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THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

FACULTY OF CONSTRUCTION AND ENVIRONMENT
建設及環境學院

DEPARTMENT OF BUILDING & REAL ESTATE
建築及房地產學系
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Constructing Smart Cities

17 – 21 June 2019 (Monday – Friday)
The Hong Kong Polytechnic University,
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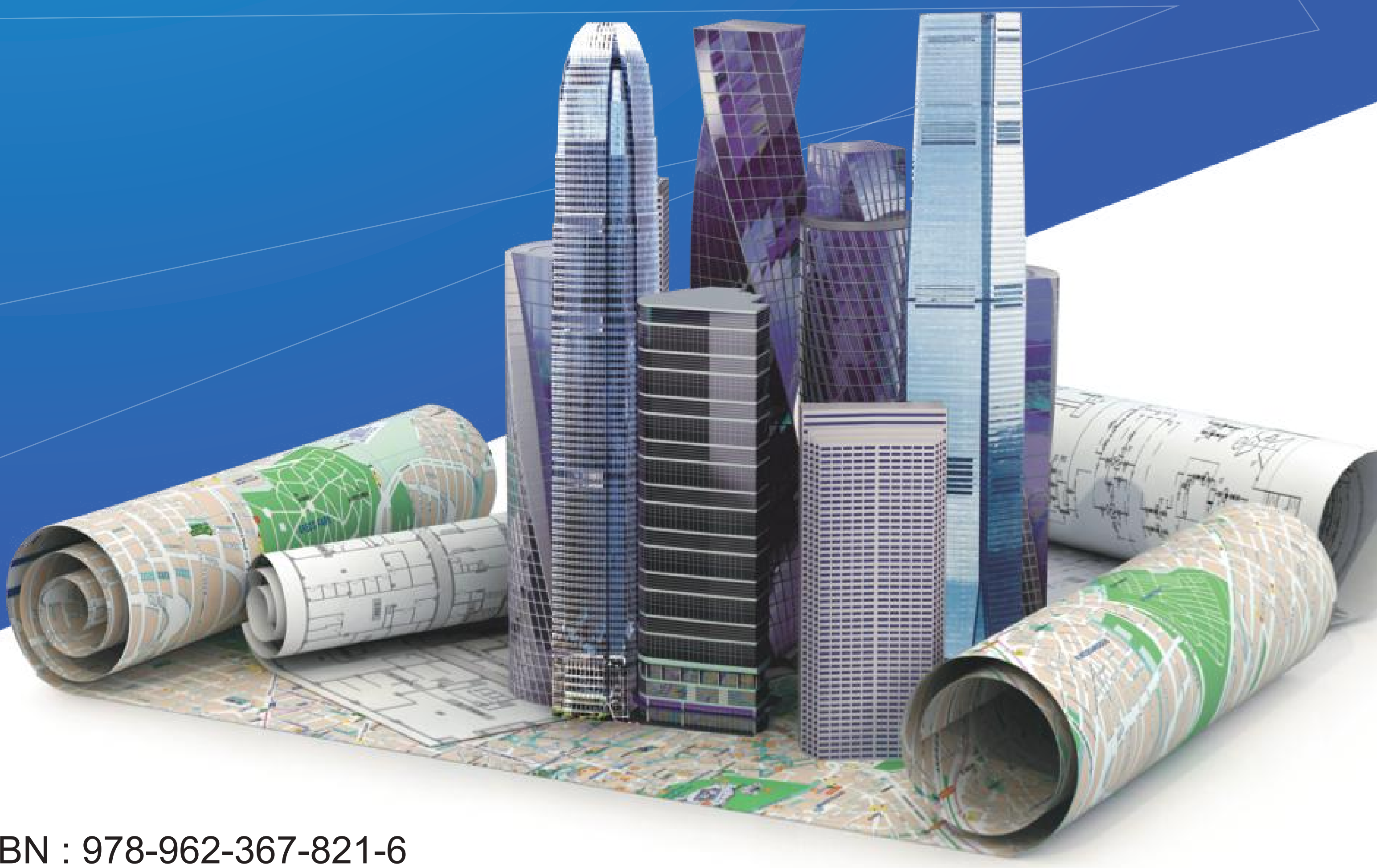

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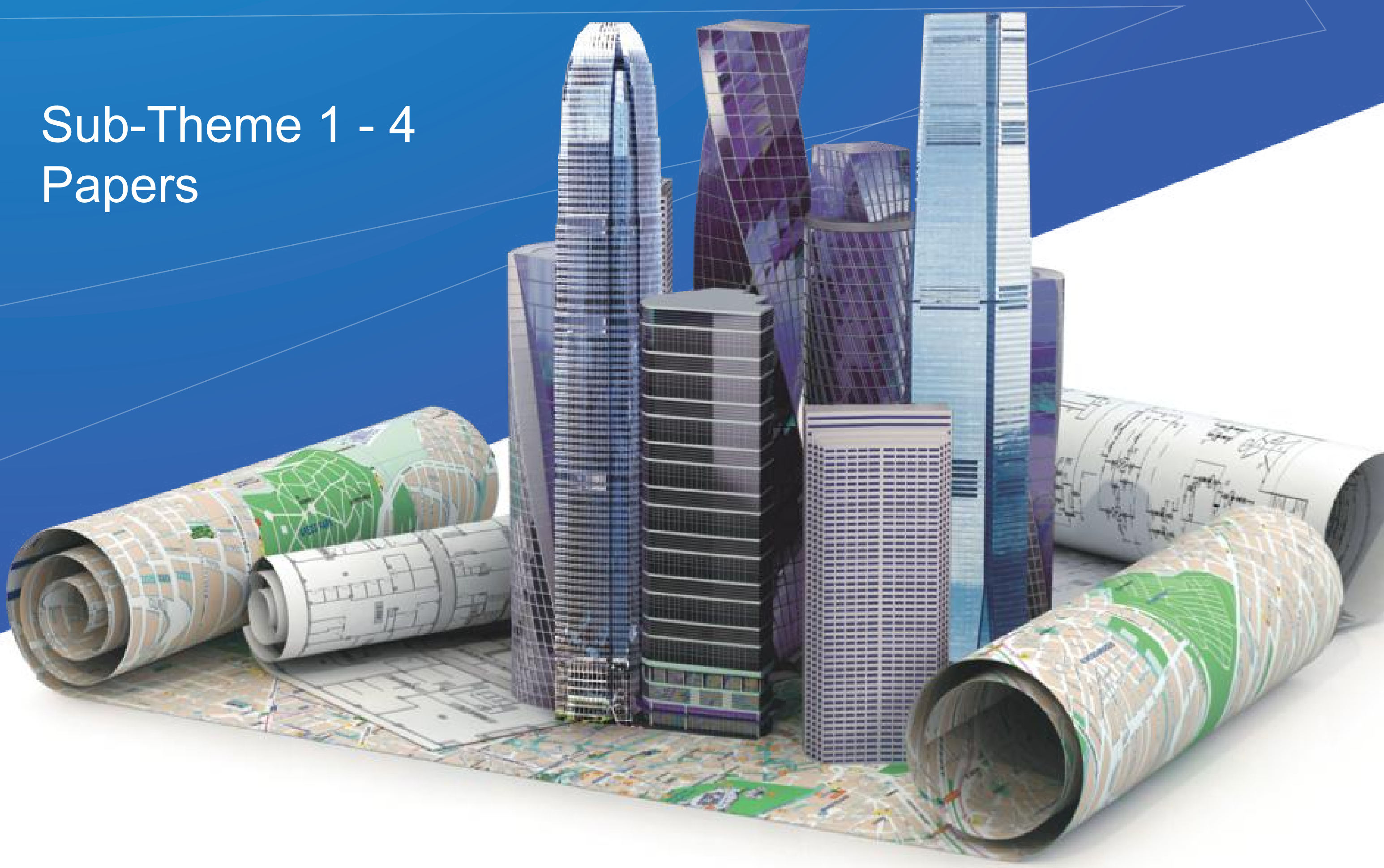

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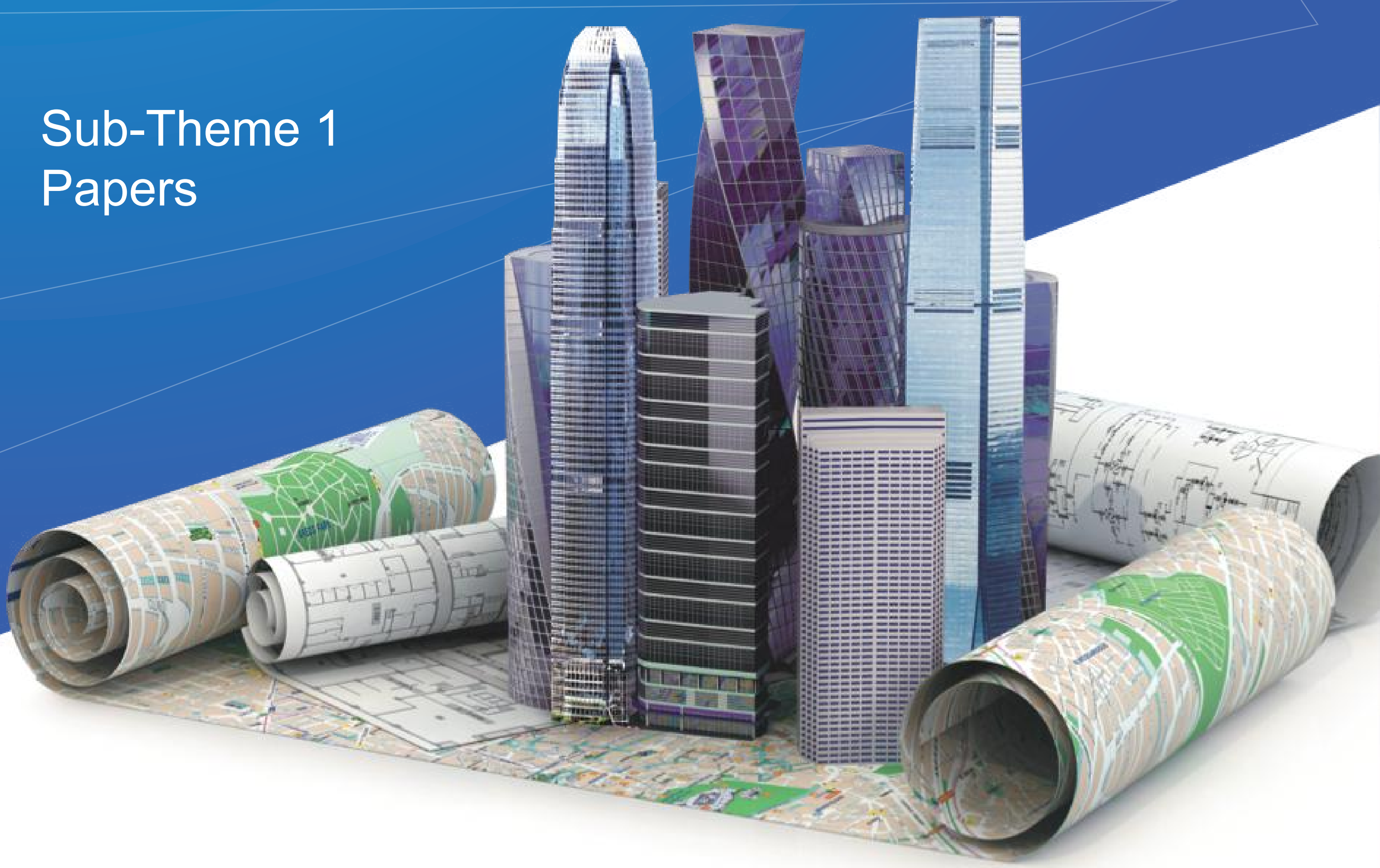

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From Hour to Minute: Non-technical Challenges for Measuring Office Space Utilization with Smart Technologies

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Abstract

Space utilization data can reveal patterns in space usage, and employees' and customers' presence and occupants' mobility within the building. Nowadays, emerging technology, such as smart sensors and devices, can revolutionize the field which was originally dominated by the judgment of a human observer registered with paper and pencil. However, these novel instruments are often used in an old fashion, which restricts the exploitation of their full potential.
This study sheds new light on the benefits and limits of smart technology in measuring space utilization, and discuss the challenges and opportunities in analyzing space utilization data measured by smart sensors, through the case study of a bank located in Verona, Italy.
First, we reviewed the most relevant literature regarding common methods and previous studies about office space utilization. Then, we carefully evaluated the 18 meeting rooms' space utilization data obtained from the bank, and compute the space utilization result based on two methods with different granularity.
Our result shows that the number of occupied hours calculated at an hour level is 1.44 hour larger than the number of occupied hours calculated at a minute level. As both result reveals the concept of space utilization, which is the amount of time space was occupied, this paper revealed a gap between two space utilization calculation methods, and further discussed the issues and challenges for future space utilization data analysis and benchmarking.

Keywords: Space utilization, Observations, Sensors, Workplace management, Corporate real estate.

1. Introduction

Technological and cultural changes have been affecting the way people work. Employees' works are more mobile, often work from the clients' premises or even on the move, which affects the way they use the office building and third places (Puybaraud, 2017; Slumbers, 2017). Activity Based Working (ABW) approach has been adopted in many corporations so that spaces to re-adapt more and more often to the evolving Businesses (Veldhoen, 2004; Appel-Meulenbroek, Groenen & Janssen, 2010). Nowadays, both designers and facility managers are interested in the manner in which offices are occupied (Bedford et al., 2013). Designers use this information to match demand, and facility managers seek to ensure efficient occupation of space. Understanding how spaces are used allows consideration for more efficient space use and effective reconfiguration.

Space utilization data, such as occupancy rate, has always been an important indicator of companies' spatial efficiency, which is closely associated with cost savings and reductions (Bell, 2010). More and more organizations are pushing toward more efficient use of space, by trying to optimize utilization rates. There is plenty of literature reporting punctual data about downscaling trends in space and office buildings occupancy costs (Miller, 2013). Efficient space usage reduces required square footages and, consequently all the costs related to space occupation (i.e. rent, operation, and maintenance). Indeed, facilities, including design and construction, bring about significant costs for companies (Gordon Brown, 2008; Miller, Casey and Konchar, 2014). Real estate expenditure is the second-largest expense item for corporations, only less than labor cost (Pole & Mackay, 2009). Five percent of savings in real estate costs will result in up to a 1% saving in total cost and increase gross profitability by 9% (Weatherhead,1997). The need to reduce real estate costs is reasonable and desirable particularly for those mature, less profitable companies (Weatherhead, 1997). The constraints faced from the 2008 global financial crisis have led all companies to pay more attention to the impacts of the instrumental assets on their economic returns since about 2/3 of prime office occupancy costs across the globe have increased in the past years (CBRE, 2012). All these facility management decision makings depend on an accurate understanding of space utilization.

These trends above have emphasized the need to better study space utilization. JLL (2017) surveyed 81 companies and organizations globally, totaling 550 million square feet of space, and found that 57% of the clients track space utilization, which is the second most-relevant occupancy metrics after the vacancy rate (Percent of seats that are vacant compared to capacity). Regarding types of space, 57% of clients track utilization for all kinds of spaces, and nearly 50% track the utilization of meeting and open collaboration space. Measuring space utilization is one of the main issues in recent office space studies (Nik et al., 2015).

1.1 Definition of space utilization

However, there has been little agreement on the definition of space utilization. Space utilization may be assessed by the amount of time the accommodations are in active use, by the number of people who use the area, or by a combined measure that reflects the organization's priorities (Aronoff & Kaplan, 1995). The UK National Audit Office proposed a way to quantify the space utilization rate for education buildings in 1996 (NAO, 1996; Rusek, Llinas & Frigola, 2018). The utilization rate can be expressed as follows (NAO, 1996; Space Management Group, 2006):

$$\text{Utilization rate [\%]} = \text{Frequency rate [\%]} * \text{Occupancy rate [\%]}.$$

Frequency (F) refers to the number of hours space is in use (percentage of time), while Occupancy (O) refers to the number of users (percentage of the total seats available). Abdullah, Ali & Sipan (2012) called this calculus the 'UFO' method, with utilization (U) consisted of two components – frequency (F) and occupancy (O). Since there is no specific conceptual limitation on building type in this quantification method, it could also be applied to other types of facilities.

However, Oseland et al. (2013) notice that the UFO method is not that common in offices, where frequency and occupancy tend to be measured and calculated separately. Oseland et al. (2013) remark the dissimilarities between different concepts: 'Utilization level' described the average amount of time that a space is in use for different types of spaces or floors, while 'Occupancy level' is defined as the number of people present in the building as peak or average percentage, typically across a week or other time periods. The Workplace Consulting Organization (WCO) recommends specific definitions to be applied to workplaces other than learning environments, to fill the void in industry standard terminology (Oseland et al., 2013). In more recent cases, space utilization is more likely to be calculated as the amount (percentage) of time that space is occupied (Space Management Group, 2006; JLL, 2017). This definition is closer to the concept of frequency, with the number of users not taking into consideration. Besides, space utilization is also defined as a concept related to the area of physical space in some other studies, such as the space usage by people, products or processes, calculated by the total square feet divided by the number of people (Knapp et al., 2009). Bedford et al. (2013) define utilization rate as the percentage of workplaces in use over the total capacity, where capacity means the total number of workplaces planned in the building. It is commonly expressed by square feet/meter per worker (Miller, 2013), which is also defined as space 'density' (Bedford et al., 2013).

It is noticeable that different definition and calculation methods for space utilization makes the space utilization benchmarking difficult. Although identifying and eliminating vacancy can save millions of dollars, without consistent and reliable measures, it is difficult for corporate facility managers to understand how much vacant space they actually have in their portfolios (Curtis et al., 2009). The various way space utilization is defined and measured may also lead to misinterpretation of the actual property space use. After all, industrial design standards do not help much on increasing efficiency as they are based on widely used but unchallenged assumptions about office density and tend to average wide variations in space needs (Apgar, 1993).

1.2 Space utilization measurement

Regarding methods, most organizations use visual observation snapshots of the workplace to understand and quantify how their spaces are used. It has been codified during the 1990s by the British design consultancy firm DEGW as the "Time Utilization Survey" (Oseland et al., 2013). This data collection method involves people walking around the building perhaps once an hour observing the use of each workstation, meeting rooms, or kitchens and so on. To gather sufficient data, the survey needs to last for 3 weeks and it will record who is doing what and where (Wiggins, 2010). Consultancy companies (e.g. Alexi Marmot Associates – AMA) have verified that a survey performed over one 'busy' week is sufficiently robust as those carried out over two or three weeks. Thus, a large number of studies do not last longer than one week (Oseland et al., 2013).

The result is usually summarized in the unit of hours/day to describe the frequency of use. Since Time Utilization Survey and manual observation studies rely on regular visits by the observer that happen on a relatively short period (Oseland et al., 2013), they are also appropriate to record sedentary behaviors in the office (Rashid, Wineman and Zimring, 2009). However, it is easy to notice that this methodology has several drawbacks. As the observations on how space is used are for just a few seconds, and only over a fixed period, there is a limit to the accuracy of information. If space was just used for several minutes while the observer was away, this use would not be recorded. It is almost impossible to test whether the data collected truly represent the user's presence and length of use in that hour.

This method also demonstrates several limitations in detecting mobile and flexible ways of working. Nowadays, the use of environmental sensors, portable and wearable devices and other digital tools facilitate presence detection and data collection. These smart tools can measure and transmit a variety of data to remote locations. In particular, Passive Infra-Red (PIR) based sensor is one of the most widely used detection methods for measuring occupancy on presence and location (Dong et al., 2010; Dale, 2005). It can detect subtle temperature changes in the environment, triggered by the human body or any other objects emitting infrared radiation within its direct view. Usually, PIR sensors are equipped with an external data acquisition system and return binary data to tell if there are any motions (Guo et al., 2010). Studies have revealed that PIR sensors are accurate in measuring occupants' presence in a room level. Compared with a digital video recording and a human observer noting method, the PIR sensor estimation results show good agreement, less than 2% difference, in a 2-day period (Dodier et al., 2006). Dale et al., (2007) compared PIR sensor data with a human observer's measure and video records, and found that the difference in identifying if the room was occupied was less than 1%.

The presence information that PIR sensors measure is critical for identifying underutilized spaces. This technology demonstrates to perform better regarding accuracy and granularity, even though it is also the most expensive to implement (Oseland et al., 2013, p. 12). However, data acquired by PIR sensor has limitations that it can only tell if an area is occupied or not, it is not able to measure the total number of occupants without complex probability modeling. A single-node PIR sensor can only detect the presence and return a binary data, but nothing more (Teixeira, Dublon & Savvides, 2010). As the manual observation is more accessible to start with, JLL (2017) found that 45% of the clients use manual visual observation methods, while 55% use technological methods to obtain utilization data. Only 4% of the clients used hardware devices to gather utilization data, including but not limited to heat, desk, seat and motion sensors.

Researchers and practitioners are currently debating whether in utilization studies it is better using automated data collection rather than human observers. One of the main differences in the two methods' capacity is the number of spaces that can be observed at the same time. It must be taken into consideration that one observer can only visit 200-300 spaces per hour, including desks, enclosed offices, meeting rooms, and so on (Oseland et al., 2013). Through sensors, instead, thousands of spaces can be recorded simultaneously and for a much longer period, although data gathered through sensors still need to be analyzed and visualized for proper interpretation by researchers and workplace managers. Another critical difference is the number of possible measurements per day. With manual observations, measurements may occur every two hours, one hour, or maximum twice hourly. With automated systems, data collection happens typically every 10 minutes (Oseland et al., 2013), and it can be set according to the needs.

1.3 Issues discussed in this paper

Although sensors like PIR sensors can offer finer granularity by monitoring shorter time periods, e.g. minutes rather than hourly observations, previous literature has not thoroughly investigated what the specific advantages are in increasing data collection granularity. As many sensors record how much time an enclosed space is occupied in a minute-level, there is a need to compare the space utilization result operationalized in different granularity levels. It is unknown that whether results measured in minutes level would show significant misalignments compared to standard hourly recordings. Responding to the questions discussed above, this paper aims at: 1) identifying the challenges stem from the inconsistency of different utilization definitions and measurements, 2) identifying the differences among the space utilization results calculated in two methods with different granularity, based on an existing 18 meeting rooms space utilization dataset, 3) discussing the challenges that space utilization study faces when applying emerging technologies in the future. The goal of this study is to offer evidence about the different interpretations of space occupancy deriving from the variability of data collection frequency and data analysis methods.

2. Method

2.1 The case building

The themes mentioned above are explored via a case study. The case building is an Italian commercial bank, located in a middle-size city in the north-east of Italy, is part of a large European financial group, whose instrumental property portfolio comprises 8,700 buildings spread all over the world, accounting for an area of 6.4 million square meters. This vast asset takes up to 10 percent of the group's total administrative expenses. In January 2018, the company initiated a special project to consolidate its real estate portfolio and applied passive sensors to measure its space usage in our case study building for six months. The total initiative involves headquarters and branch offices in 25 major European cities. Two main drivers of the Project are: 1) to shrink the total annual occupancy cost of 160 million Euros; and 2) to rethink and redesign the remaining portfolio while transitioning to a new way of working for the employees.

The spaces in our case building were continuously monitored by sensors to collect information about space utilization and to see whether they properly matched the users' needs and expectations. In order to obtain the space utilization data, the company's research team implemented occupancy monitoring sensors, and a mobile application on smartphones. For the organization, this network of sensors and apps is functional to continuously test workplace strategy concepts, assumptions, and hypotheses on which they design the layout, facilities, and services of the current workspace. In total 6,500 sensors were embedded throughout the spaces in the building. The majority of the sensors were based on Passive Infra-Red (PIR) technology, which would be explained in more detail in the following section. Sensor distribution on each floor has been evaluated to monitor meeting room and desk usage.

2.2 Meeting room space utilization data

Our analysis is based on the dataset consisted of 18 meeting rooms' space utilization collected by this organization from January 1st to May 31st, 2018. Meeting room's space usage was recorded by the PIR sensors that detect the presence of one or more people in that defined space. The PIR solution chosen for meeting room occupancy detection considers a meeting room as 'Occupied' when the sensor detects someone's presence in the room, and when the room has been booked for a certain amount of time. Booing can be done via mobile app by any employees who intend to organize a meeting there. The room stays 'Occupied' if all the people leave it for less than 10 minutes within the booked time. If the people leave it for more than 10 minutes, but still within the booked period, then the room appears as 'Soon occupied'. However, if people leave the room and the remaining booked time is shorter than 15 minutes, it will appear as 'Free'. The meeting room shows to be 'Occupied' if anyone comes in at any time, instead it shows 'Free' when the booked time is finished, and nobody is in the room. The room might be 'Not available' when someone sends a notification through the ticketing system via the app. This means that intervention from the building manager is expected and is necessary for the room to return 'Free'.

Taking out holidays and weekends, the sensors measured the meeting rooms' utilization for 109 days, from January 1st to May 31st, 2018. As there were some days that the meeting rooms were not occupied at all, a variable represented the vacant days, 'Day (0)', was calculated to show how many days the rooms were unoccupied. The raw data of space utilization was recorded in an excel spreadsheet with the number of minutes occupied of each hour from 8:00 am to 6:00 pm for each day. The raw data was transferred to two space utilization variables with different granularity:

1) Hour_(hr). Partially based on the NAO (1996)'s definition of space use frequency: the space utilization was represented by the number of hours that space is in use. In this method, as long as the number of the occupied minute in the hour is larger than 0, the hour was counted as occupied. The total number of hours throughout the measuring time, which was 11 hours in maximum, was taken as the space utilization for that day.

2) Hour_(min). This method was based on more recent JLL (2017)'s definition: the amount of time that space is occupied at the granularity of a minute level. The total number of minutes throughout the measuring time for each day was calculated first, and then the number of minutes was divided by 60, to get the average hour that the meeting room was occupied.

2.3 Data analysis

Statistical analyses were performed using JMP version 13.1 for Mac. Significance was set at $p > 0.05$ for all statistical tests. To compare the difference between the space utilization calculated based on the above two methods, each room's total number of occupied hours for each day was calculated first. Paired sample t-test was then conducted to see if there is a significant difference between the two groups of space utilization result, and the average difference between the two groups was also calculated. The average number of occupied hours throughout the 109 days for each room was then calculated, and a One-way ANOVA analysis was conducted to see the difference between the average occupied hours calculated in the two methods for the 18 rooms. Finally, a regression analysis was conducted to test the effect of space utilization and the rooms' vacant day on the difference of the average occupied hour calculated by the two methods.

3. Results

Hour_(hr) vs. Hour _(min). The total vacant day, average occupied hours calculated by Hour_(hr) and Hour_(min), and the result of paired sample t-test for each room were summarized in Table 1. The average occupied hours in a day calculated by Hour_(hr) method for the 18 rooms is 5.54 hrs, with a range of 1.70 to 8.86 hrs. The result calculated by Hour_(min) method is smaller, with an average of 4.10 hrs ranging from 0.22 to 7.81 hrs. The result of the paired sample t-test for each room's space utilization suggests that there is a significant difference ($p<.0001$) between the occupied hours calculated by the two methods. On average, the Hour_(hr) is larger than Hour_(min) by 1.44, which means that on average, the occupied hour calculated by Hour_(hr) method will be 1.44 hour larger than the result calculated by Hour_(min) for each day, only because of the difference in calculation method. The 1.44 hours difference accounts for 13.1% of total 11 measured-hours, which means that if the space utilization is calculated as a percentage of the total work hours, the difference between the two methods' results is 13.1% on average.

To better understand how the result difference was affected by the fluctuation of occupied hours number, regression analysis was conducted for both Hour_(hr) and Hour_(min) groups. The result suggested that the difference between the two methods' results was significantly affected by the Hour_(hr) result ($p=0.0004$) with a coefficient of 0.235 (As shown in Figure 1). The difference between the two methods' results was also significantly affected by the Hour_(min) result ($p=0.0203$) with a coefficient of 0.215 (As shown in Figure 2). It suggested that if the number of occupied hours is small, the difference between the two methods' results is also small. As Figure 1 suggests, if the number of occupied hours is larger than 4 hours per day, which is about 36% of the total 11 measured-hours, the difference between the two methods' results was larger than 1 hour and can be as large as 3 hours.

The number of vacant days. Figure 3 suggests that there is a tendency that the average occupied hour per day may decrease as the number of vacant days grows. It is understandable that the average occupied hour will be diluted by the increase in the number of vacant days. However, Figure 3 cannot clearly explain how the number of vacant days affects the difference between occupied hours per day calculated by the two methods. A regression analysis was conducted to test the effect of the number of vacant days on the difference (As shown in Figure 4). The result suggests that there is a significant effect ($p=0.0005$) of the vacant days number on the difference with a coefficient of -0.024244. Figure 4 shows that when the number of vacant days is larger than 15, the difference between the two methods is small, as the number of vacant days diluted the average occupied hours.

Table 1: Difference between space utilization (hours/day) calculated in two granularity levels

NO	Days (0)	Hour_(hr)	Hour_(min)	Difference	Prob >|t|	t-Ratio
1	7	M= 6.13; (SD= 3.20)	M= 4.49; (2.96)	M= 1.64; (1.29)	<.0001	-13.2353
2	14	M= 3.58; (2.85)	M= 2.00; (2.46)	M= 1.58; (1.15)	<.0001	-14.3303
3	9	M= 8.24; (3.60)	M= 7.81; (3.72)	M= 0.43; (0.68)	<.0001	-6.6039
4	6	M= 8.61; (3.07)	M= 6.03; (2.24)	M= 2.58; (1.16)	<.0001	-23.2764
5	81	M= 1.70; (3.42)	M= 1.57; (3.26)	M= 0.13; (0.41)	0.0013	-3.2914
6	73	M= 0.45; (0.75)	M= 0.22; (0.40)	M= 0.23; (0.43)	<.0001	-5.6320
7	7	M= 8.86; (2.76)	M= 5.97; (3.43)	M= 2.89; (2.50)	<.0001	-12.0958
8	3	M=7.97; (2.45)	M= 6.07; (2.15)	M= 1.91; (0.92)	<.0001	-21.6157
9	8	M=5.54; (2.85)	M=4.02; (2.35)	M=1.52; (1.01)	<.0001	-15.7966
10	10	M= 5.04; (3.19)	M= 3.96; (2.71)	M= 1.07; (0.93)	<.0001	-12.063
11	4	M= 7.26; (2.70)	M=5.47; (2.38)	M=1.79; (0.99)	<.0001	-18.8602
12	12	M= 5.94; (3.13)	M= 4.48; (2.61)	M= 1.47; (0.97)	<.0001	-15.8156
13	14	M= 5.79; (3.37)	M= 4.48; (2.94)	M= 1.31; (0.94)	<.0001	-14.6137
14	44	M= 2.85; (3.40)	M= 2.17; (2.84)	M= 0.68; (0.78)	<.0001	-9.0362
15	6	M= 8.61; (3.07)	M= 6.03; (2.24)	M= 2.58; (1.16)	<.0001	-23.2764
16	52	M= 2.46; (3.06)	M= 1.85; (2.50)	M= 0.61; (0.79)	<.0001	-8.11534
17	4	M= 6.44; (2.94)	M= 4.92; (2.60)	M= 1.52; (0.87)	<.0001	-18.3624
18	11	M= 4.24; (2.71)	M= 2.27; (1.85)	M= 1.97; (1.27)	<.0001	-16.1124

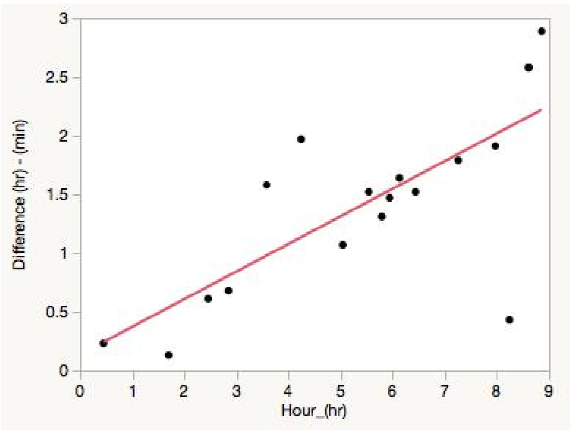

Figure 1: Difference (hr)-(min) vs. Hour_(hr)

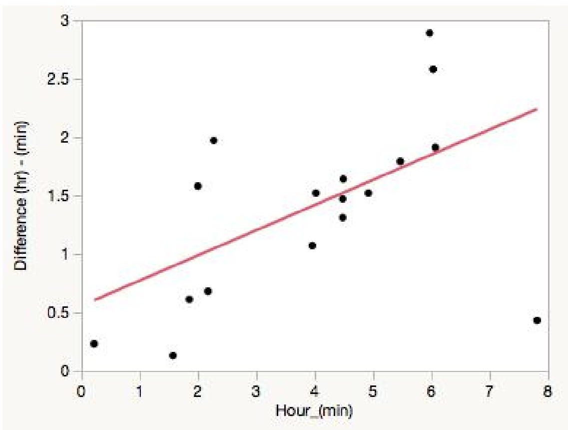

Figure 2: Difference (hr)-(min) vs. Hour_(min)

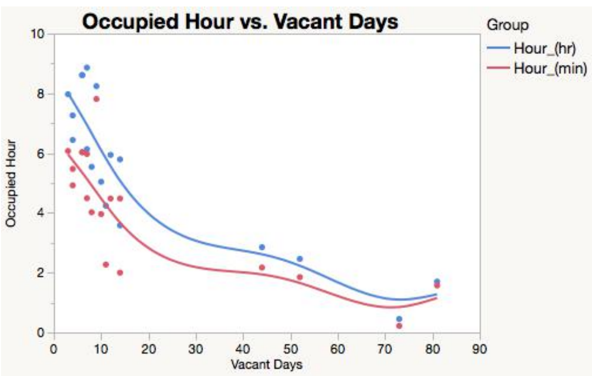

Figure 3: Occupied hours vs. Vacant Days

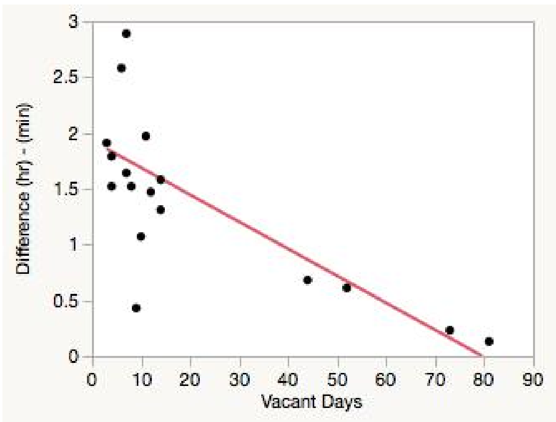

Figure 4: Difference (hr)-(min) vs.Vacant Days

4. Discussion

How to interpret the difference? It is noticeable that the Hour_(hr) and Hour_(min) represent two operationalization of the space utilization concept. The Hour_(hr) refers to the idea of the number of hours that space is occupied, while the Hour_(min) refers to the idea of occupied hours based on total occupied minutes. The Hour_(hr) method aligns more with the NAO (1996)'s definition of space use frequency and may be closer to the result measured through Time Utilization Survey.
The difference in results may be caused by the average meeting length and meeting time distributions. If the meetings are short, random and more dispersed throughout the day, it is more likely to increase the number of occupied hours that Hour_(hr) counts. The difference between the two methods' results might reveal useful information to interpret the pattern of the meeting schedules. Taking Room 3 and Room 7 as an example, although the Hour_(hr) result is close, there is 1.8 hour difference in the Hour_(min) result, and it might be explained by the length of meetings and pattern of the meeting schedules. It is possible that the meetings held in Room 7 are shorter and more dispersed throughout the day so that although the Hour_(hr) is larger than Room 3, the actual minutes occupied is smaller. It shows that there is more unoccupied time between meetings in Room 7 than Room 3.

The granularity of space utilization measurement. Studies have not proved yet to which extent the sensors data can offer innovative insights about space utilization because they provide more detailed information than human observers. The result of this study evokes a more in-depth discussion about the concept of space utilization, and its level of granularity in measurement. Introduction of sensor technology in data collection is at the same time introducing a new measurement to operationalize the concept of space utilization. The Hour_(min) is a new operationalization of the space utilization concept because of the sensor's new capability of measuring if space is occupied at a minute level. However, our study suggests that the result calculated through this more "accurate" method will be different from the result calculated at an hour level, and it is going to be inevitably smaller than the Hour_(hr) result.

Challenges for benchmarking. Traditionally space utilization data have been used in benchmarking and post-occupancy evaluations by facility managers to verify whether the spaces are underutilized. In this study, the difference between the Hour_(hr) and Hour_(min) results for the same dataset is astonishing, and it underlines an urgent need to establish new guidelines for space utilization calculations methods based on sensor measurement datasets. The difference between the two methods result is also related to the room's actual utilization. For rooms with low space utilization, such as under 3 hours occupied per day in this case, the difference between the two methods is limited. It means that the difference caused by the calculation method is less of concern if the goal of space utilization is only to identify underutilized spaces.

5. Conclusions

The debate in utilization studies about using automated sensors rather than observers should also take data analysis methods into consideration. Comparing to the human observer method, although data measured by sensors can provide finer granularity, right now there is a lack of standard methods to analyze the data collected by sensors. The result of this study shows that the space utilization result based on sensors measured data can be significantly different because of calculation methods based on different granularity. In this case, further research is needed to understand the nature of space utilization and its calculation methods, so that a future benchmarking method can be proposed combing data collected through different methods.
In conclusion, this paper contributes to some major reflections, which are worth of further investigation. First, the topic of granularity of space utilization measurement calls attention to both the definition of the term and the methods and practice of analysis. Homogeneity is already scarce for human observations, and it is even more challenging with the most recent application of sensors.
Also, when the capacity of data collection is dramatically improved with new sensing technology,

analysis of space use related data needs more research. This study started an in-depth exploration of using rich and real-time space utilization data for the description of the use of highly-shared workplace spaces and for informing workplace strategies for both design and operation. More efforts can be put in this scope, first by enlarging the sample of analysis to more meeting rooms in different companies. Secondly, it would be interesting to compare different visualization methods for understanding which can be more appropriate for interpreting space utilization data.

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