SMU Libraries: "Sensory" in Library Spaces

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Abstract
The Li Ka Shing Library recently included a new section, "Heat Maps" on the library website, providing users instant access to the physical occupancy spaces across all the different levels in the library. The indoor location-aware system is one in the latest slew of additions in tracking the library patrons' visitations. It is the first of the many forms of library usage data sources that seek to provide an impetus in engaging the SMU community through real-time data visualizations. This enhances the perception of SMU Libraries as a creative nexus that nurtures and champions innovative methods of information access through technology innovations. This paper details the various forms of library usage data sources and how they impact the student patrons' experience. It also outlines a case study on how data harnessed solutions can further foster a safe space that enriches and embodies the SMU Libraries experience.

Keywords
Culture of Assessment, Technological Innovation, Data Visualization, Information Access, Library Spaces

Introduction

Figure 1- Main entrance of Li Ka Shing Library

The topic of library spaces in Singapore Management University's city campus has been revisited by some authors through the past few years. (Cribb et al, 2015; Yeo, 2008).

Yeo (2008) introduced social learning spaces in her case study on the conceptualized Collaborative Study Area (CSA) at the Li Ka Shing Library. She quoted Gayton (2008) as describing that "the communal activity in academic libraries is a solitary activity: it is studious, contemplative and quiet" and that the "social activity is a group activity: it is sometimes studious, not always contemplative, and certainly not quiet" and reiterated her views that the library needs to provide different learning spaces to accommodate the differentiated needs of students.

Cribb et al. (2015) cited Hunley and Schaller (2009) in establishing that the "relationship between pedagogy and use of learning spaces is an evolving one and will continue to change depending on factors". The different forms of learning spaces in SMU Libraries have evolved as a result of the Library Learning Space Initiative in 2014. Cribb et al. (2015), further illustrated through their findings that "assessment and analysis activities need to be carried out on an on-going basis to ensure learning spaces remain relevant and dynamic to the changing needs and requirements of the campus", effectively introducing the strategy of a 'Culture of Assessment' that demonstrates value and impact, and evidence based decision making amongst libraries.

Sensory spaces in SMU Libraries have been accepted as the usual library order in collecting data on library spaces for assessment and analysis activities. Sensory here is defined as smart technologies that save time, and improve efficiency and library services. The more established ones in the SMU Libraries include the RFID, People Counter and the Card Reader. Figure 1 shows the main entrance of Li Ka Shing Library as the library patron walks in and Figure 2 shows the main entrance once the library patron has entered the library.

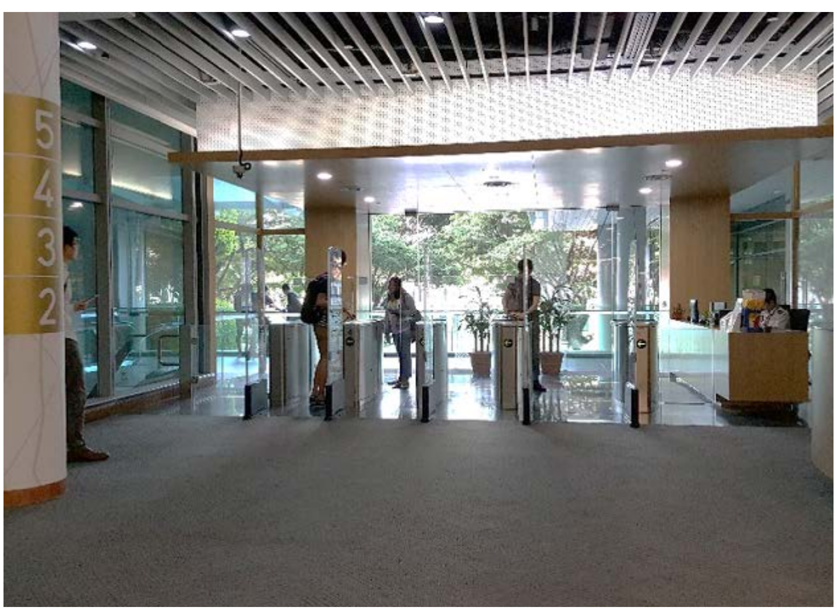


Figure 2-View from inside the Li Ka Shing Library facing the main entrance.

What the library patron may not have realised is that as one enters the Library, one would have passed through the various smart technologies that capture varied information about one's entry (see Figure 3).

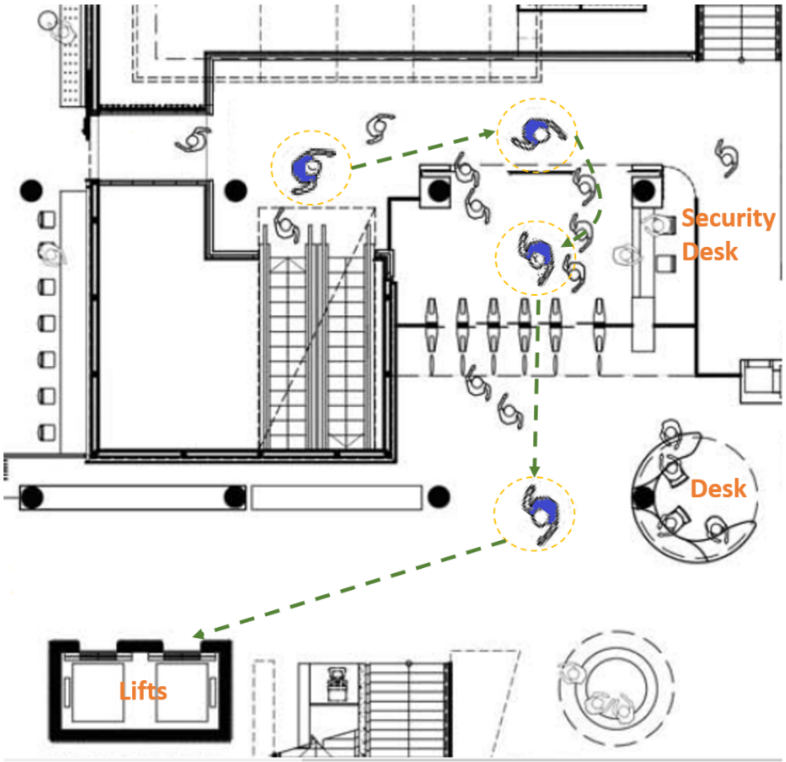


Figure 3-Trail of library patron accessing the library.

For example, the turnstile card reader captures the individual's access when a patron taps their SMU–identification card; the RFID sensors collect the count access as one walks past the RFID gantry; and the People Counters motion sensors detect the individuals movement direction as they walk past the foyer and into the library. (Refer to Figure 4).

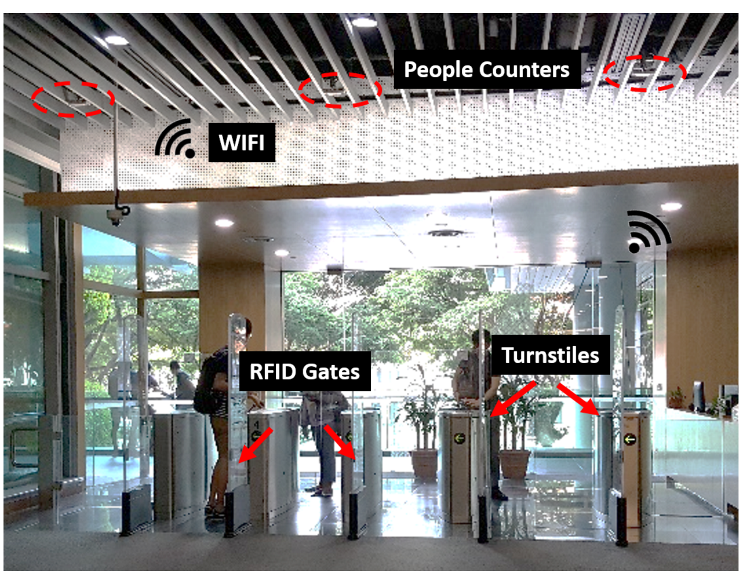


Figure 4 - Equipment and devices at the library entrance

The raw data captured by these devices are subsequently used for various library collaborative projects and are most often leveraged to analyse the library spaces.

Technological Innovations

Technological innovations in the current SMU Libraries landscape take the form of seed (collaborative research and development) projects that introduce new technologies that challenge the status quo and are based on novel ideas conceived to solve issues in the library.

For all intents and purposes, the librarians have exclusive access to the People Counter, RFID and card taps data to view and extract the library physical visitations data. The Library Heatmap however offers an alternative way of measuring physical visitations (i.e. using WiFi signals) and an almost real-time data update in the form of data visualization. This visualization allows the SMU community to access and view the physical occupancies that can be further filtered to view the different levels in the library. This measuring of level-specific occupancy data was not possible with the proprietary systems i.e. RFID, People Counter or the card taps, as the gantries and the cameras were only installed at prominent locations such as the library entrance, nor was this data accessible beyond the librarians' pool prior to the availability of the Library Heatmap.

We will be addressing two such technological innovations. The first is the Occupancy Density Detection (Library HeatMap) and the second is the Seat Occupancy Detectors, which utilize capacitance-sensors as a novel method of distinguishing whether the seats were occupied by a subject or an object. A case study will further illustrate the plausibility of closing the library earlier on week nights and weekends based on the Library HeatMap WiFi data.

Library Heatmap (WiFi data)

The library collaborated with SMU LiveLabs, a research institute attached to the School of Information Systems, in providing occupancy density detection map (indoor localization). This detection map (Library HeatMap) has been embedded into the SMU Libraries website (see Figure 5), and is based on WiFi data that is collected through WiFi devices that are attached on the ceiling at various locations in the library. The data is translated into visualized occupancy rates across the different levels in the library. LiveLabs continuously tracks the indoor location of a large number of WiFi enabled devices using a novel indoor localization algorithm. (LiveLabs, n.d.) Further description of the underlying Library Heatmap technology can be found on the LiveLabs website.

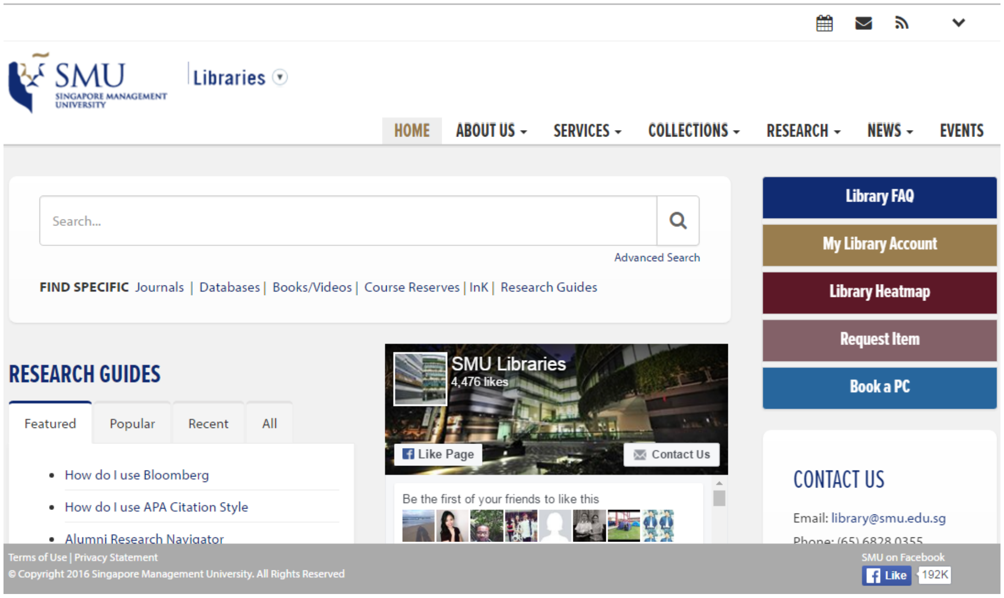


Figure 5-Library HeatMap on SMU Library Website

The Library HeatMap is split into sections where the denser occupancy (i.e. more WiFi signals detected in the area) is represented by a darker shade of the section as shown (see Figure 6). When shared with the SMU community, it helps users to be aware of overcrowded spaces in the library and seek the less crowded ones instead.

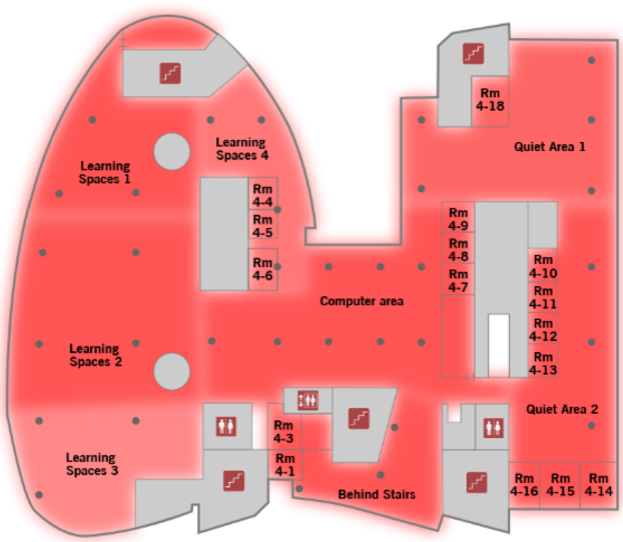
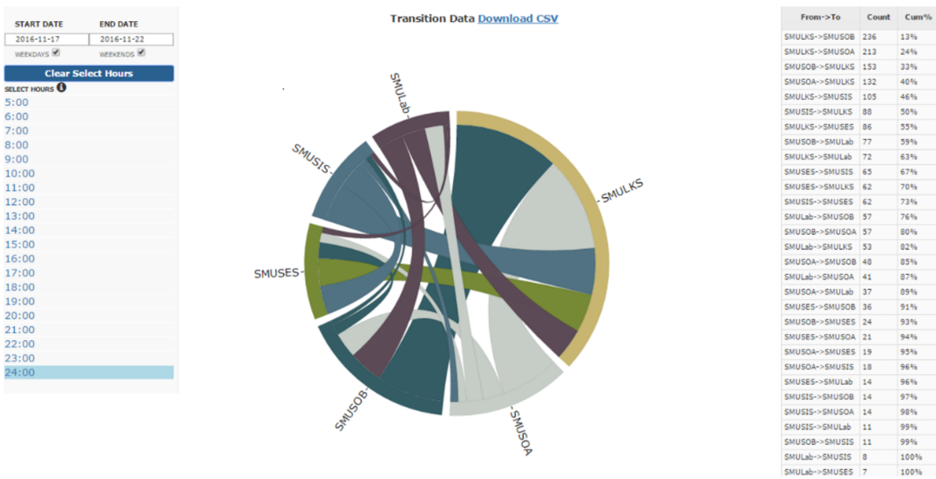


Figure 6-Library HeatMap Level 4

The main difference between the data that captures library patrons' visitations at a single access point (e.g. RFID, PeopleCounter and Card Reader) as opposed to WiFi data is the latter's ability to produce the distribution of library patrons according to the spread of WiFi signals across the different levels in the library building.

In addition to the Library HeatMap, there are other interesting data visualizations that are privy only to the development team and SMU librarians. One of these is the Transition Map that shows the cumulative percentage of patrons moving across the Library, SMU Labs and the six schools that can be filtered to show such movement during any given time period. (see Figure 7).
This gives the library new insights into the patrons' movement behaviour that was once tediously obtained through physical head counts across the different levels in the library, while the patrons' movement patterns beyond the library was impossible to obtain.



From->To	Count	Cum%
SMULKS->SMUSOB	236	13%
SMULKS->SMUSOA	213	24%
SMUSOB->SMULKS	153	33%
SMUSOA->SMULKS	132	40%
SMULKS->SMUSIS	105	46%
SMUSIS->SMULKS	88	50%
SMULKS->SMUSES	86	55%
SMUSOB->SMULab	77	59%
SMULKS->SMULab	72	63%
SMUSES->SMUSIS	65	67%
SMUSES->SMULKS	62	70%
SMUSIS->SMUSES	62	73%
SMULab->SMUSOB	57	76%
SMUSOB->SMUSOA	57	80%
SMULab->SMULKS	53	82%
SMUSOA->SMUSOB	48	85%
SMULab->SMUSOA	41	87%
SMUSOA->SMULab	37	89%
SMUSES->SMUSOB	36	91%
SMUSOB->SMUSES	24	93%
SMUSES->SMUSOA	21	94%
SMUSOA->SMUSES	19	95%
SMUSOA->SMUSIS	18	96%
SMUSES->SMULab	14	96%
SMUSIS->SMUSOB	14	97%
SMUSIS->SMUSOA	14	98%
SMUSIS->SMULab	11	99%
SMUSOB->SMUSIS	11	99%
SMULab->SMUSIS	8	100%
SMULab->SMUSES	7	100%

Figure 7-Transition Map based on virtual foot print (WiFi traces and smart phone connections)

Seat Occupancy Detection: Seat Hogging Issues
Overcrowding especially during the crunch period (i.e. during school term and during peak periods such as before exams) is a recurring issue for most libraries. The Seat Hogging project was designed to alleviate that. As the library is one of the key places that students go to for studying, many seats in the library are occupied during these crunch periods. "Seat hogging" as defined by Nguyen et al. (2013) as "the occupation of objects as a form of impromptu reservations" is the norm.

The seat occupancy detector system uses a capacitance-based sensor (chip MPR121) attached underneath the table to detect the presence of people and object occupancy. It is processed by a microcontroller (Raspberry Pi revision 3) to generate the occupancy status and is then posted to a relational database that is connected to a web module and web service which provides the visualization (HTML Canvas) in the form of a seat map. (See Figure 8).

Figure 8-The map of library with seat occupancy status overlay colour.

The detection logic can be read at length in the paper (Nguyen et al., 2013) but in summary it employs a baseline tracking to deal with a multi-layer threshold in detecting variances in signal reading. (See Figure 9)

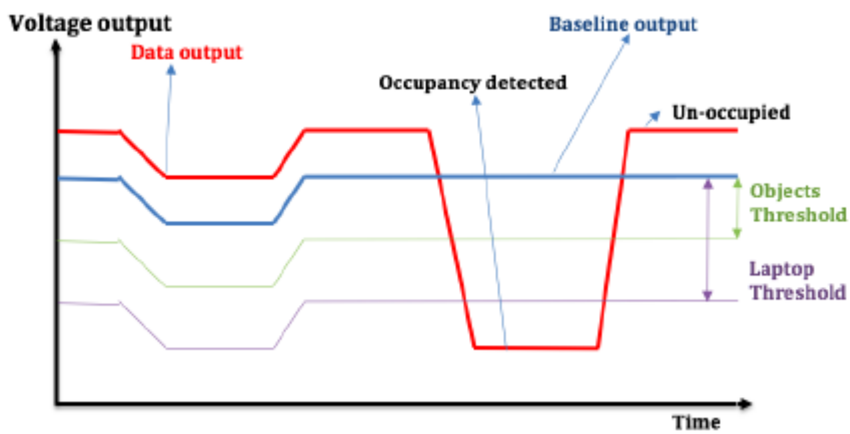


Figure 9-Baseline Detection

Note: Reprinted from Small Scale Deployment of Seat Occupancy Detectors by Nguyen Huy Hoang Huy et al. (2013) Retrieved from Industrial Technology (ICIT), IEEE International Conference.

This project is still in the preliminary stages and was initially deployed in two phases. The first phase was deployed in a span of two months across 6 seats for fine-tuning performance testing. The second phase was a mass deployment across 36 seats in the library. As of January 2017 it has been deployed across 90 seats. As shown in Figure 10, for visualization purposes, three colors (red, yellow, green), were chosen to represent people occupancy, object occupancy and unoccupied state respectively and time for occupancy session (See Table 1).

Color	**State**
Red	People Occupancy
Yellow	Object Occupancy
Green	Unoccupied

Table 1-Different States in different colors.

The accuracy of the data was monitored and the system was accordingly tuned until the team is comfortable with the systems performance. Accuracy of data is measured by comparing the system results against ground-truths (i.e. information provided by direct observation at the location). The results were then presented on the occupancy states confusion matrix (See Table 3).

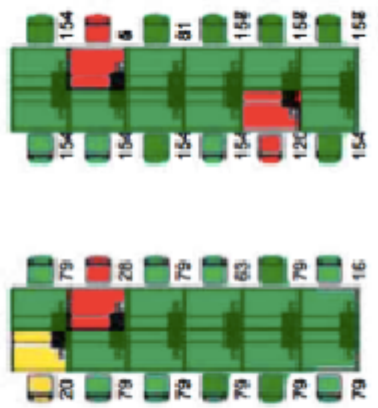


Figure 10-Close up of time for occupancy session across seats.

Accuracy here is defined as the sum of true positives and true negatives over the total number of seats deployed for the seat hogging experiment. False positives are defined as false alarms and false negatives are defined as misses with both (false positives and false negatives) categorized as misdetection of states. (Accuracy, 2010; Wikipedia, 2016):

$$Accuracy\ (ACC) = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Seats\ Deployed\ for\ the\ Seat\ Hogging\ Experiment} \quad (1)$$

Precision is defined as correctly identified states over the sum of correctly identified states and false alarms, i.e. total number of states that are retrieved (Ting, 2010; Wikipedia, 2016):

$$Precision\ (Positive\ Predictive\ Value, PPV) = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (2)$$

Recall or sensitivity is defined as correctly identified states over the sum of correctly identified states and misses i.e. total number of relevant states (Ting, 2010; Wikipedia, 2016):

$$Recall\ or\ Sensitivity\ (True\ Positive\ Rate, TPR) = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (3)$$

The precision and recall results (see Table 2) "show a good accuracy of over 90% for hogging detection" (Nguyen et al., 2013).

States	Precision	Recall
Unoccupied	91%	84%

Object Occupied	97%	63%
Laptop Occupied	81%	75%
People Occupied	89%	98%

Table 2-Detection performance of capacitive sensor

Note: Reprinted from Small Scale Deployment of Seat Occupancy Detectors by Nguyen Huy Hoang Huy et. al. (2013) Retrieved from Industrial Technology (ICIT), IEEE International Conference.

The occupancy states confusion matrix clearly shows that although the system still has trouble distinguishing between the different states properly, there is still a good number of object occupancy (as shown with objects misclassified as 6 being unoccupied, 4 being laptops and 11 being people) and empty seat state (as shown with empty seats misclassified as 7 being laptops and 9 being people). (See Table 3).

The more common misdetections such as having smaller and less conductive objects (e.g. pens, papers etc.) that hinders the system from detecting and causing false negatives for unoccupied state can be improved by increasing the size of the capacitive sensors. Measuring time during transitioning states will improve the management of the wide range of body movements across the different seats. However, for misdetections caused by stationary patrons (i.e. students sleeping) misclassified as laptop occupancy and laptops that periodically change their state (i.e. different electromagnetic noise) and thus misclassified as human occupied can be trickier to deal with. For these issues, the team is still looking at ways to filter and improve the analytics algorithms that can accurately differentiate the different states of occupancy detection. (Nguyen et al., 2013).

		Predicted			
	States	**Unoccupied**	**Object**	**Laptop**	**People**
Actual	**Unoccupied**	81	0	7	9
	Object	6	35	4	11
	Laptop	0	1	71	23
	People	2	0	6	344

Table 3-Occupancy states confusion matrix.

Note: Reprinted from Small Scale Deployment of Seat Occupancy Detectors by Nguyen Huy Hoang Huy et. al. (2013) Retrieved from Industrial Technology (ICIT), IEEE International Conference.

Case Study: Determining the Library Closing Hours

As part of SMU Library’s “Culture of Assessment” we monitored the utilization of the library’s space by studying the library closing hours as a case study in 2015. This also allowed us to test whether the different data sources collected during the same time period correlate with each other.

In the Internet Librarian International (ILI) conference held in London in October 2016, Rafael Ball argued that "…the greater the volume of data, the less likely it is all accurate – but the more data underpins research, the better the research will be…" (International Librarians Network, 2016). When applied to our case study, this may be translated as observing if the two data sources collected through separate means, motion sensor data versus WiFi data but for the same purpose i.e. counting physical visitations, have any correlation.

Both LiveLabs and the RFID raw data were pulled for analysis. For the RFID data, we added up RFID IN data and subtracted RFID OUT data up to 10pm to estimate the number of people in the library (as at 10pm) and compared this to the LiveLabs data. As is evident, there is a positive correlation between the two data sources (see Figure 11).

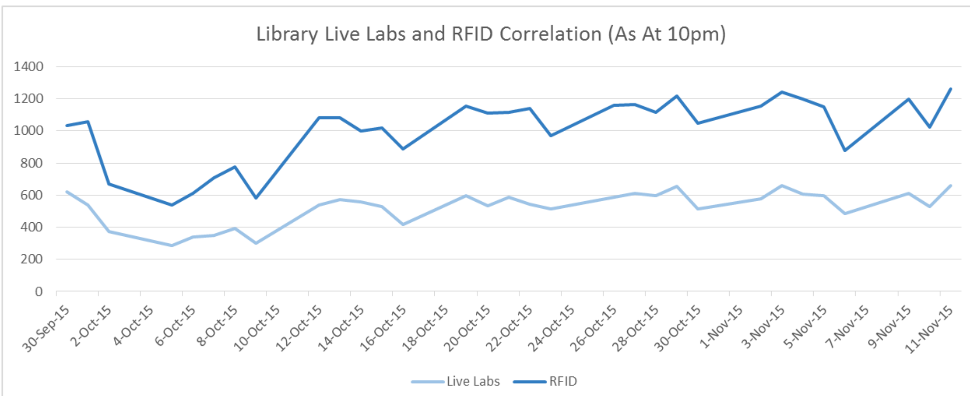


Figure 11-Library Live Labs and RFID Correlation (As at 10pm)

In studying the closing hours for the library, we based our observations on four different time periods. We took/collected WiFi data from all levels in the library (i.e. levels 2, 3, 4 & 5). As WIFI (raw) data are really WiFi signals, it has to be normalized to give a better over view of the number of library patrons across the levels. The red line is the maximum capacity of the 24/7 Learning Commons i.e. the learning space that remains open after the main library building closes. (See Figure 12).

On a normal week day, the library closes at 12 midnight hence we observed the number of library patrons as at 10pm (see Figure 12) and 11pm (see Figure 13) as plausible earlier closing hours. The analysis showed that for most part of the time period observed, there is high usage of library space during the time observed and it is not possible to squeeze all the library patrons into the 24/7 Learning Commons should the library close earlier.

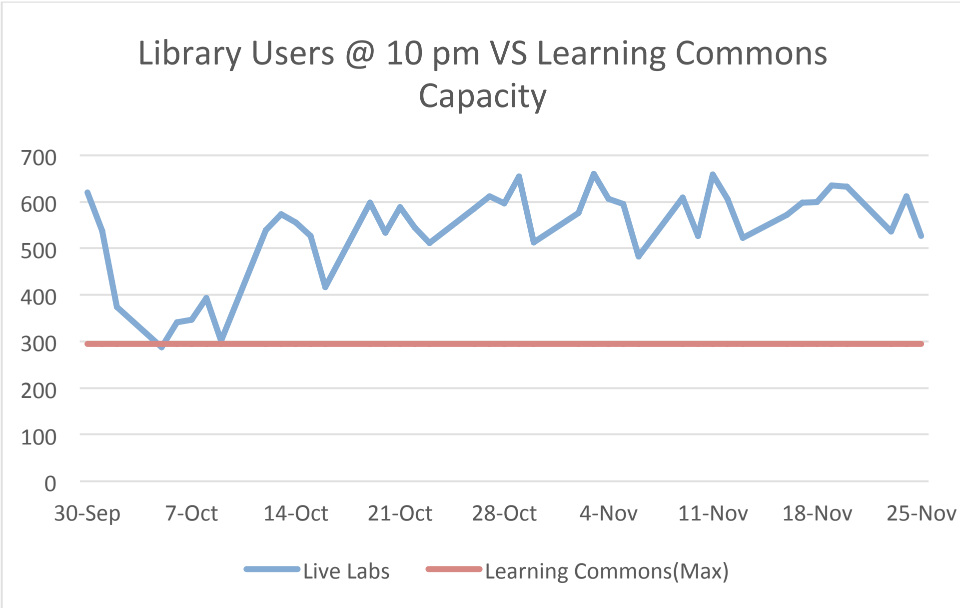


Figure 12-Library Users @ 10pm Vs Learning Commons Capacity

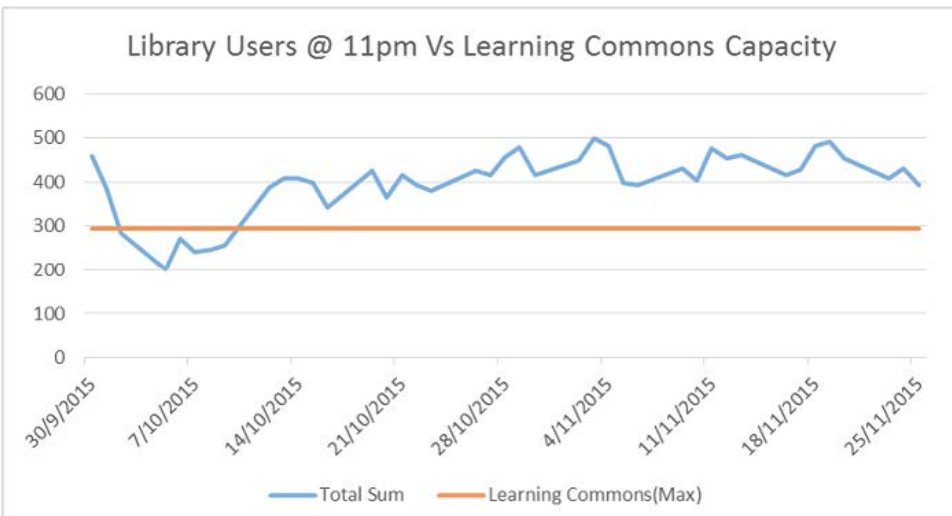


Figure 13-Library Users @ 11pm Vs Learning Commons Capacity

On a normal week end, the library closes at 9pm thus we observed the number of library patrons as at 7pm (see Figure 14) and 8pm respectively (see Figure 15) as plausible earlier closing hours. The analysis also showed the same results of high usage of library space during the time observed and it is not possible to squeeze all the library patrons into the 24/7 Learning Commons should the library close earlier. With this analysis, it was decided that there will be no changes to the Li Ka Shing Library closing hours.

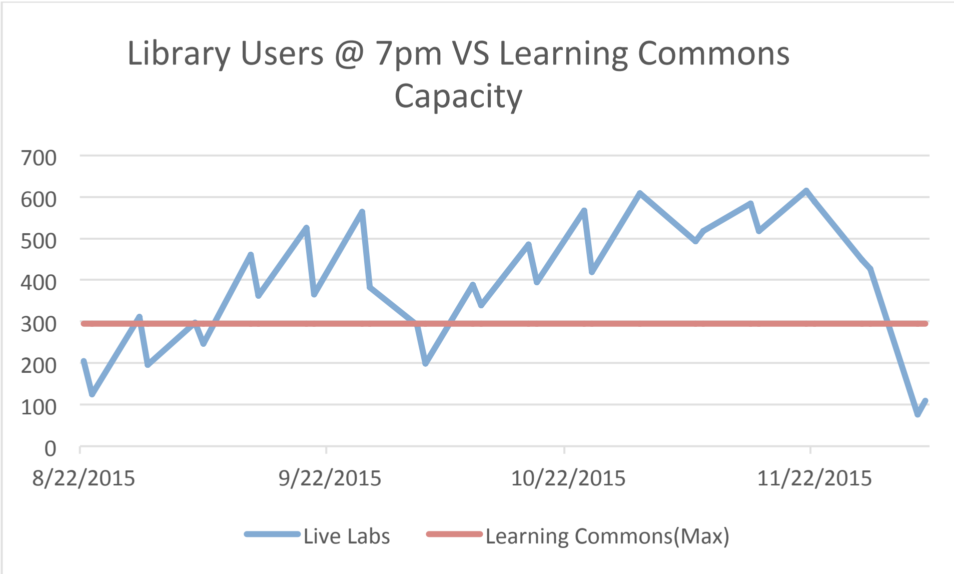


Figure 14-Library Users @ 7pm Vs Learning Commons Capacity

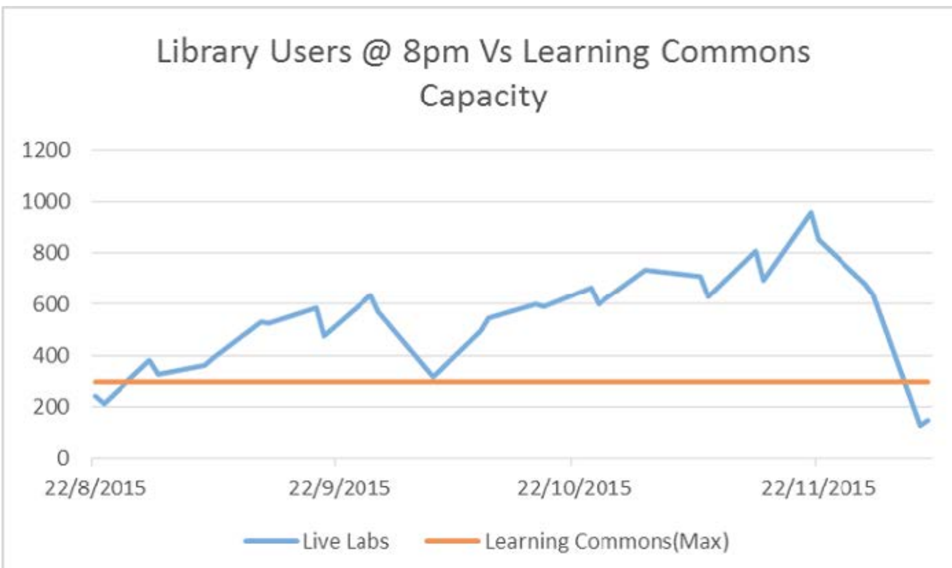


Figure 15-Library Users @ 8pm Vs Learning Commons Capacity

Conclusion

Findings from the case study have shown that the raw data collated from the library patrons' digital footprint based on WiFi signals contributes to SMU's library "Culture of Assessment". It also exemplifies evidence-based decision-making on the library's closing hours. In the words of Rafael Ball, "…librarians need courage to let go of accuracy." (International Librarians Network, 2016). In the case of WiFi signals that have to be normalized in order to reflect the number of patrons visiting the library, accuracy on data is not something tangible and efforts on guesstimate work had to be applied. The library seed projects reported here have demonstrated that technological innovations provide an impetus in improving the efficiencies for the library, reveal insights to library patron movements not otherwise viable through previous means and sharing of library data (almost) real-time through data visualizations – all measures that are beneficial to the SMU community.

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