatherings and Parties:** Building on the calculated baselines, we progressed to identifying potential parties. We determined a specific criterion where a **client_count** at a given timestamp and location exceeding twice the average **client_count** for the corresponding period would be flagged as a potential party.
This criterion was designed to detect unusually high WiFi usage, which we hypothesized could signal the occurrence of social gatherings or parties. This allowed us to systematically identify data that significantly deviated from the mean, providing us with a dataset of potential social gatherings or parties.

Table 6 shows the sample inferred potential party data after running the analysis method mentioned above

5 RESULTS AND DISCUSSION

Due to limitations in our anomaly detection approach, which identifies potential parties based on a threshold of the client count exceeding twice the baseline for the corresponding period, biases can arise for specific periods, specifically during low-activity periods like the summer break in July and August when many dorms are mainly empty. Even minor increases in the client count in this period can be mistakenly identified as potential gatherings or parties. This can result in an overestimation of gatherings or parties.

To mitigate this artefact and avoid the potential overestimation, we decided to exclude the data for July and August from our analysis. By removing these low-activity periods from the dataset, we aim to reduce the likelihood of falsely identifying small increases in the client count in low-activity periods as potential parties.

After identifying potential parties based on our defined criterion, we further grouped the data by street to gain insights into the distribution of parties in different locations. This involved aggregating party data from different buildings located on the same street. For example, party data from 'Calslaan 1' and 'Calslaan 2' were both grouped under 'Calslaan'.

5.1 General Party Behavior

Figure 1 represents the monthly party count from September 2019 to June 2023. The X-axis represents time in months, and the Y-axis shows the number of potential gatherings or parties detected each month.

The almost flat lines at the bottom of the graph, representing the streets Sky, Mondriaan, Drienerburght, and Witbreuksweg, indicate fewer parties taking place in these areas than in others. This is likely due to the nature of the accommodations on these streets, which primarily consist of self-contained studio apartments. By their design, they have less common space available for hosting gatherings or parties. This context could explain the lower incidence of parties observed in these areas throughout the study period.

An interesting pattern can be seen in the graph is the consistent peak in party count observed in December of each year. This might indicate increased potential gatherings and parties towards the end of the year and the beginning of the winter break. Such a pattern might be linked to various factors, including the holiday season, Christmas, the new year and the pre-vacation period.

For Calslaan and Matenweg, the graph also indicates a significant increase in the party count in May. This potential wave in gatherings and parties could be attributed to various public holidays observed this month, including Kings Day and Liberation Day.

The graph also shows a decrease in the party count across Calslaan, Campuslaan and Matenweg from March 2020 to February 2021, as well as the peak for May 2020, which is also significantly lower compared to the same month in other years. This drop in social gatherings and parties aligns with the global outbreak of the COVID-19 pandemic and the subsequent restrictions put in place to control its spread. Given the circumstances, social gatherings, including parties, would have been limited due to safety measures such as social distancing, lockdowns, and curfews.

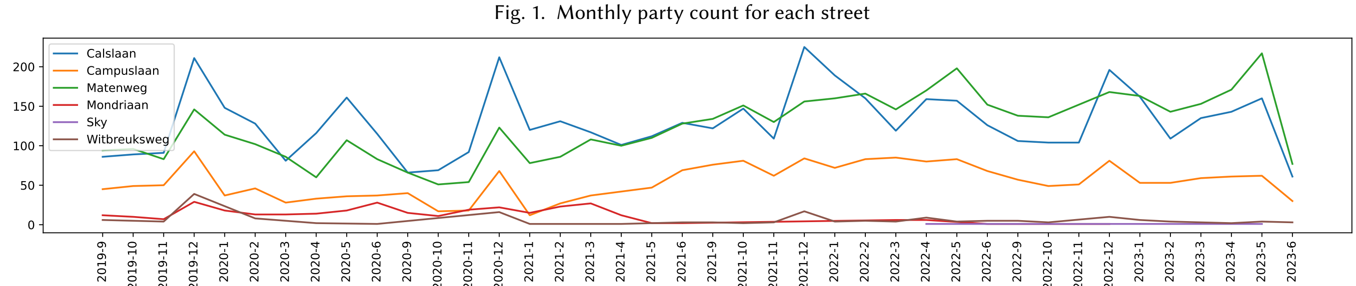
Table 5. Client count mean sample data

From	To	Mean
2019-07-1	2019-08-01	25
2019-08-01	2019-09-01	36
2019-09-01	2019-10-01	36
2019-11-01	2019-12-01	30
2019-12-01	2020-01-01	24

Table 6. Sample identified party data

Location	One Week Before Without Party	Client Count	Baseline	Timestamp Party Day	Client Count
Calslaan X	2023-04-22 18:52:48	28	39	2023-04-29 18:52:52	79
Calslaan X	2023-04-22 18:56:46	28	39	2023-04-29 18:56:50	85
Calslaan X	2023-04-22 19:00:48	28	39	2023-04-29 19:00:51	79
Calslaan X	2023-04-22 19:04:44	28	39	2023-04-29 19:04:45	81
Calslaan X	2023-04-22 19:12:43	29	39	2023-04-29 19:12:47	83
Calslaan X	2023-04-22 19:16:46	30	39	2023-04-29 19:16:52	85
Calslaan X	2023-04-22 19:20:54	30	39	2023-04-29 19:21:00	98
Calslaan X	2023-04-22 19:24:48	29	39	2023-04-29 19:24:49	107
Calslaan X	2023-04-22 19:28:46	30	39	2023-04-29 19:28:50	112
Calslaan X	2023-04-22 19:32:45	28	39	2023-04-29 19:32:47	119
Calslaan X	2023-04-22 19:36:46	27	39	2023-04-29 19:36:53	118
Calslaan X	2023-04-22 19:40:43	27	39	2023-04-29 19:40:47	115
Calslaan X	2023-04-22 19:44:46	27	39	2023-04-29 19:44:51	113
Calslaan X	2023-04-22 19:48:44	28	39	2023-04-29 19:48:45	112

Fig. 1. Monthly party count for each street



We can answer the first and second research questions based on the graph. It is evident from the graph that most social gatherings or parties on campus happen in the Calslaan residential area. Alongside the location, the graph also highlights patterns in student party behaviour. There is a distinct peak in party count in December each year, suggesting it to be the most active month for social gatherings and parties.

5.2 Party Behavior By Weekdays

Figure 2 shows the total party count for each day of the week, broken down by different streets. Each street is represented by a unique colour on the chart. The x-axis represents the weekdays from Monday to Sunday, and the Y-axis represents the party count for each weekday.

Similar to the figure 1, the bar representing Sky, Mondriaan, Drienerburght and Witbreuksweg streets on this graph is also almost at the base of the chart.

For the other streets, there is a steady count of parties from Monday through to Wednesday, with a peak typically occurring on Wednesday. This suggests that the early part of the week tends to see a consistent level of social gatherings or parties and intensifies by the middle of the week.

Furthermore, Monday's relatively high party count could be attributed to parties extending from the weekend into the early part of the week. This could be the case if parties started late on Sundays and continued past midnight, hence being recorded as Monday parties in our dataset.

The graph indicates a steady decline in party count from Thursday to Saturday, with the lowest point typically reached on Saturday. This trend could potentially be affected by the Dutch students, where many of them are known to travel back to their parents' homes over the weekend, where they typically leave on Friday.

The graph also shows an increase in party count on Sundays. This could suggest that social gatherings and parties happen again towards the end of the weekend, likely because students return to campus after their weekend visits home.

Based on what we observed in the graph, we could answer the third research question that social gatherings and parties are most active on Wednesdays, followed by a decline towards the end of the week and a resurgence on Sundays.

5.3 Party Behavior Before and During Pandemic

Figure 3 represents the number of devices connected to a particular location across 30 hours. Each of the four lines represents a different day but within identical hours. Two of these days are before the COVID-19 pandemic, and two of them are during the pandemic.

We have learned from figure 1 that the party frequency dropped during the pandemic period. There is another interesting fact we observed in figure 3.

Although the timing and duration of potential social gatherings or parties remained steady during the pandemic (19:00 - 1:00), a significant change was detected in the morning connection patterns following these gatherings. More devices were connected the following morning during the pandemic compared to a post-party morning before the pandemic.

A possible explanation for this shift is the implementation of a curfew due to the pandemic. With a curfew from 21:00 to 4:30, more students seemed to stay overnight following a gathering or party, reflected in the increased device connections the following day.

Both points show the effect of the pandemic on student social behaviour.

6 ETHICAL CONSIDERATIONS

In this study, we collected and analysed WiFi connection data from the LISA department of our university to examine patterns of social gatherings and parties on campus. The data used in this study had potential privacy implications as it tracked device connections to WiFi access points, which could indirectly reveal individual students' location and movement patterns.

We took several ethical aspects in mind during our study:

(1) **Anonymity:** All WiFi connection data was fully anonymised before we received it. Every collection round re-assigned all devices and users with a random identifier, ensuring we could not identify or track individual users across multiple collection rounds.

(2) **Data Minimization:** We only used data necessary for our research. Any additional data that are not relevant to our research questions were excluded.

(3) **Data Handling:** All the data was stored in the university's PostgreSQL database, and only the research team was permitted access.

(4) **Location Aggregation:** Our study aims to identify which campus dorms have the most student parties. However, publicising these specific locations could bring unwanted attention and potentially negative consequences for students living in these dorms.
To avoid these concerns, we have adjusted our methodology. Rather than specify individual dormitories, we presented our results in an aggregated form at the street level. For instance, we discussed trends on "Calslaan" as a whole instead of distinguishing between individual dorms on that street.

7 FUTURE WORK

While the current study provided insightful findings, there is room for methodological advancements. Although effective for this preliminary research, our anomaly detection approach was quite simple, relying on a static threshold to define anomalies.

We aim to implement a more sophisticated anomaly detection method for future work. Potential improvements could involve leveraging statistical and probabilistic models that account for natural variations and trends in the data rather than treating all deviations equally. This could enhance the accuracy and sensitivity of our detection mechanism.

These advanced models could also help us understand the nuances better, such as identifying different types of gatherings based on the magnitude and duration of the anomalies. Investigating whether certain events could be differentiated based on WiFi usage patterns would be particularly interesting.

In doing so, we expect to refine our understanding of student behaviour, thereby offering more nuanced insights into the social dynamics within the campus residential areas. This, in turn, would inform more effective and targeted policies for managing student life on campus.

8 CONCLUSION

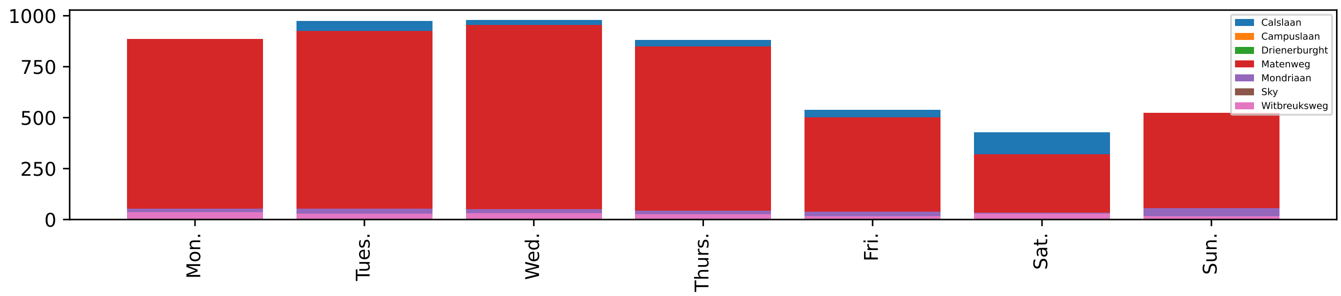
In conclusion, this research provides insightful findings on the patterns of social gatherings and parties in residential areas of the campus using WiFi connection data from the LISA department of the university. The study highlights the utility of leveraging digital footprints for understanding student behaviours and trends.

The data showed a clear correlation between WiFi usage and the frequency of parties. Parties were found to occur most frequently in the Calslaan residential area, suggesting this to be a significant social hub within the campus. Temporally, December emerged as the most active month for social gatherings, possibly due to the conclusion of holiday celebrations.

In addition, the study illustrated the impact of external events on student party behaviour. The global COVID-19 pandemic, for example, led to a noticeable decrease in the frequency of parties between March 2020 and February 2021.

While the study used a relatively simple anomaly detection method to identify potential parties, future research could explore more sophisticated statistical and probabilistic methods. It would also be beneficial to examine the long-term effects of the pandemic on student behaviours and whether these will permanently alter social patterns on campus.

Fig. 2. Total party count grouped by week day



This research shows the importance of monitoring and understanding student behaviours for effective campus management. As digital data becomes increasingly available, such analyses can offer valuable insights for policy-making and campus resource allocation.

9 ACKNOWLEDGEMENT

I would like to thank my supervisor Prof Roland M. van Rijswijk-Deij, who supported me and provided lots of feedback and suggestions. Also, I would like to thank Dr Berend J. Meijerink for being at the supervisor meeting and providing suggestions. Lastly, I would like to thank the University LISA department for providing the dataset so I can do the research and also thank Jeroen van Ingen Schenau, who helped explain and connect to the database.

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Fig. 3. 30 Hours Timeline For Parties Before and During Covid-19