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Peer Engagement as a Common Resource

Managing Interaction Patterns in Institutions

by W. Michael Johnson, Danuta A. Nitecki, Michael John Khoo, Ronak Nathani, and Sundar Ram Swaminathan

SCUP Society for College and University Planning 50 YEARS

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THE PERRY CHAPMAN PRIZE

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On the cover: A sample image of the Proxmap research method.

About the Society for College and University Planning (SCUP)

The Society for College and University Planning is a community of higher education planning professionals that provides its members with the knowledge and resources to establish and achieve institutional planning goals within the context of best practices and emerging trends. For more information, visit **www.scup.org**.

What is Integrated Planning?

Integrated planning is a sustainable approach to planning that builds relationships, aligns the organization, and emphasizes preparedness for change.

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Background

Understanding how physical settings in universities affect student learning behaviors has been an elusive goal in higher education for several decades. Institutions have sought varied metrics and assessments to prudently direct capital and operating resources. These studies have largely examined academic performance simultaneously with, but independent of, physical factors or changes within environments. Confounding interrelationships among changes in pedagogy, technology, and facility improvements have hampered the usefulness of conclusions drawn from such studies in understanding specific relationships between physical environments and learning.

Problem Statement

Academic activities within physical spaces on campuses have long been associated with a variety of learning behaviors. Among the range of identified learning behaviors, face-to-face collaboration is now the focus of extensive academic study across scientific disciplines. Face-to-face collaboration has been theorized to be a key element in intellectual development and cognition. Yet no formal method of quantitative measurement has been applied to understand collective face-to-face learning in academic institutions or how patterns of interaction and individual reflection may reveal information exchange among students within educational institutions. To address this gap, this study introduces a novel imaging tool to record physical activities occurring in physical space. We then used the tool to establish a method to generate quantitative data from digital images. The method offers a framework to promote the systematic study of peer collaboration for general use in education.

Results of our applied research will be useful to architects, interior designers, librarians, educators, and researchers interested in obtaining empirical evidence and applying it to the design of learning environments and the assessment of how well spaces intentionally relate to learning. Such decisions affect major expenditures within higher education and the distribution of public tax revenues. In fiscal year 2014, public and private U.S. institutions of higher education spent well over half a billion dollars (Fox 2014) on major changes to library spaces. This research project introduces a common means for researchers in space design, education, and information science to develop principles and best practices to improve return on investment in the design of informal learning environments. The method provides institutions common imaging tools and methods of analysis to identify, study, and collaborate on key physical mechanisms that universally promote peer engagement and the social motivations on which engagement depends.

Literature Review

For several decades groups have focused attention on the relation of space to learning, including EDUCAUSE (2015), the Society for College and University Planning (SCUP) (Painter et al. 2013), the PKAL Learning Spaces Collaboratory (Project Kaleidoscope 2010), and collaborative partnerships on numerous campuses (Garrett 2014). These initiatives share similar goals of seeking to identify assessment metrics, predictive evidence, and illustrative cases that relate space to learning in classrooms or formal environments so that teachers can practice pedagogy conducive to their disciplines. Recognizing that developing a performance assessment approach to tie learning space to positive learning outcomes is likely to be both too expensive and time-consuming to be viable, some

instead have created a Learning Space Rating System (LSRS) similar to those systems used for LEED or other building certifications (Felix 2011). FLEXspace, a nonprofit service that originated at SUNY, is developing, with help from community crowdsourcing, a sustainable, reliable, and consistent database of images and descriptors of learning environments to help plan and build classrooms (Stephens 2015). Among the common insights that have emerged from these efforts are the realizations that "experiential learning enhances student engagement and success" (Garrett 2014, ¶ 1) and engaging study behaviors foster learning. However, these works focus on classrooms and teaching environments and have not addressed libraries or other informal learning settings.

The value of libraries and other informal learning spaces in academic settings has proven complex and difficult to understand in the Digital Age (Association of College and Research Libraries 2010; Temple 2008). There are no commonly held metrics relating environmental factors to learning, no factual evidence to predict learning outcomes from study behaviors undertaken in library spaces, and no demonstrated improvements in student learning skills resulting from investments in library building or renovation. Traditional metrics based on usage such as gate counts, space audits, and customer opinion survey analyses are descriptive of occupancy and observed activities, but increasingly administrators seek substantiated evidence of how the library and other informal learning spaces are fundamental places within the academic enterprise. As a recent Gensler study of building trends concludes, "academic libraries can benefit from a better understanding of how and why students use them" (Thaler and Pittman 2015, p. 10).

Theoretical Framework

We acknowledge that attempting to correlate relationships between space and learning appears on the surface to be an intractable problem. Physical space is perceived by external senses; in contrast, learning seems as if it is subject to internal cognitive processes. This observation has formed a robust foundation of Western thought over millennia (Damasio 1994; Kalkavage 2001). The idea that the process of learning must be separate from the design of facilities has continued to be commonly held, and learning assessment has traditionally evaluated students in disregard to their physical and social surroundings. Kuh et al. (2015, p. 82) recently observed this systematic lack of consideration of spatial factors in identifying "*all* the places where learning occurs." However, there is now a growing acceptance across academic disciplines that cognition and information sharing cannot be removed from either physical or social contexts (Dunsmoor et al. 2015; Karsai, Perra, and Vespignani 2014; Miyake et al. 2010). For educators, this consensus can be seen in varied pedagogies surrounding experiential learning from John Dewey (1938) to the present (Cook-Sather 2010; Donovan, Bransford, and Pellegrino 1999).

Our approach begins with the assumption that relationships between learning and space variables cannot be effectively removed from their context. Learning and space are not independent of each other but rather deeply interrelated. Patterns of social exchange are profoundly complex and intertwined with opportunities for social engagement enabled by sets of physical resources in particular places. This premise does not mean that the study of relationships between space and learning must be limited to individual anecdotal conclusions. All possibilities are not equally probable in complex systems. Complex systems may be difficult to predict but they are not random in their

unpredictability. Buildings, rooms, and furnishings all form patterns at different scales that facilitate how we are able to engage with and socially motivate each other.

Second, we posit that face-to-face informal exchanges, albeit poorly understood, are key components of student learning. Patterns of such physical exchanges are known to reflect fundamental components of social motivation (Goffman 1967; Hall 1963; Haslam 2001). Social motivations are now recognized by many as essential elements of study in interdisciplinary research linking education, behavioral economics, developmental neurosciences, and social psychology (Graziano 2013; Meltzoff et al. 2009; Pentland 2014).

Therefore, we propose that relationships between physical resources and social motivations tied to learning be studied by examining the complex relationships between patterns of face-to-face interaction and the physical environments that foster these interactions. Public patterns of face-to-face interaction are readily observable and have the potential to become particularly fertile sources of data to support robust evidence-based observational research.

Learning and Social Behavior

We look to a wealth of previous work linking learning to behavior to anchor our research and develop the basic assumptions of our thesis. Many branches of psychology, sociology, anthropology (Collins 2004; Dunbar, Marriott, and Duncan 1997; Goffman 1967; Hall 1963; Pentland 2008; Turner 1991), and, more recently, neuroscience and machine learning studies (Dunsmoor et al. 2015; Gershman, Blei, and Niv 2010; Klingberg 2013; Meltzoff et al. 2009) have studied face-to-face behavior and learning: how people behave and exchange information when they interact and engage one another. Recent works in turn owe significant debts to foundational texts examining social identity theory and behavioral economics that articulate important interrelationships among social, emotional, and cognitive framing (Haslam 2001; Kahneman and Tversky 1982; Turner 1991). These studies form one of two bases for our framework by demonstrating the fundamental human dependence on social relationships as a means of obtaining, interpreting, and recalling information and establishing links between social motivation and salient social contexts.

Behavior and Environments

The second theoretical base guiding our study consists of the foundational works that have examined relationships between learning behaviors and environments. In the late 1990s, researchers studying how people learn began to question the characteristics of spaces and formulate implications for the design of learning environments, suggesting four perspectives: "the degree to which [learning environments] are student centered, knowledge centered, assessment centered, and community centered" (Bransford, Brown, and Cocking 1999, p. 141). Later, Felix (2011) summarized the shift to the constructivist learning paradigm in which we conceive of learning as an active and collaborative act through which knowledge is constructed from engagement with information. This paradigm has evolved from work mostly undertaken in formal learning settings such as classrooms. The paradigm may also apply to informal learning environments and parallels, for example, a series of evolving core library objectives—helping students make connections between their previous knowledge and their academic tasks, ensuring contextual access to well-organized information resources, offering feedback to students on their information navigation, and building a sense of community welcomed in library spaces. At numerous academic libraries each of these

objectives concentrates on the relationships between library staff and students. What are missing from these approaches though are the collective support systems and social motivations that students seek from each other. Peer assistance, studying with, or studying along are today fundamental characteristics of student learning behaviors in libraries.

Bennett (2009) modeled three paradigms of library space over time. The *user-centered paradigm* is associated with the invention of movable type and library buildings designed around the needs of scholars accessing relatively small collections of printed material. The *book-centered paradigm* originated during the 19th-century industrial revolution, which led to an explosion in printed material and a need to house ever more expansive stacks of physical volumes with study areas increasingly arranged around the perimeter. This paradigm reached its height in the 20th century, and the architectural legacies are still concretely apparent in many academic library buildings. Digital technologies now support a *learning-centered paradigm* in which users engage in solo and group learning using digital resources. Book stacks are less visible while spaces for learning and collaboration are moving to the center, for instance in the form of "information commons" and "learning commons." Such spaces support intentional learning in which acquiring learning as a skill becomes part of the student's motivation for engaging in study. Students want to learn both as a means and an end and especially in groups, "taking responsibility for high-level skills normally exercised by the teacher" (Bennett 2009, p. 192).

Montgomery (2014) drew on the ideas of Bennett (Library Space Planning n.d.) and others to inform a survey modeled on questions from the National Survey of Student Engagement asking students how different spaces in a library worked for different types of study (solo, studying along, and group study). She found a range of behaviors in differently configured spaces and identified student needs for solo spaces, for social and group spaces, and also for solo spaces in the middle of group spaces.

Influenced by these theories and insights, this study explores relationships of space and learning that have proven resistant to systematic understanding. Specifically, its objective is to establish a method to challenge the practicality and wisdom of relying solely on context-independent assessment. We present here a novel, systematic method of detailed observation that records relationships between face-to-face interactions and physical resources over time. To date no such method has been fully developed or widely verified. Kuhn (1962) noted over 50 years ago that common methods of study are the single most important factor required for many scientific disciplines to succeed and thrive. Codified observational methods that allow comparative analyses are often now a requirement for publication in order to avoid the uncertainty of applying conclusions from anecdotal research out of their specific context. We directly address how to study relationships between social behaviors and informal study spaces by offering a common, testable observational method not to replace but to complement the existing qualitative literature examining student perceptions of learning space.

The broad topic of this inquiry relates physical space and learning. It falls within what the Institute of Museum and Library Services (2014) May 2014 convening session on learning spaces acknowledged as the need to develop effective evaluation tools to help educators and librarians address the challenge of how to evaluate the effect of library spaces on learning—including the learning happening beyond classrooms.

Research Questions

The research questions that govern the study are twofold:

1. Does the proposed methodology measure the interrelationships among space, place, social proxemics, and technology use in an informal learning environment?
2. Do the method's image processing analyses of pixels (sum, distribution, and clustering) correlate with individual or group study?

Research Overview and Design

Project Overview

The study applies both quantitative and qualitative data-gathering methods to an inductive observational approach. The research strategy begins with using smartphones to record time-lapse photography to measure and correlate specific physical factors with student behaviors. Quantitative photographic data are computationally processed to record the specific physical conditions that support peer interaction and individual study within specific public settings. Samples of the resulting individual and social engagement behavior patterns are then compared with space design and resource distribution patterns present in informal learning spaces and baseline engagement behaviors within these spaces. Finally, the quantitative results are studied and compared with conclusions drawn from qualitative ethnographic observations and analyses of student learning behaviors.

This method produces a simple set of tools that we call Proxmap. The Proxmap tool set establishes a common framework and method of analysis to allow accurate observations and unbiased experimental conditions to be independently repeated, quickly and at minimal cost, across diverse institutional settings. The research method does not seek to find causes of learning and engagement among students; rather, it evaluates the specific physical conditions that promote peer engagement over time using reiterative observation and experimentation.

Research Design

The research was undertaken between October 2014 and June 2015 at Drexel University, a private urban research university in Philadelphia, Pennsylvania. Twelve physical sites were selected to capture data on student behaviors on the campus:

1. Nine sites within the W. W. Hagerty Library, the main campus library located on the University City campus.
2. One innovative "library" site, the Library Learning Terrace (LLT), designed to allow self-directed learners to take ownership of configuring their learning environment by moving any of the furnishings in this open 3,000-square-foot facility. Security guards are the only staff present on an ongoing basis; librarians and other learning coaches come intentionally to conduct training or offer assistance. The LLT is located at the busy traffic crossroads adjacent to several residence halls on the main campus.
3. One outdoor site on the main campus plaza that includes outdoor seating.
4. One lobby site on the first floor of the Gerri C. LeBow Hall, home to the LeBow College of Business, a newly constructed college building where seating and traffic patterns invite student gathering and informal study.

Over two dozen potential sites were identified and evaluated by the study researchers and research assistants. Four basic criteria were used to select the recording sites and viewing angles. Sites were selected for high density of use, ease of access, and compliance with Drexel Institutional Review Board (IRB) protocol to protect individual privacy. Sites were also selected to maximize the number of different types of physical designs and resources that could be recorded from a single location. Many potential recording sites outside the control of the Drexel libraries were not used simply because of the difficulty of getting administrative approvals. Within the Hagerty Library, initial viewing angles were also selected based on the student occupancy heat maps established by Khoo et al. (2014) in 2012.

The Drexel IRB conducted reviews of two research designs. One protocol prepared for the qualitative data gathering portion was accepted. Review of the other protocol for the image recording concluded with the issuance of a Letter of Determination that this portion of the study was not human subject research; the image resolutions were sufficiently out of focus, thereby protecting personal identity.

The academic quarter-based calendar at Drexel uses four 11-week terms per year. Recordings started on October 22, 2014, during week six of the first quarter of the 2014–15 Drexel academic year. Recordings at three locations in the Hagerty Library were taken during the first quarter to investigate the recording technique and establish recording and file transfer protocols, specifically to verify the primary recording sites, sample recording times, recording and data transfer protocols, and student availability as well as to develop image processing methods. The vast majority of recordings for the second quarter began during the sixth week of the term, using the same three locations and documenting the time of day, day of week, and week of term; these recordings continued to establish baseline levels and variance of activity over the academic term. Third-term recordings began in the first week and ran through week eight. The third-quarter recordings explored alternative viewing angles and additional sites ranging from a central exterior plaza to informal high-density-use study spaces in the LeBow College of Business and learning spaces associated with the LLT near the dormitories.

Throughout the project, a blog was maintained through SCUP to share findings, tie the research to current issues in higher education, and communicate the development of the theoretical underpinnings of the work. Appendix 1 documents the blog posts.

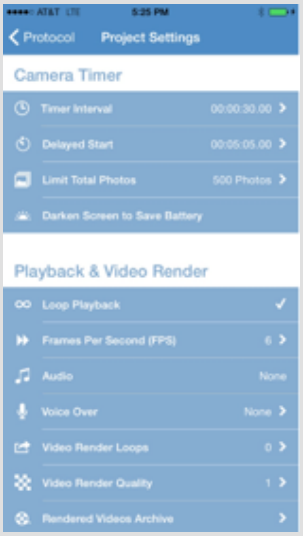
Quantitative Data Gathering

Photographic data were recorded in this study using six iPhone 4 cameras with standard iOS 6 operating systems and OSnap! smartphone time-lapse recording applications. To reduce costs and control how data were transferred, the iPhones operated without SIM cards and used the university's wireless network to transfer data. Figure 1 illustrates how the smartphones were set up.

Undergraduate research assistants were hired to set up the cameras and record and transfer data. Each research assistant was given a device with software setup and protocol manuals to ensure human subject identity protection and trained in hardware operation, software application, data management protocol, and safety procedures prior to recording. (Appendix 2 presents the camera setup instructions.) Two additional engineering and computer science graduate research assistants worked throughout the year to develop the image-processing software code and GUI application interface. Standard recording settings were

Figure 1 **Smartphone Setup**

Apple iPhone 4 smartphone cameras were used to record student activity at 12 locations around the Drexel University campus over the 2014–15 academic year. The cameras were typically set in acoustical tile ceilings as shown above.



OSnap! iOS applications were installed in each camera with identical time-lapse settings. (Most smartphones now have native time-lapse capabilities.) Each 100-minute video file averaged 4.5 MB in size, enabling the files to be transferred by e-mail to dedicated hard drives for processing. The smartphone screenshot shows the time-lapse settings used for the 400+ recordings taken over the year.

used for all of the time-lapse recordings. An average of 200 images were taken at 30-second intervals to obtain a record of activity across individual 100-minute periods.

Time-lapse image data were transferred from the smartphones via internal university e-mail networks to two redundant external hard drives. Files were labeled for location, time of day, day of week, and week of term. Incoming files were reviewed and verified on a weekly basis prior to transfer for image processing. The processed images and statistical data used to compare images and image types, together with the MATLAB applications and GUI interface, are available for academic nonprofit research under a Creative Commons CC NC-SA license. These are maintained in the Drexel University institutional repository data archive, accessible through the Libraries.

The lead researcher met with both student assistants involved with the quantitative work on a weekly basis throughout the year to coordinate programming and recording efforts, monitor data consistency, and set image processing objectives.

Method for Processing Data

Raw time-lapse video .mov data were processed to condense each set of 200 images into a single .png picture file. The .mov video file was first cropped to minimize the effect of foreground activity and isolate areas of interest and then processed via MATLAB image processing using code developed specifically for the project. Each cropped .mov file was then analyzed as 200 consecutive two-dimensional gray-scale images approximately 100 x 400 pixels in size. Three algorithms were then applied to return four types of data used for analysis:

1. An algorithm was first used to count the number of times each pixel value changed sequentially over the 200 images that made up each video. The algorithm counted only if the value of a particular pixel changed from one image to the next image (not the amount of the change).
2. A second algorithm then normalized each image to account for slight differences in image cropping and

recording duration to allow each image within a set to be directly numerically compared with another. This algorithm returned two kinds of data:

A. Monochromatic *pixel change images* consisting of the sum of changes in light levels for each pixel over time (see figure 2).

B. Dimensionless numbers (pixel change values). The pixel change value describes the degree of change in light level for the entire image.

3. A third algorithm was then used to identify the number and distribution of peak areas of activity within each video. The third algorithm returned two kinds of data as well:

A. Black/white *cluster images* consisting of areas of highest activity.

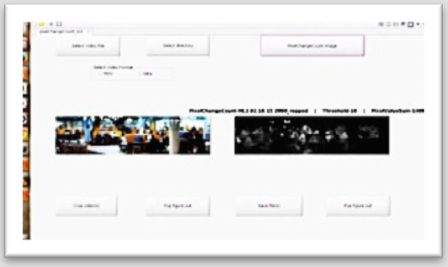
B. A second dimensionless number describing the number of clusters of peak activity. The *cluster value* counts the areas of high-activity clusters within the cluster image (see figure 3).

Data Quality Control

Data were selected for comparative analysis in two steps: First, the lead researcher deleted recordings that did not meet IRB-approved face cognition or site density protocols for privacy. Second, after processing each set of pixel change images taken during that academic quarter we identified atypical (outlier) results. Three kinds of atypical results were found and used to exclude data from subsequent analysis (see figure 4):

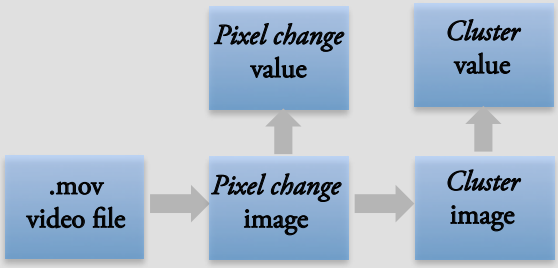
1. Several very high pixel change values were the result of differences in ambient light levels caused by alternating periods of sun and shade resulting from moving clouds, background movement outside recording areas (street traffic), and periodic headlights (again street traffic).

Figure 2 **Proxmap MATLAB GUI Interface**



The Matlab graphic user interface (GUI) shown here in a screen shot allows video files (shown on the left) to be imported, cropped, and processed without directly accessing the Matlab code. The output returned is the right hand black-and-white image with the file name, *pixel change* threshold and *pixel change* value shown above the *pixel change* image.

Figure 3 **Proxmap Processing Schematic**

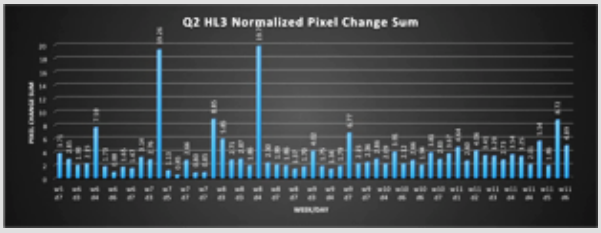


We cropped and processed the video files using four computational tools developed in MATLAB. The *pixel change* images were processed as described in figure 5. The *pixel change* values were obtained by adding all the values for all pixels in the *pixel change* images. A second *clustering* algorithm was then used as a filter to analyze the densest clusters of activity. These clusters were then counted to generate a *cluster* value for each image.

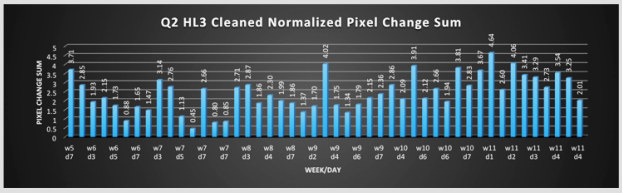
2. A significantly smaller number of very low pixel change values were found to occur during snowstorms in the second quarter.

3. Several recordings were eliminated due to excessive camera tilt and/or views that varied significantly from the protocol viewing angles established at the beginning of the project.

Figure 4 **Data Quality Control**



a. HL3 week of term trend before outlier examination



b. HL3 week of term trend after data quality control

An example of the range and distribution of data before and after outlier data sets were excluded. Data sets were excluded based on identification of external variables (exogenous factors). Recordings with corresponding *pixel change* values more than 1.5 standard deviations from the mean were reviewed and excluded if external factors could be identified. Of the 58 recordings in this data set, four were identified as abnormally low (significant snow storms occurred on each of these days). Six were identified as abnormally high due to variable background daylight conditions that occurred during days with intermittent sun and clouds.

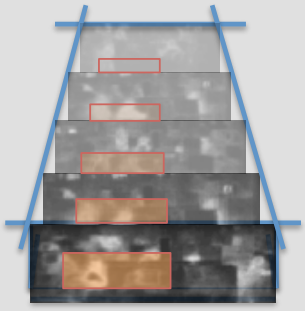
Each set of *pixel change* values was also normalized computationally to account for both the exact number of pixels cropped for each image and the exact length of each recording.

Data Analysis

Pixel change values for each camera site and academic term were sorted by time of day, day of week, and week of term to analyze temporal variation across common time scales. We calculated means, standard deviations, and linear regressions for each camera site and term and compared activity trends over time.

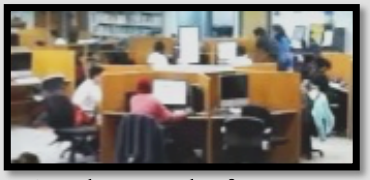
Each pixel change image was compared with the raw video data from which it was derived to systematically verify that locations in the image corresponded with student occupancy and types of student activity. (Appendix 3 describes the physical elements of each site.) From these reviews areas of interest were identified and specific features explored using "window-box" sampling techniques borrowed from archeological and ecological research. Figures 5, 6, and 7 illustrate these techniques. Identified features were in turn assayed in detail to determine common repeated activities. The activity patterns were then used to develop templates of activity associated with specific furniture and resource types in order to identify behaviors associated with densities of occupancy. Pixel change images, pixel change values, cluster images, and cluster values were compared with patterns of seating use described by Khoo et al. (2014) and with qualitative data obtained through student surveys to identify differences and commonalties between the analytic approaches.

Figure 5 **Feature Assay Method**



Each set of *pixel sum images* were examined to identify areas for detailed study by comparing common patterns within *pixel change images* over time. This type of method that examines the "depth" of features within multiple images is analogous to assay "window-box" methods commonly used in archeology. Both techniques identify smaller areas of interest for detailed analysis and both correlate time-series of two-dimensional information to locate small scale patterns for detailed study within a larger three dimensional study area.

Figure 6 **Feature Assay A: Hexagonal Carrels**



a. Sample HL2 video frame

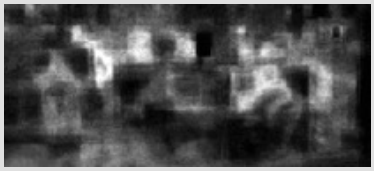
b. 3.01 1300 3.60 *pixel change value*

c. 3.04 2300: 3.73 *pixel change value*

d. 3.04: 2100 6.81 *pixel change value*

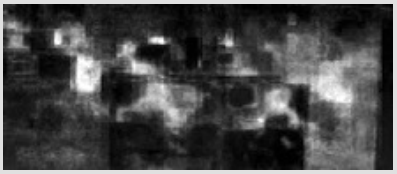
e. 3.05: 1300 6.42 *pixel change value*

f. 2.11 1900: 6.23 *pixel change value*



g. 3.01 2100 9.09 *pixel change value*

h. 2.18 1700 9.08 *pixel change value*



i. 2.25 1900: 9.75 *pixel change value*

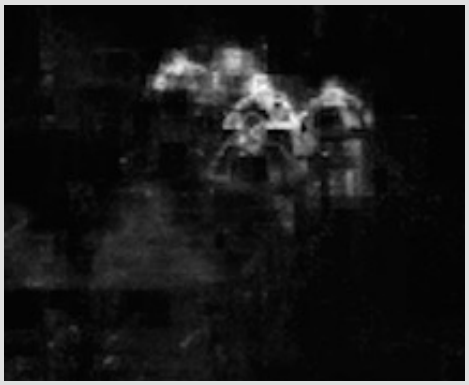
Here carrels were identified as a feature of interest in order to study behavioral trends related to specific physical conditions. Details of an identical portion of a series of normalized *pixel change images* from one camera location (HL2) are shown over time. The images record behaviors at different occupancy levels at four adjacent hexagonal carrels with 16 possible seat locations depicted. Each image is identified with a date and time (for example 3.04 2300 was recorded on March 4 at 11:00 p.m.) Images (b-c) are samples taken at low occupancy with *pixel change values* one (1) standard deviation below the mean of the 52 data sets at this camera location. Images (d-f) have *pixel change values* close to the mean value (6.76). Images (g-i) have *pixel change values* one (1) standard deviation above the mean reflecting conditions close to peak occupancy. For this camera location (HL2) *pixel change values* over the second quarter ranged from 2.48 to 12.32 with a standard deviation of 2.17 (n=48).

Note the increased percentage of light areas and increased density of distribution in images with higher pixel change values.

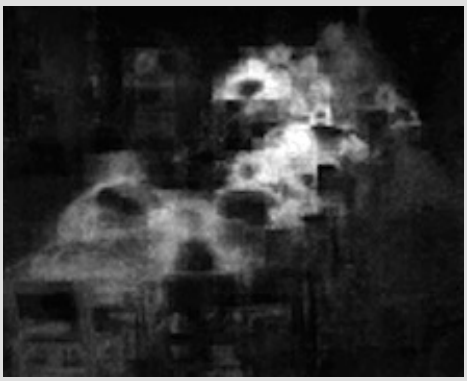
Figure 7 **Feature Assay B: Rectangular Tables**

a. Sample HL2f video frame

d. 4.26 1800 16.97 *pixel change value*



b. 5.07 1900: 5.17 *pixel change value*



e. 5.05 1900: 11.6 *pixel change value*

c. 5.04 1900: 8.99 *pixel change value*

f. 4.30 1700 9.31 *pixel change value*

Here rectangular tables were identified as a feature of interest in order to study behavioral trends related to specific physical conditions. Details of an identical portion of a series of normalized *pixel change images* from one camera location are shown over time (HL2f). The images record behaviors at different occupancy levels at six adjacent rectangular tables with 24 possible seat locations depicted. Each image is identified with a date and time.

For this camera location (HL2f) *pixel change* values over the third quarter ranged from 16.97 to 5.17. (n = 7, mean *pixel change* value 10.74)

Note that in each case the distribution of students is not even, especially at higher densities. In addition, note the increased density of "cloud" figures at higher *pixel change* values, indicating proportional increases in collaboration as the population of the space increases.

Qualitative Data Gathering

The qualitative study design incorporated two survey methodologies: observation and in-person interviews. The data gathering protocol and instruments adapted tools developed by Khoo et al. (forthcoming) and were designed to explore the interrelationships among space, technology use, and learning in order to examine the correlation of pixel analyses with individual or group study. The resulting qualitative data are intended to triangulate insights gained from the analysis of the Proxmap quantitative measures.

First, observation techniques were used to collect occupancy data for each of the areas surveyed by the Proxmap cameras using a map-based data recording instrument. This instrument included a detailed diagram of each space and the position of every furnishing (e.g., tables, carrels, chairs, couches, computer workstations) in the space. Initial usability testing of the instrument and its instructions guided preparation of the actual survey book, which included instructions, space plans, and a notation key (see Appendix 4). Since both employees and space occupants can move furniture around, only permanent rearrangements of furnishings were recorded for a revised version of the survey book.

Second, a semi-structured questionnaire survey was used to gather self-reported data on students' study practices and perceptions of places beyond classrooms where they worked. Survey design work included the design and pre-test of the survey script, training of interviewers in how to conduct a face-to-face interview and record responses, submission of an IRB protocol to cover the research, and training of student workers in IRB procedures for ethical research.

Data gathering was scheduled over a period of four weeks in April and May 2015. Two student research assistants were trained to conduct both observations and interviews after passing the IRB training required for anyone undertaking research involving human subjects. These research assistants were equipped with interview scripts and recording charts (see Appendix 5 for details).

Sites selected for this portion of the study were the basement, entrance, and second floors of the Hagerty Library. Participants were selected by opportunity from among those students studying in these physical sites. To gather occupancy data, the student research assistants were directed to record the location of people in each area on the appropriate paper map and then submit the annotated maps to the lead researcher.

The student research assistants also approached individual students studying in the library areas surveyed by the Proxmap cameras. Following the supplied script, the interviewer explained the study, obtained consent to participate, and asked for basic demographic information. The interviewer then asked students what they were doing, who they were with, why they chose that particular spot, how they would describe that particular spot, and what technology they were using. The interviewer also asked a series of Likert-scale questions regarding how well the space suited their needs based on a survey measuring learning in different library space configurations reported by Montgomery (2014).

A completed "set" of surveys consisted of one complete recording of occupancy data for each floor along with one or more of the semi-structured interviews. A set took between 45 and 60 minutes to complete.

Findings: Quantitative Data and Analysis

A total of 416 90-minute recordings were taken over the three academic quarters spanning October 2014 to June 2015, as summarized in table 1.

Table 1 **Recording Summary: 10/14–06/15***

Recording Period	Recording Locations	
1st quarter (weeks 6-11)	3 sites in library	54 videos
2nd quarter (weeks 6-11)	3 sites in library	176 videos
3rd quarter (weeks 1-8)	12 sites in library, business school, and informal learning environments	186 videos
	Total	**416 videos**

*Drexel University's 2014–15 academic calendar was organized into four 11-week quarters beginning in September 2014.

Each of the 176 video recordings from the second quarter and the 186 recordings from the third quarter were processed to obtain pixel change images and pixel change values for each image. In addition, the 176 recordings from the second quarter and 68 of the third-quarter recordings were processed to obtain cluster images and cluster values. In total, we produced 362 pixel change images and values and 242 cluster images and values. (For more detail on each specific recording location see Appendix 6.)

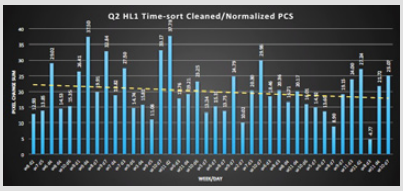
Long-term Activity Trends

We found great variation in activity across time scales. Figure 8 shows hourly, daily, and weekly trends across the second quarter at three locations. The pixel change values at each location and time scale show large individual variances within long-term trends. Not surprisingly, pixel change values for each site show steady increases over the term of study. Average activity density increases steadily at the end of the term by 0.2–0.5 standard deviations. In contrast, weekly activity followed a distinct rhythmic pattern regardless of whether exams occurred in the immediate future. Average activity density during the week decreased dramatically (1.0–2.0 standard deviations for both pixel change values and cluster values) on Fridays and Saturdays. Furthermore, the Sunday average was lower than the average from Monday through Thursday (0.5–1.0 standard deviations), holding true even over the last two weeks of the term.

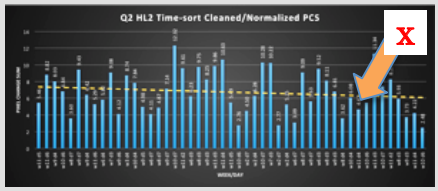
Figure 8 **Long-term Activity Trends**

Data was analyzed over the second term from three different high-density sites in Hagerty Library to identify consistent long term trends. The *pixel change values* using linear regression shown as yellow dashed line (x) in all graphs. (a-c) shows time of day trends (9AM-11PM), (d-f) trends for the days of week (Sunday-Saturday), and (g-i) trends for the week of term (1-11). Each camera location was located on one of three different floors of the library.

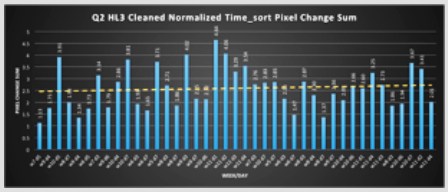
Previous qualitative studies (Khoo, 2014) have shown that the noise, activity and behavior levels differ at each level. The basic characteristics of each recording site are as follows: HL1was perceived of as the loudest, had a seat count (102), and smallest percentage of carrel seats (12%). HL2 was located on the entry level. This site has a seat count of 110, with 38% carrels. HL3 was perceived as a quiet floor with 43 seats, with 21% carrels.



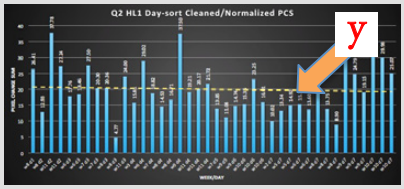
a. HL1 time of day trend



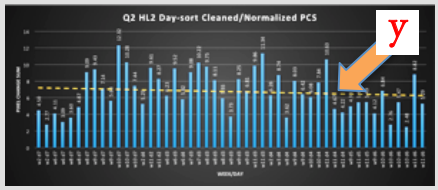
b. HL2 time of day trend



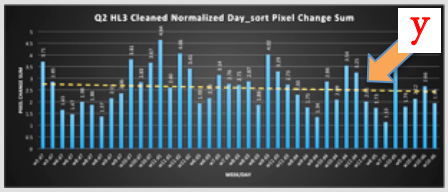
c. HL3 time of day trend



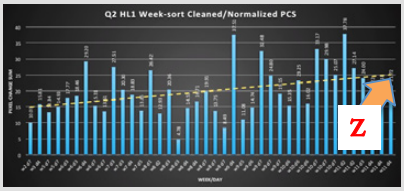
d. HL1 day of week trend



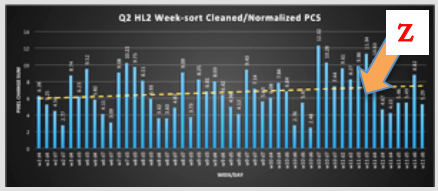
e. HL2 day of week trend



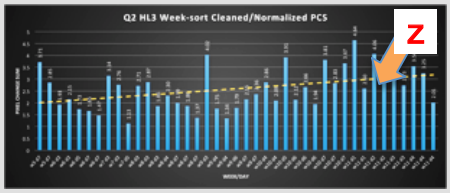
f. HL3 day of week trend



g. HL1 week of term trend



h. HL2 week of term trend



i. HL3 week of term trend

Summary of long-term pixel change value trends:

- No statistically significant trends in *pixel change* values were seen in time of day use across the three sites (x).
- Low *pixel change* values are common to all 3 sites from Friday and Saturday (y).
- Increases in *pixel change* values of at least one standard deviation at all 3 sites over the term (z).

(HL1: *n*=41, HL2: *n*=49, HL3:- *n*=41. In all cases shown recording schedules were not randomized.)

Pixel Change Images and Occupancy

We found that the intensity of the pixel sum images corresponded directly to the density and distribution of occupation recorded in the videos. Figure 9 shows a typical example from two consecutive recordings along with the proportional relationship in pixel change values for each recording.

Figure 9 **Pixel Change Images and Occupancy**

a. LT1 04.22.15 1900

b. LT1 04.22.15 2100

c. LT1 04.22.15 2100: Sample video frame:

Here a comparison of *pixel change* images, *pixel change* values and occupancy from two successive recordings of an open learning environment adjacent to student residential buildings. This space was designed in 2010 specifically to be a environment for collaborative study.

Any comparison of *pixel change* images show that no two images are identical. Similar and consistent patterns may be identified among images, but as with fingerprints each image is unique.

Note the increased density and distribution of activity from the lower *pixel change* image to the upper image, as well as the corresponding increase in *pixel change* values from bottom to top image.

The student populations represent average occupancy counts at four points over the recording period. In contrast the pixel change images record occupancy over the entire 100-minute period.

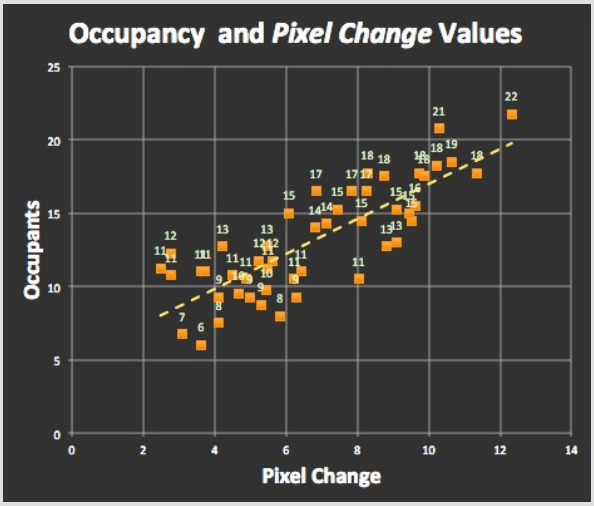
a.) April 22, 2015 7:00-8:40PM
25 occupants - *Pixel change* value **35.35**

b.) April 22, 2015 9:00-10:40PM
13 occupants - *Pixel change* value **16.38**

Occupancy and Pixel Change Values

To validate the relationship between occupancy and pixel change values we reviewed 48 videos and sampled the population in each video by counting occupants at four consistent intervals. Figure 10 shows the range of data and the statistical analysis indicating that occupancy is significantly related to pixel change value using a Pearson's *r* test ($r = 8.17$, $p < 0.0001$). It should be noted that while this relationship is statistically significant, the range of the distribution is broad.

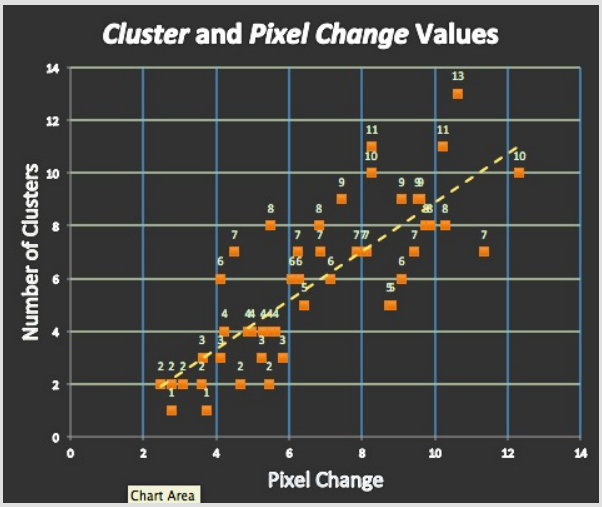
Figure 10 **Occupancy and Pixel Change Values**



We compared *pixel change* values with occupancy. We reviewed .mov files from a single site and counted the student population at four intervals for each file. We then compared *pixel change* values to see if the values could be used to predict occupancy as well as activity. We found that increased numbers of students were strongly correlated with increased *pixel change* values.

n= 48 *Pearson's r* = .817 *p-value*< 0.0001.
The result is significant at p<0.05

Figure 11 **Cluster Values and Pixel Change Values**



We calculated the statistical variance between *cluster* and *pixel change* variables. We found that the number of clusters were significantly correlated with increases in *pixel change* values. Analysis of the spatial variables that are correlated with increases *cluster* values is a central goal of future research.

n= 48 *Pearson's r*= .804 *p-value*< 0.0001.
The result is significant at p<0.05

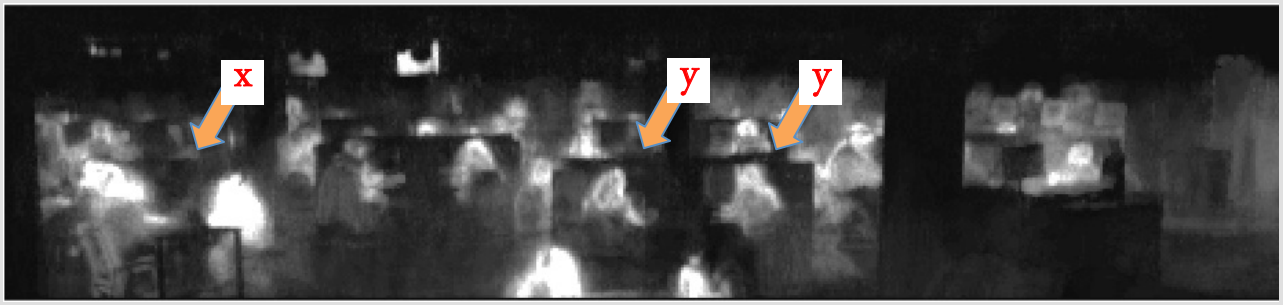
Cluster Values and Pixel Change Values

We also examined the relationship between the peak cluster values and pixel change values of each recording. We found again a strong correlation between the two values (r = .804, p < 0.0001), which was expected given that one value was derived from the other. But it should be noted that alternative results were possible. Figure 11 reflects statistical analyses that showed that cluster concentrated activity grows proportionately with pixel change values. We alternately could have found that activity becomes more concentrated into fewer large groups or many smaller points as the overall activity becomes denser. Neither was the case, which suggests that the ratio of student individual to sharing study behaviors in the space remained the same regardless of the level of occupancy in the space.

Identifying Types of Student Behavior

As we compared pixel change images with the matching raw video we found consistent relationships between the distributions of intensity at areas of concentrated activity and particular types of student activity. Two distinct types of distribution were identified on the pixel change images. The first type of distribution was characterized by a bright outline around a darker area. We call these areas with a bright perimeter and dark middle "halos." In contrast, the other distribution type is less distinct in outline and has a middle that is brighter than its perimeter. We call these "clouds." The less distinct "clouds" also appeared to have characteristics of stochastic probability as one would find in images of electrons in subatomic physics. Figure 12 illustrates "halos" and "clouds."

Figure 12 **Types of Student Behavior**



a. ***Pixel change*** **image:** Collaborative group study "*Clouds*"at table (x) and individual study "*Halos*" at carrels (y)

b. Sample photo overlaid with ***pixel change*** image

c. Sample video frame of area of study (HL2)

This *Proxmap* image shows distinct patterns that corresponded to where and when seats were occupied (b). The processed images do not clearly show the patterns of people walking through the space.

All *Proxmap pixel change images* had areas of "*Clouds*" and/or other patterns that looked more like ghosts or *"Halos"* (a). We found that a "*Cloud*" occurred with people talking and studying close enough to one another to be heard (x). The "*Halo*" areas corresponded to students who were studying by themselves independently (y).

These students who studied alone were characterized by having torsos that did not move with the frequency of those who chose to study in groups. This lack of core body movement created a consistent identifier, a bright outline creating a halo around their position in space.

We found patterns of specific activities common to particular types of furniture. In the images above group behavior tended to be associated with tables, and individual study corresponded strongly with carrels. Individual study behaviors existed at both computer carrels like we see here and regular carrels.

We reexamined the raw video data corresponding to these two types of distributions and found that the "halos" corresponded to individuals working alone and the "clouds" corresponded to students working in close proximity with others. The nature of direct interpersonal face-to-face communication causes a broader range and distribution of movement than working alone at a computer or with books and paper. This finding is consistent with anthropological studies looking at patterns in the structure and dynamic organization of face-to-face communication (Kendon, Harris, and Key 1975). The broader range of motion associated with engaged face-to-face interaction is recorded by the pixel sum images as a blur.

Findings: Qualitative Data and Analysis

The qualitative data consisted of the results of two surveys: an observational occupancy survey and a face-to-face interview survey.

Observational Surveys

Seven occupancy surveys were conducted by student survey takers over a period of four weeks in April and May 2015. These occupancy surveys were a form of observational survey, with the data being collected without contact with the research subjects. A detailed map was prepared of three of the areas surveyed by the Proxmap cameras. All three areas were on the ground floor of the Hagerty Library. The maps recorded the position of items of furniture, such as tables, chairs, carrels, and, in this case, a series of hexagonal workstations, each with public computers. The survey taker was asked to record with an X the position of every person at each space. The survey book was developed over several iterations of usability testing of the tool and its instructions.

Interview Surveys

Each occupancy survey was followed at the time by one or more interview surveys, and a total of 13 interview surveys were collected. The results in the rest of this section focus on interview data collected at the entrance floor of the library. These data include eight of the 13 surveys and were collected on five separate occasions. The lead qualitative researcher reviewed the data collected.

Of these eight students surveyed, five were undergraduates, two were master's students, and one was a Ph.D. student. They came from at least four different colleges across campus (two did not specify a college) and a range of programs and majors, including biomedical science, health sciences, accounting, information systems, operations management, and finance. Four were aged 18–20; two were aged 24–26; one was aged 27–30; and one was aged 31–35. They had been at Drexel an average of 2.9 years. All lived off-campus except one.

Six students were observed studying alone, one was studying with a friend, and one was in a group studying for a midterm. Most (seven of the eight) students reported using an Internet-connected device, including laptops, tablets, and smartphones. When asked to describe the place they were in, students responded both in terms of location (for example, "near scanners") and in terms of ambience (for example, "quiet"). Several respondents mentioned the need for more outlets.

Most respondents to the interview questions about their reason for being in the library specifically mentioned tasks related to learning or knowledge goals whether they were studying alone or in groups. For example:

- » "Reading books and doing my assignments."
- » "I am writing a paper for a class, & this place is convenient (books, computer . . .)."
- » "Studying for marketing midterm."
- » "Studying."

In addition, some of the reasons given for their choice of location included wanting somewhere quiet to work alone, wanting somewhere to work with friends, and wanting somewhere to work that was convenient for a range of technological reasons, such as access to outlets or printers and scanners. Students expressed these motivations as follows:

- » "Completing HW for class. I am working on homework and I was looking for a quiet space with lots of desk room."
- » "Calculating work study hrs. Quiet area, so thinking, working & calculating."
- » "I would like to work wit [sic] a group."
- » "I am studying for a midterm and I needed space for my notes & computer."

The survey data also reported a range of items present on the desks of respondents (see Appendix 7 for examples of annotations). Tables 2 and 3 summarize the findings. The observed items can be divided into several overall categories, including electronic technologies such as laptops, tablets, smartphones, and headphones; paper items such as notebooks, printouts, and binders; note-taking items such as pens, pencils, and rulers; and personal items such as bags, water bottles, food items, wallets, and tissues. It is assumed that, overall, students consider each of these items as supporting their presence in the library in one way or another.

Table 2 **Objects Students Brought for Study**

Objects	Number of students with object	Percent of students with object
Laptop	6	46%
Papers	5	39%
Notebook	5	39%
Cellphone	4	31%
Wallet	4	31%
Earphones	2	15%
Backpack/book bag	2	15%
Water bottle	2	15%
iPad	1	8%
Electronic device charger	1	8%
Pen	1	8%
Ruler	1	8%
Food	1	8%
Tissues	1	8%
No Objects	5	39%

(Several students brought more than one object. *n*=13)

Table 3 **Cross-Analysis with Montgomery Study of Intentional Learning in Libraries**

Survey Statements	Montgomery 2014	Drexel
1. This space helps me work alone on class assignments.	4.0	3.8
2. This space helps me work with other students on class assignments.	3.6	4.4
3. This space helps me work alone on class assignments, but in proximity to other students working in the same way.	3.9	4.0
4. This space helps me discuss my work with other students.	3.9	4.3
5. This space helps me work on a paper or project that requires integrating ideas or information from various sources.	3.9	4.1
6. I know where to find assistance in this space.	3.9	4.4
Mean for all Likert-scale statements	3.9	4.2

(Drexel 2015 sample n=8, Montgomery 2014 sample n=240. Likert-scale was used where 1= "disagree" and 5 = "agree.")

Discussion

We have reviewed the results of our work during this past year in different ways, and we discuss our insights here in three sections. First, we offer our interpretation of the response to the research questions posed at the start of our study, with recognition of the study's limitations. Second, we share reactions to our work following a presentation to stakeholders. Third, we suggest questions for future study that have emerged from our initial work. Appendix 8 summarizes costs to undertake this project.

Response to Research Questions

This study posed two research questions discussed here in terms of our findings. The questions were exploratory, and the results suggest hypotheses for future research.

> *Does the proposed methodology measure interrelationships among space, place, social proxemics, and technology use in an informal learning environment?*

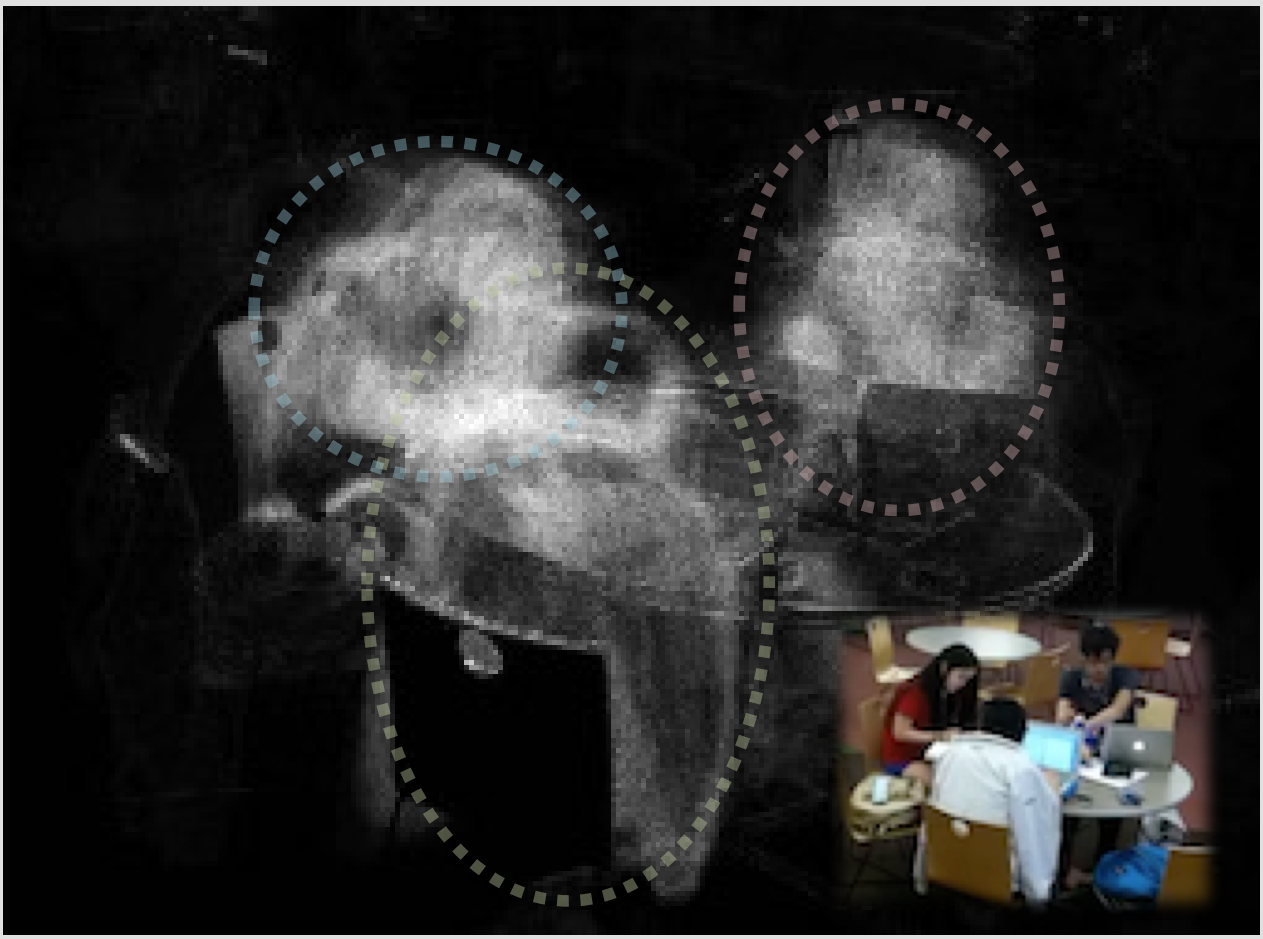
At a base level the question asks us to relate observations of behavior to physical contexts through measurement. The pixel sum images created a digital record of spatial interrelationships over time between place and social proxemics. These images each recorded a numeric matrix of quantitative observations that measured the distance, movements, and density of relationships between space and the proximate activities distributed in that space. We demonstrated that a series of these records established the relative degree of activity, range of human and object movements, and density of those movements across multiple recordings at individual recording sites (for example, see figures 6 and 7).

We used these digital records to understand relationships between social proxemics and technology use. For example, figure 13 shows ranges of social behaviors surrounding laptop and tablet use. To assist in our understanding of the nature of social dynamics tied to particular places we used a new metric (pixel change value) to summarize the overall degree of change within each image. Pixel change values provided us with a shorthand method to understand the relative quantity of activity and correlate that activity with population levels (figure 10).

> *Do the method's image processing analyses of pixels (sum, distribution, and clustering) correlate with individual or group study?*

We were not able to develop algorithms to automatically distinguish cooperative activity from individual study. However, we observed and accurately distinguished "cloud" and "halo" activity types and established relationships between types of pixel change image characteristics and individual and group study. We theorized that students working alone may appear immobile to observers under normal conditions, but the pixel change images show that these students studying independently are far from static. However, students' range of motion when studying independently tends to be more limited, efficient, and predictable, resulting in a bright outline of their body ("halos"). The bright outlines are clearly seen in the majority of pixel change images. In contrast, we believe that students who are in communication with one another have a random, less predictable, and less distinct pattern of activity surrounding them. Gesticulation, change in social posture, and other nonverbal communication methods are well known to modify and augment how humans communicate. Patterns of face-to-face communication have been closely examined in descriptive observational studies in a variety of settings, but we know of no work that

Figure 13 **Sample Image of the Method**



This image was processed from a single 90-minute recording of students actively studying with each other around a 48" diameter table. The blurred light areas show the range and density of body motion over the period with the brightest areas representing the most active areas.

The range of motion of each student is indicated by the dashed lines. Note the space taken by personal items (laptops, smartphones, books, paper, food, and other personal items) distributed over the table in the sample video frame shown as an inset.

has previously identified activity commensurate with peer communication in academic settings as reflecting stochastically random movements.

In addition, through observed student behavior and interviews we cautiously confirm that, overall, the respondents found the different study environments to be conducive to different work and learning activities. However, the sample of qualitative observations and interviews was very small for each type of learning configuration studied. As indicated by early heat map displays of occupancy counts, levels of activity could be characterized and thus compared to insights gained from the Proxmap measure of activity level.

While the study design did not aim to identify causal relationships between learning, location, and artifacts, analysis of the qualitative survey responses suggested associations between learning activities, location choice, and the presence of various artifacts and paraphernalia in the immediate personal environment of the subject(s). In other words, it appears that the

respondents were mainly in the library to study and, by extension, to learn (however defined). In doing so they were both choosing their locations (for various reasons) and then modifying the personal environment at that location using both digital and analog artifacts that are directly and indirectly related to learning support.

Study Limitations

Several limitations are intrinsic to the quantitative methods we have described:

1. Sources of error caution against comparing pixel change values from different locations. Each camera location is tied to a particular perspective of activity, and small changes in camera focal length angle and location can result in large effects on pixel change values. This is true for camera lens selection as well. The use of wide-angle and telephoto lenses varied pixel change values by up to two standard deviations.
2. One can only infer the probability of a certain type of activity occurring based on a statistical analysis of similar conditions. We found density of activity to vary substantially over time. It is difficult to generalize levels of long-term activity from isolated individual recordings without an understanding of the overall context of the range and distribution of activity at a particular site as well as an appropriately sized test sample.
3. Cyclical ambient lighting conditions and other exogenous factors are potential sources of data error. For example, variations in data created by the sun or traffic headlights seen outside exterior windows create problematic conditions when making direct comparisons with stable ambient lighting conditions. Varying seasonal and daily light levels also can distort Proxmap images and values due to changes in the sun's angle of incidence over the year and/or the individual nature of weather and cloud formation.
4. The research design intended to triangulate the quantitative findings by undertaking qualitative interviews and observations during the general periods in which the recordings occurred. However, the specific correlations between behaviors and space were not identified in time to be incorporated into the design of the interview and observation studies.
5. The attempt to triangulate insights from the video recordings with qualitative observations and interviews was premature in this study. We were unsuccessful in obtaining a sufficient number of observations and interviews to recognize repetitive patterns. It was therefore difficult to associate recorded student learning behaviors with observed behaviors and self-reported assessments of the usefulness of specific types of learning spaces as well as the reasons for selecting them.

Stakeholders' Feedback

The research team made a presentation about this study to approximately 75 session attendees during the SCUP Annual, International Conference in Chicago on July 14, 2015. Entitled "Measuring Patterns of Student Interactions to Improve Learning Environments by Design (CN176)" (Johnson, Khoo, and Nitecki 2015), the hour-long session gave participants an opportunity to learn about the study and offer feedback to the authors on the applicability of its results.

After presenting an overview of the development of the Proxmap protocol, illustrations of the pixel recordings against spaces, and some initial insights about the tool's use, the authors engaged participants in two exercises that examined sample images from the pixel displays of student engagement in different spaces. Participants were invited to identify "halo" and "cloud" indicators of individual and group study behaviors and then map these to the proposed types of learning spaces. The session ended with time for questions as well as a general closing discussion triggered by the question, "Does this approach have application and value to practitioners?" We sought feedback on whether to continue to pursue the development of the Proxmap protocol and data gathering instrument.

The session participants fully engaged in the exercises. Many handouts left behind had annotations and notes on them. The volume of conversation was high during the exercises, and only three individuals left before the end of the session. Comments during the closing discussion and afterward to the authors included

- reference to theoretical work about face-to-face interactions by William Whyte (1988) and Amos Rapoport (1976),
- encouragement to explore applications in both outdoor spaces (for landscape designers) and open-plan office spaces,
- questions regarding additional interpretations of the pixel changes (e.g., whether students cluster at ends of tables), and
- suggestions to compare student behaviors in other campus locations.

The formal evaluation conducted by SCUP indicated that participants agreed with statements that the presentation was fresh and creative and engaged the audience well (Society for College and University Planning 2015). A few comments about the value of the study were recorded, ranging from reservations about its applicability to enthusiastic interest in the approach. For example, skepticism about practical benefits was expressed as

- "More conclusions are needed."
- "The topic was interesting but I didn't feel I gained much new insight from the presentation."
- "The jury is still out."

Those encouraging the authors to conduct further study noted their interest as follows:

- "I enjoy innovative ways of learning of students' study habits."
- "Creative research approach to assessment."
- "An intriguing first step in quantifying the intangible aspects of environment."
- "The topic is relevant and valuable for space planning and architecture."

The authors were encouraged to continue work on developing Proxmap as a tool for practitioners to use. Earlier in 2015 they submitted a preliminary proposal to do so to the Institute of Museum and Library Services and received favorable comments from reviewers as well as an invitation to submit a full proposal for the institute's competitive National Leadership Grant Program. Although the proposal submitted in June for a two-year grant was not awarded, the authors received additional advice and encouragement to resubmit; they did so in October and await word from the review process, expected by the end of 2015.

Future Study

This study demonstrated that time-lapse videos can record student behaviors within physical settings and that changes in pixels from the resulting images can be analyzed to illustrate patterns of engagement. This was primarily a proof-of-concept study that developed an initial protocol by which to capture and display quantifiable data for further study of the relationship of space to learning behavior.

There are at least two major areas for further study. One is to validate the protocol, and the other is to pose questions that might be addressed through use of the protocol.

First, three major objectives will guide our next study to develop and validate the Proxmap protocol, focusing on academic library spaces as a venue representing informal non-classroom settings:

1. To design reliable templates illustrating patterns of individual and group study behaviors within diverse library spaces described in terms of pixel change images that measure activity, social proxemics, and social interactions.
2. To identify the usability and usefulness of such templates for librarians and others who make decisions about space design and programs.
3. To contribute to conversations among librarians, designers, and campus planners about library spaces and their relationship to learning and to build an interdisciplinary knowledge community that will pursue further inquiry.

These might be addressed by several research questions such as

1. How does the Proxmap tool measure relationships among space, place, social proxemics, technology use, and learning in an informal learning environment?
2. How well do the template designs replicate relationships of pixel activity across institutions serving different student populations?
3. How do pixel analyses (sum, distribution, and clustering) correlate with individual or group study?
4. How easy do practitioners find the Proxmap tool, its protocol, and its instruction pack to use in developing evidence to make decisions about space?
5. What barriers to implement the Proxmap program do practitioners identify?
6. What applications do practitioners foresee for the tool?
7. What are effective ways to present the resulting analyses?
8. What topics of research are addressed in the literature across disciplines relating learning, informal academic learning environments, and learners?

Second, in terms of further queries that use Proxmap data, our findings suggest that physical design templates can be correlated to different student activity types that reflect individual and group activity. We also suspect that comparatively small changes in areas of dense activity have unpredictably large effects. However, this study's samples were insufficient to draw generalizations and were not adequately designed to ensure statistical testing. A few topics may frame further research using data generated through the Proxmap method to study the relationship of physical space and learning. Among these are

1. Examination of circumstances where small facility changes influence behavior.
2. Association between face-to-face interactions among students and elements of the learning environment.
3. Predictive models of behaviors within informal learning environments that can be used to design spaces that optimize encounters and interactions among students.
4. Correlations between student academic performance and various design templates across multiple institutions.

Conclusions

Scholars in various fields have increasingly become interested in how the physical form of the university is related to its academic effectiveness. However, the ways that space and learning are related are not fully understood, and these relationships have tended to be overlooked when planning decisions are made. Both prior recipients of the M. Perry Chapman Prize have articulated the difficulties of this issue, beginning with the 2012–13 recipients, Painter, Fournier, Grape, Grumman, Morelli, Whitmer, and Cevetello, who summarized the state of research through a thorough literature review (Painter et al. 2013). The 2013–14 recipients, Boys, Melhuish, and Wilson (2014), noted that even basic thinking about these relationships has been daunting due to an "underlying problem of how we conceptualize relationships between material space and its occupation . . . in relationship to learning. . . . Interrelationships between space and the activities that go on in it are . . . an ongoing and inseparable process" (p. 6). The study of the relation of space and learning has not yet become disciplined. Though characterizations of behaviors correlated to learning are found, there is an absence of commonly held terminology and standard descriptions of learning settings.

Looking outside of classrooms, and in particular within library facilities, we have developed a method for understanding how informal communication patterns may be altered to improve the flow of information across a campus. While traditional assessment methods are essential, the increasingly dynamic nature and use of informal spaces and the relationship between social behaviors and emerging technology-supported student social and study practices are little understood phenomena. Measurements that accurately reflect actual use and can provide insights into these dynamics will help academic planners, designers, administrators, and librarians better understand the distribution of space configurations appropriate for individual and group study activities.

Until now, analyses of activities in informal learning environments have depended on recording and then looking at and interpreting videos. This traditional approach is time-consuming and dependent on the observer's ability to see changes over time and focus on details such as space relationships, use of technology, social distance between students, and duration of interactions. The pixel change image method we describe captured images easily, automatically, and consistently, allowing us to measure interrelationships among space, place, social proxemics, and behaviors related to technology use in informal learning environments. In addition, pixel change values allowed us a single metric to efficiently organize and compare images, reducing the time it would require to manually review and quantify relative activity levels. Pixel change also offers new ways to "see" what occurs (and is captured by image recordings) in spaces.

The Proxmap methodology is promising in that it minimizes both sampling and observational biases. Sampling and observation both individually and together potentially introduce error that can obscure the true behavioral variance that is the object of the work. Sampling biases in our system are largely addressed through very large numbers of observations obtained through the efficiency of the recording and analysis method. Many of the pixel change images digitally measured physical conditions surrounding hundreds of interactions of dozens of students in a single image with a setup investment of about 15 minutes and a processing time for a single recording of less than 30 seconds. The sheer quantity of image and numeric data that can be obtained with relatively little effort substantially reduces the potential for sampling errors.

Several types of observational biases common to many behavior studies are also eliminated by this method. Individual occupancy counts and categorization of behavior are all affected by the subjective attention and recording biases of each observer. The Proxmap method automates data collection and processing in a way that preserves the range, density, and types of activity in detail. Alternative automatic tracking and occupancy count methods now available are able to obtain massive data sets to study select aspects of patterns of certain behaviors. However, none of these methods are able to measure the temporal or physical details necessary to distinguish types of behaviors in informal learning environments.

The Proxmap tool set offers a pathway to integrate information derived from direct observation into decisions about how to manage informal study areas as a common resource. Our immediate challenge now is to develop this approach so that it can be scaled across higher education.

We explored a method to accurately record student activities in order to describe learning behaviors. We established variables to measure and began to frame their applicability to the research agenda. Through inductive methods we gained initial insights about the use of pixel change images as measurements of learning activities within a physical space. However, we had insufficient samples to adequately analyze the results and thereby draw confident conclusions to our research questions. The study's value rests in recognizing the complexity of forming a disciplined approach to the topic of the relationship of space to learning. The study concludes with new questions to explore, investigating further the relationships between individual and group behavior, personal space, tasks and activities, personal artifacts, and learning.

Over 70 years ago Winston Churchill (1943) argued for the rebuilding of the Gothic Revival House of Commons as it was before the Blitz by declaring, "We shape our buildings and afterwards our buildings shape us." Taking Churchill's thought further, we have shown here that institutions have the potential to actively understand and interrelate material space and types of learning activity. By systematically observing how material space is related to activity and behavior and acknowledging the complex nature of the problem, this work points to a future where visual records of activity within informal learning spaces can be leveraged to empirically shape and adapt how spaces support higher education.

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Author Biographies

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DR. DANUTA A. NITECKI. As Drexel University's dean of libraries and professor in its College of Computing and Informatics since 2010, Dr. Nitecki has been transforming the library to be responsive to changes in technologies, information seeking behaviors, scholarly communications, and pedagogy. She holds a Ph.D. and an M.S. in library and information sciences and an M.S. in communications. Previously, she held administrative positions in the libraries at Yale University, University of Maryland at College Park, University of Illinois Urbana–Champaign, and University of Tennessee, Knoxville. She has taught courses on evaluation and research methods in library and information science graduate programs; been active in national, state, and regional associations; served as a consultant; and published over 80 articles, books, and compilations on such topics as library spaces, user-based evaluation of library services, research methods, document delivery, and management of library services and information technology applications. With co-authors Robert E. Dugan and Peter Hernon, she received the 2010 Best Book in Library Literature for *Viewing Library Metrics from Different Perspectives: Inputs, Outputs, and Outcomes* (Libraries Unlimited 2009), awarded by the American Library Association. She current serves as liaison to SCUP from the Association of College and Research Libraries (ACRL).

MICHAEL JOHN KHOO'S research interests include the qualitative and sociotechnical analyses of libraries, archives, and digital repositories with a focus on the users of these institutions. He uses qualitative methods based on ethnography, observation, interviews, and surveys. He has degrees in anthropology and communication and 15 years of ethnographic and qualitative research experience in a wide range of field sites, including libraries, archives, and digital libraries. He has published research results in a variety of journal and conference venues.

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Appendices

Appendix 1: Team Blog

Monday, June, 22, 2015

Managing a Campus as a Resource Distribution Problem

In the previous post, we wrote that higher education should be managed to promote conditions that maximize opportunities for learning and posited the question, "How can an institution effectively manage distributed physical resources to maximize opportunities for learning in ways that can be understood within a context of fiscal management?"

We look at higher education management as an economic resource distribution problem in the broadest sense to help identify a path to answer the question. By that we mean the ultimate value of an institution must be its success in offering robust opportunities for learning. The work of this year's Perry Chapman Prize team proposes a theory and method to inform one particular part of student learning. The object of study examines the critical "social underpinnings" that tie the success of student learning to their experiential context outside of classrooms.

Why should faculty and administrators be interested in student activities outside of class? The majority of students' academic life is spent outside of classrooms, seminars, and lecture halls, and the ability for students to engage with academic material outside of class in fundamental both to build the reiterative habits required for higher order thinking and the temporal reinforcement required for robust learning. Optimizing informal student learning environments are not a means of supplementing opportunities for student success, but rather a necessary requirement that enable most students to succeed.

Social Underpinning

If these opportunities for social underpinning are so important, how would one then begin to maximize student opportunities for learning outside of classrooms? To begin we need to understand what conditions exist outside of classrooms; how, where and when students exploit the enabling physical resources that exist on a campus. We have concentrated our work on areas of dense exchange, studying patterns of learning behaviors as the means by which information exchange is related to the "social underpinnings" of student achievement. This approach has allowed us to evaluate relationships between student activity and the physical distribution of resources on a micro-scale. By resources we mean any physical part of the environment that supports social interaction. The "things" that support the exchange of information in spaces range from study rooms to open lounges, and include diverse architectural elements such as desks, chairs, carrels, light, whiteboards, media screens, electrical power, broadband wireless access. We have assembled deeply detailed maps of how micro-scale distributions of such resources are related to student use, density of resource utilization, and interrelated student behaviors that occur surrounding these resources.

Student activity allows us to map how resources actually function, how resources relate to specific contexts, where resources may be underutilized, and where resources are scarce and potentially subject to hoarding by students. This is an important concept, for while institutions are fundamentally aware of scarce monetary resources, the idea that students compete for scarce distributions of resource may not be at the forefront of planning decisions. There are however

hidden costs associated with the overall impact of individual choices made independently from one another and these costs can have broad impact on collaborative exchange. These "commons" costs have been well studied for almost fifty years. While it may not be self-evident that a "market" exists in learning resource hubs (in that the transaction costs of tuition, fees and student time are so distant in time and conception) hoarding access to electrical power plugs, study rooms, technologies, desks and tables clearly exhibit the hallmark characteristics of all "tragedy of the commons" problems studied by economists.

Librarians in particular are familiar with these problems and have a long history of evolving policies to manage shared use and minimize potential abuse of resources. But administrators in and outside libraries have lacked a quick, cheap and reliable methods to understand and quantify both the success as well as the unintended results of management policies.

We have a wealth of specific questions worthy of close analysis, and for this we are grateful for the opportunity that the Hideo Sasaki Foundation has afforded us through the M. Perry Chapman prize. It will take some time for our team to thoroughly analyze the depth and subtlety of this year's massive dataset. Part of this has to do with the amount of data, but also the understanding that we need to be doubly cautious as we are both establishing and evaluating a new method of study. In the meantime, we will shortly publish introductory findings from our work at Drexel.

We aim to disseminate our insights through publications and conference presentations, but our explicit goal is to extend the research to five additional institutions over the next two years. We have applied for a federal grant both to replicate the findings and develop an open-source crowd-sourced application tool. Such a tool will enable communities of scholars and administrators to empirically explore how research universities, liberal arts colleges, and community colleges may all come to a deep understanding of how to adapt their individual resources to manage how students "socially underpin" what is learned in classrooms throughout higher education.

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Posted by W. Michael Johnson at 13:19:44

Friday, June, 19, 2015

College as a Commodity

A key value of higher education lies in the fact that it provides sites that extend opportunities of learning. Students have the responsibility of managing their opportunity to draw from these sites the potentially inexhaustible resource that is knowledge. In return, higher education must manage and promote conditions that maximize opportunities for learning not only through the teaching and information resources that it provides, but also through the learning environments it builds. The success of these environments rests in their usefulness to inspire and connect students with existing knowledge, expert guidance, and an inquiring community of peers to create their own set of new knowledge.

This week, Hunter Rawlings, the President of the Association of American Universities, wrote "If we are going to treat college as a commodity, and an expensive one at that, we should at least grasp the essence of its economic nature. Unlike a car, college requires the 'buyer' to do most of the work to obtain its value. The value of a degree depends more on the student's input than on the college's curriculum.[1]"

His distinction is important, but we argue that Rawling's thesis needs to be taken a step further. For colleges are not primarily sites of a quid pro quo transaction of goods. Not only is it important for students and society to judge the merits of higher education on a broad interpretation of return on investment, but colleges also should base facility decisions on robust and broad interpretations of return on investment. An investment that fosters student engagement with the educational environment the institution builds and maintains.

The question at hand then is, "How can an institution effectively manage distributed physical resources to maximize opportunities for learning in ways that can be understood within a context of fiscal management?" The main problem with this question has been that it has been understudied, and as we have seen understudied problems are often seen as intractable. The Perry Chapman Prize award team this year has worked to parse the problem and being to address one of the topic's many questions.

[1] Hunter Rawlings. WAPO 06.09.15

Posted by W. Michael Johnson at 10:22:16

Wednesday, May, 13, 2015

Triangulating Educational Research With Patterns of Behaviors in Space

As Robert H. MacArthur noted in his seminal work on ecology, "To do science is to search for repeated patterns, not simply to accumulate facts." Our research employs the massive computational power on smart phones (that is now largely taken for granted) to systemically find patterns of behavior in learning environments. As we process and statistically analyze over 300 datasets of images, it has become abundantly clear that patterns of social behavior among students occur over time in predictable ways, and that physical changes to the design of spaces affect the distribution and density of learning behaviors.

What we cannot determine from this study alone is that a density of learning behaviors improves learning. For that we can only infer learning by triangulating assessment research relating academic performance to specific engagement behaviors. But we can offer institutions open access to a tool for examining and comparing the character of each institution's social

behavior in the collective effort to understand how individual missions may be augmented by studying these patterns of social physics; the patterns of face-to-face information exchange.

Our goal is to develop a foundation for a science of human learning behaviors, much as MacArthur did with his foundational study of geographical ecology working with Jared Diamond and E.O. Wilson.

MacArthur, Robert H. *Geographical Ecology: Patterns in the Distribution of Species*. Harper & Row, New York. 1972. Page 1.

Posted by W. Michael Johnson at 13:39:33

Tuesday, May, 12, 2015

Learning and the Design of Space

Many who have looked at the links between learning and the design of space have assumed that empirical questions relating the fields cannot be answered, and many scholars have taken refuge in nature's complexity as a justification to oppose any search for patterns. From the beginning our approach has assumed that relationships between learning and spaces are deeply interrelated (complex). This does not mean our work must be limited to individual anecdotal conclusions. Complex systems may be unpredictable but they are not random in their unpredictability.

All possibilities are not equally probable in complex systems.

We are searching for those patterns that are common, and then empirically examining the conditions that promote the patterns we see. We are looking for patterns in a system with limited predictability and we cannot find these patterns without conducting a systemic search. We cannot find that which we do not see and attend to.

Posted by W. Michael Johnson at 12:43:51

Monday, May, 11, 2015

The Intractable Problem: How is learning related to space?

Often during this year, my colleagues and I have pondered over a fundamental question: *How could physical space be related to learning?* The question has reappeared again and again as if our conversations were governed by an unseen gravitational anomaly. At the surface, the question of space and learning looks like an intractable problem. Physical space is perceived by external senses, and by contrast learning (though a somewhat opaque concept) feels at least as if it is subject to internal cognitive operations. Furthermore, learning is most often evaluated under conditions that are designed minimize or disregard physical surroundings. The idea that learning is separate from the design of facilities is commonly held. In the recently published *Using Evidence of Student Learning*, George Kuh and his colleagues summarize decades of work now centered at the National Institute for Learning Outcomes Assessment. Spatial effects on student performance are barely mentioned in the book, and when noted are marginalized within a group of "exterior factors".

How then could these external and internal phenomena come to be understood as interdependent? And secondly, how could you begin to think about finding associations between space design and learning?

We have chosen to study the observation of behavior as a way to study the linkage between space design and learning. Our specific interests are limited to how and when do students alternate behavior between self-directed study in isolation and studying collaboratively with peers. Our work focuses on the probability that elements of the design of space will influence behavior.

We look to a wealth of previous work linking learning to behavior to anchor our work. Many branches of psychology, and more recently neuroscience and machine learning research, have studied the links between face-to-face behavior and learning; how people behave and exchange information when they interact and engage one another. These studies form the base for our framework of research.

Secondly, to guide our study, we have reviewed the foundational theoretical works that have examined relationships between learning behaviors and environments. To verify these theories a common method outside of laboratory experiments is needed. To date no such a method has been fully developed or widely verified. But as Thomas Kuhn noted over fifty yeas ago, common methods of study are the single most important factor required for many scientific disciplines to succeed and thrive. From academic assessment to epidemiology, biology and ecology, the codification of observational methods have been necessary to avoid anecdotal studies and in some disciplines recently for a requirement for publication. Our observational method uses smart phone cameras to record linkages between behavior and space using foundational theories linking behavior and spatial environments together with the robust assessment literature linking learning and behavior to establish that our work records behaviors consistent with learning.

Posted by W. Michael Johnson at 12:53:15

Tuesday, February, 17, 2015

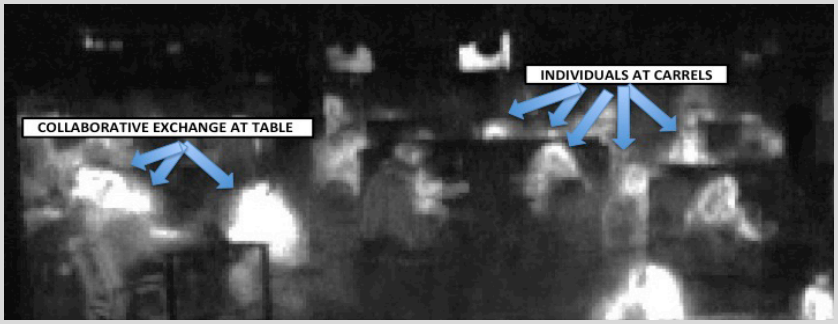
Interpreting Pixel Change Images

In figure 2 below, we show a detail of the pixel change sum image we introduced earlier this week. Though the image appears blurry or unfocussed, the data is not. It is just that the image is a composite of over a thousand single frame images that describe the range of small movements over time.

The detail does show an expected result. In the left bottom corner of the image there are three bright spots at a table. These spots indicate both that the amount of movement is greater around the table, and more varied. We believe this is so because there are three students studying together and sharing information demonstrably. They are actively studying together or along side of each other in a way the other students studying at carrels are not. This is not meant to suggest that the students at carrels are not studying consciously and effectively, only that there is less intensity of small movements than anthropologists and psychologists would associate with the interpersonal non-verbal communication that occurs during conversation and discussion.

In this way the pixel count sum depicts student behaviors over time within informal study areas. It does so in a way that is objective, able to be replicated, while preserving personal privacy.

Figure 2 **Pixel Change Sum Image Detail**



Posted by W. Michael Johnson at 09:31:11

Monday, February, 16, 2015

Thinking about "Pixel Change Sums"

When my colleagues first saw the "pixel change sum" images, they instinctively called the light areas of the image "ghosts". In a way they picked up on the idea that the images are traces that are built up imperceptibly over time. They record the memory of thousands of small activities, in a manner that is extremely difficult for any of us to cognitively keep track of when we observe a space full of students.

Recently two neuroscientists Daniel Lieberman (*Social: Why Our Brains are Connected*) and Michael Graziano (*Consciousness and the Social Brain*) have both separately addressed this point. Lieberman's interests focus on the social thinking in our overall cognitive lives.

This relationship between thinking socially and thinking non-socially may make it hard to do both at the same time. In many case mental processes facilitate one another rather than competing. For instance, seeing and hearing complement one another. Seeing someone's lips move as they speak helps our auditory processes unpack what the other person is saying. Though there have been studies that showing the social and non-social reasoning systems operating in a complementary fashion, it is far more common to see them at odds with each other. (Page 272)

As Lieberman has studied the potential for social awareness, in a complementary fashion, Graziano's work has looked at the physical attributes of social attention. Graziano has concentrated on gaze attention and a broad tendency in populations to quickly focus on and evaluate potential social contacts in face-to-face environments.

When people scan a picture of a face, we tend to look disproportionately more at the eyes, as though seeking information from that facial feature... We are experts at watching other people's eyes and extracting information from eyes. (Page 88)

In addition to social thinking and our persistent attention to faces and eyes, we have a general refined ability to perceive and attend to movement, and especially to attend to movements out of character with a given context. There are obvious evolutionary advantages to perceiving changes in patterns relating to both hunting and being hunted. In contemporary settings our instinctive ability to evaluate threats in public spaces often dominate our thoughts especially

when we are unsure of our context. (Lieberman's book's thesis posits that social attention is a default "resting" state of consciousness.)

Together social thinking, gaze attention, and attention to movement all appear to limit our cognitive ability to perceive and sum up subtle behaviors over time. So indeed it may make sense to think of these images as otherworldly as they are so different from how our brain appears to process people in social surroundings over time.

This method of summing up dynamic changes over time into a single image, may also have other useful applications. Danuta and I are working this winter with a Drexel graduate engineer's independent study on just such an application using GIS and satellite image processing.

Posted by W. Michael Johnson at 08:58:33

Friday, February, 13, 2015

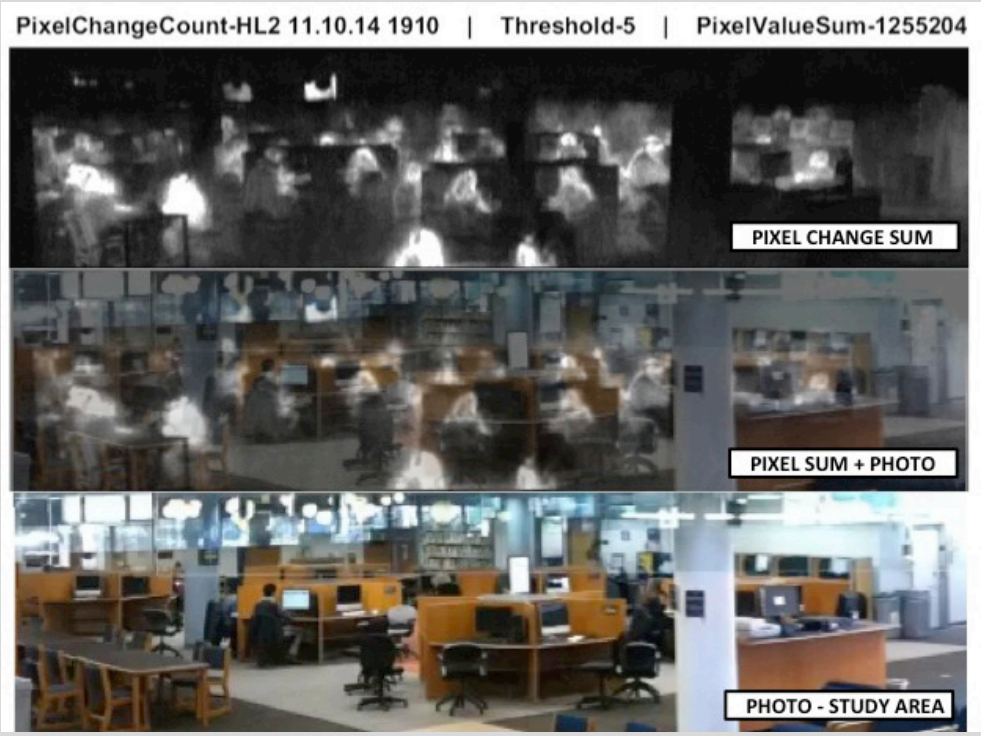
First Results

We are at the middle of Drexel University's second quarter and have obtained over 80 90-minute recordings at three locations on campus. The timing of the recordings has been randomized according to schedules determined at the beginning of each term. The randomized schedule helps us obtain statistically representative samples of the student learning behaviors where and when they are studying.

While the recording has been occurring over the last fourteen weeks, we have been busy with three additional tasks: Refining the algorithms to extract and analyze usable data while preserving student privacy, developing mathematical models to predict and make sense of our data, and preparing a series of interview questionnaires to be used to triangulate findings between separate computational and ethnographic analyses. The first goal of the computational analysis was to create a single image from 90 minutes of video that combined incremental student movements over time. Figure 1 (shown below) shows for the first time our result of one of the 80+ data sets. This method of counting pixel changes over time is now being used to categorize and rank the density of activity and types of behaviors in each dataset.

The sum of the changes each pixel over time adds light to the image, so that the most active areas are white, and the least active are are black, with many gradations of value in between the two extremes. The black and white image shows where students are active when studying even if they are studying alone at individual carrels. Each occupied position in the area of study shows the relative probability of use by the intensity of value in the image. The color image at the bottom of the figure shows a photograph of the are of study, the layout and physical resources distributed in the space. The middle image of the figure shows a combination of the two images. This overlaid image allows one to see the direct association between the pixel change sum and the furniture and resources in the space.

Figure 1 **90 Minutes of Learning Behaviors in a Single Image**



Posted by W. Michael Johnson at 11:34:14

Monday, November, 17, 2014

Random Sampling over Time

Our proximity mapping uses time-lapse data to observe behaviors. Observational studies differ fundamentally from lab experiments. In a lab, an experiment typically selects a control group in order to establish the effect that a factor(s) may have an otherwise identical group. Field studies of behavior like ours often cannot establish controls due to legal and procedural concerns. Over the last fifty years, major research findings using observational study in human and animal behavior have depended upon the rigorous random selection of observation periods over time.

Simply, if one does not randomize the timing of a group of samples, the samples may reflect unrecognized choices on part of the observer. For instance, if the observer has lunch everyday at noon, they have made a decision to eliminate data from that time period. Implementing random events into the predictable calendars of researchers is a significant logistical concern. We meet weekly with our undergraduate and graduate student group to review and coordinate our pre-determined random schedule and address this concern as a collaborative group.

For more information about random sampling and the advantages and disadvantages of alternate data collection methods, we and many others have found the following article to be very useful. (The article has been cited over 10,000 times.)

Altmann, Jeanne. "Observational Study of Behavior: Sampling Methods." *Behaviour* 49.3 (1974): 227–267.

Posted by W. Michael Johnson at 14:46:51

Thursday, November, 13, 2014

Mapping Learning Behavior

This is the fourth week that our group has been mapping student proximity over time. We are working to understand how differing types of self-directed learning behaviors interact within an environment. We are mapping a range of behaviors related to learning: individuals studying alone, in pairs, and groups.

Each kind of behavior is characterized by different sets of ergonomics, and each set tends to affect other behaviors nearby. Proximity mapping shows us these sets of ergonomics, the physical movements in close proximity indicate active information sharing of among peers. Proximity mapping also shows us how these patterns of communications shape and are shaped by neighboring learning behaviors.

Drexel's academic calendar uses four academic quarters. This Fall we are recording baseline behaviors over the quarter. We are now seeing how student behaviors change ahead of and during midterms last week. The time-lapse data shows how and when groups tend to form, and the physical conditions that promote information sharing.

Posted by W. Michael Johnson at 09:05:34

Monday, November, 10, 2014

IRBs, Identity, and Privacy

As we woke up Friday morning and heard of Harvard's struggle to understand the implications of photographing students, it became clear we should address this issue head-on in our blog.

Harry Lewis, the former Dean of Harvard College and a Professor of Computer Science wrote this post earlier this week. The post was picked up by the *Harvard Crimson* and then the national press last night.

"But none of us, students or faculty, want to be treated like inmates of some academic Panopticon, never knowing for sure whether we are being or have been under scrutiny while we were going about our daily business of teaching and learning. Can we have your assurance that all the students and faculty who were subjects of this nonconsensual study will be informed that they were under photographic surveillance?" http://harry-lewis.blogspot.com/2014/11/harvard-still-doesnt-get-electronic.html

Professor Lewis's points undeniably reflect significant ethical and legal concerns. But the details of the Harvard project approval have not yet been publicly shared, and these are important details. We would expect any Institutional Review Board's determination photographic studies of public space to include privacy protections that prevent recording of personal identity.

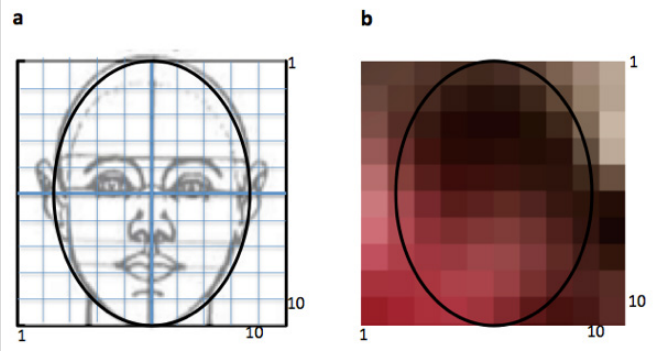
Lewis unfortunately blurs a key distinction between systematic research involving humans *subject* to an intervention and research of public spaces that are the *object* of study. This distinction separates "Human subjects research" which is subject to IRB approval from "Non-human subjects research." This is not a trivial distinction. It has existed from the very

beginning of Institutional Review Board governance and is also the specific topic of the National Academy of the Sciences new proposed revisions to "The Common Rule" federal regulations protecting human subjects.

Proposed Revisions to the Common Rule for the Protection of Human Subjects in the Behavioral and Social Sciences. Washington, D.C.: National Research Council of the National Academies. P. 47. 2014.

Our work has been determined by the Drexel University IRB to be Non-human subjects research. An essential part of that review included specific protocol to record at such low quality of resolution that identity cannot be determined. Here below is the template we use to confirm that the maximum resolution of an individual's head:

Figure 1 **Individual Identification Protection**



a. 10x10 resolution face model.
b. 10x10 pixel resuolution face image.

Examples and details of our privacy protocol are available at www.library.drexel.edu/chapman. Our team believes that this data collection method allows us to map population behaviors while preventing individuals in public spaces from being identified.

Follow the project on Twitter @Proxmap: https://twitter.com/proxmap

Posted by W. Michael Johnson at 16:38:51

Friday, October, 17, 2014

Peer Engagement and Proximity Mapping

The 2014–15 Perry Chapman Prize sponsored research has begun at Drexel University. We are studying how physical conditions influence learning outside of classrooms. The research records patterns of peer engagement among students, mapping the proximity between people as a proxy for the exchange of information.

Low-resolution time-lapse images taken with ceiling mounted cell phone cameras will form the database for much of the work. The low-resolution images protect personal privacy, while allowing us to directly study student engagement behaviors.

Our goal is to provide evidence of physical conditions that foster a broad sharing of ideas across a campus. The outcome of the year-long project will be creation and testing of a tool to measure the density and frequency of peer interaction. This proximity mapping tool is intended to allow any campus planners to easily gather evidence for improving designs of learning environments.

Follow the project on Twitter @Proxmap: https://twitter.com/proxmap

Posted by W. Michael Johnson at 17:37:54

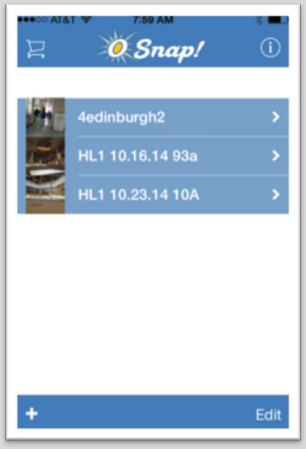
Appendix 2: iPhone 4 Time-Lapse Setup

Prepare the Phone

1. Slide the mute button on the upper left side of the phone to off (so that the red potion of the slider is shown)
2. Go to SETTINGS and turn on AIRPLANE MODE. (This will isolate the phone from interruption during recording.)

Open and Adjust OSnap

3. Go to the OSNAP ap.
4. Press the "+" icon and name the new file in the same format that the screen shows, to right.



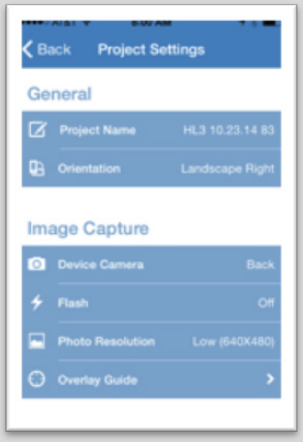
A. Enter the alpha numeric code for the location top be recorded

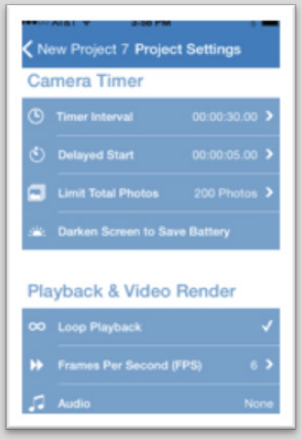
		Prefix	*Supplemental lens*
i.	For Hagerty Library Basement enter	HL1	Wide angle
ii.	For Hagerty Library Ground Floor enter	HL2	-
iii.	For Hagerty Library Second Floor enter	HL3	Fish eye
iv.	For Leaning Terrace enter	LT1	-
v.	Medical Library Ground Floor enter	MS1	-
vi.	Medical Library Second Floor enter	MS2	-
vii.	Main Building Lobby enter	MB1	-
viii.	Bossone Central atrium enter	BC1	-
ix.	Central Campus Exterior (from Disque Hall) enter	DH1	-
x.	LeBow Business Exterior Café (from Disque Hall) enter	DH 2	-
xi.	LeBow School of Business Lobby	LB1	-

B. Enter the date (November 1, 2014 would be 11.01.14)

C. Enter the time (10A is 10AM, 22 is 10PM)

5. Press CREATE
6. Press ADJUST SETTINGS to verify the camera settings.
   A. Match camera settings to those shown below.
   B. Photo resolution must be set to low.
   C. Timer Interval is 30 SECONDS (2 shots per minute, 200 total shots = 100 minutes)





7. Then scroll down to verify DELAYED START
8. Then scroll down to set VIDEO RENDER QUALITY to "1."

Check Your Settings

9. Check and verify PROJECT SETTINGS again (to avoid spending an hour obtaining bad data).
10. Press START SHOOTING

Position the Camera to Match the Template

11. Mount camera with gorillapod legs under ceiling tile at corner of tile. Follow safety rules when using a ladder.

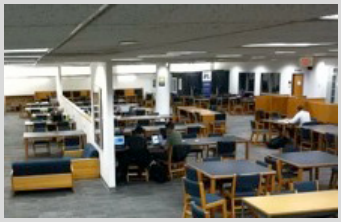
12. Adjust view to match template. Press TIMER icon. Verify timer is working.
13. Remove ladder from area during filming.
14. Remove camera after 90 minutes plus the timing of the TIMER start.

Email the File and Return the Camera to Office

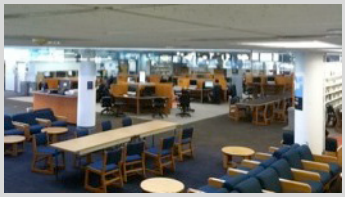
15. Share the file by Email
16. Return the camera to office.

Templates

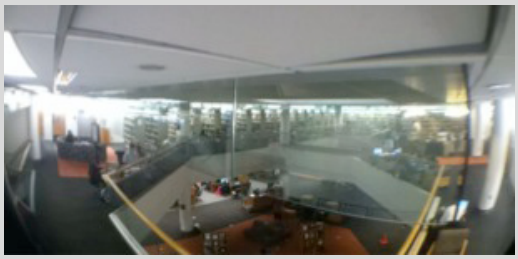
HL1



HL2



HL3



Appendix 3: Camera Site Metrics

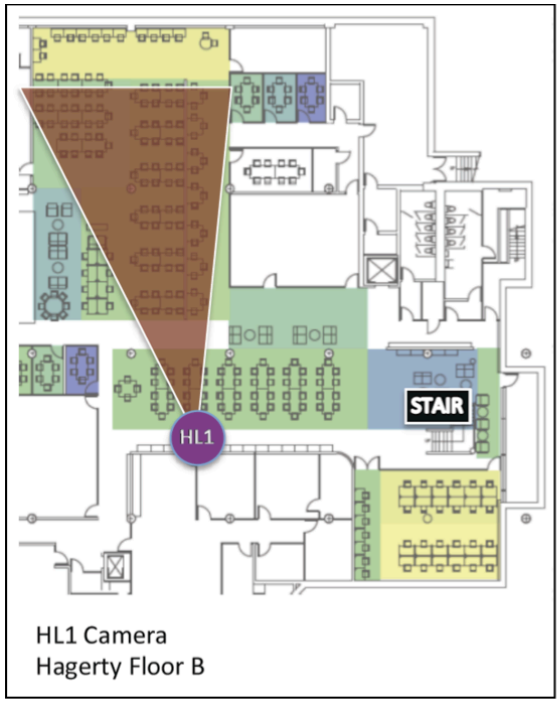
Seat Count	6Hex	1Carrel	4table	8table	4table	8table	1 chair	1 chair	2 chair	2 chair	4 chair	4 chair	TOTAL SEATS			
	6	1	4	8	4	8	1	1	2	2	4	4	Outlets	No outlets	Sum	% Power outlets	% carrel
HL1		12	3	2	5	5	2						72	30	102	71%	12%
HL2 Q2	6	6		4			4						42	36	78	54%	54%
HL2 Q3	6	6	16				4						42	68	110	38%	38%
HL2a	4	3	12				12						27	60	87	31%	31%
HL2e	2		6				16						12	40	52	23%	23%
HL2f	1	3	12				12		2				9	64	73	12%	12%
HL2g	6	4	1										40	4	44	91%	12%
HL2h																	
HL2i																	
HL2j																	
HL3		9	4					4	1	2	2		17	26	43	40%	21%
LB							12			6			12	12	24	50%	0%
LT		8			9	1							52	0	52	100%	15%
PL			8								4		0	48	48	0%	0%

SURVEY #: DATE (MONTH/DAY):
DAY: TIME:

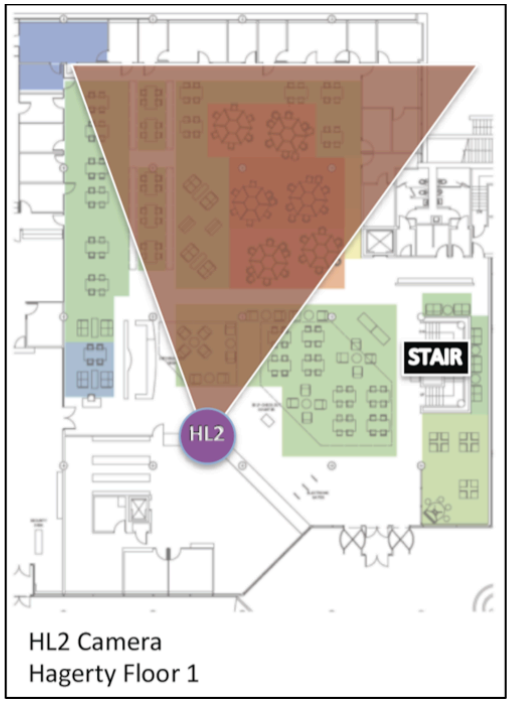
HAGERTY SPACE SURVEY

INSTRUCTIONS

- For each map, mark each person present (including those standing, sitting on floor, etc.) with an **X**.
- Mark anyone sleeping with an **S**.
- Some of the zones contain movable furniture. The map of the zone may not match what you observe. Please try and record at least the number of people present. If you have time to sketch a different layout of furniture, please try and do so, but it is not necessary.
- No informed consent form is required for this survey, so please respect peoples' privacy.
- **If you have any questions, please contact [Survey coordinator name, Survey coordinator email]**



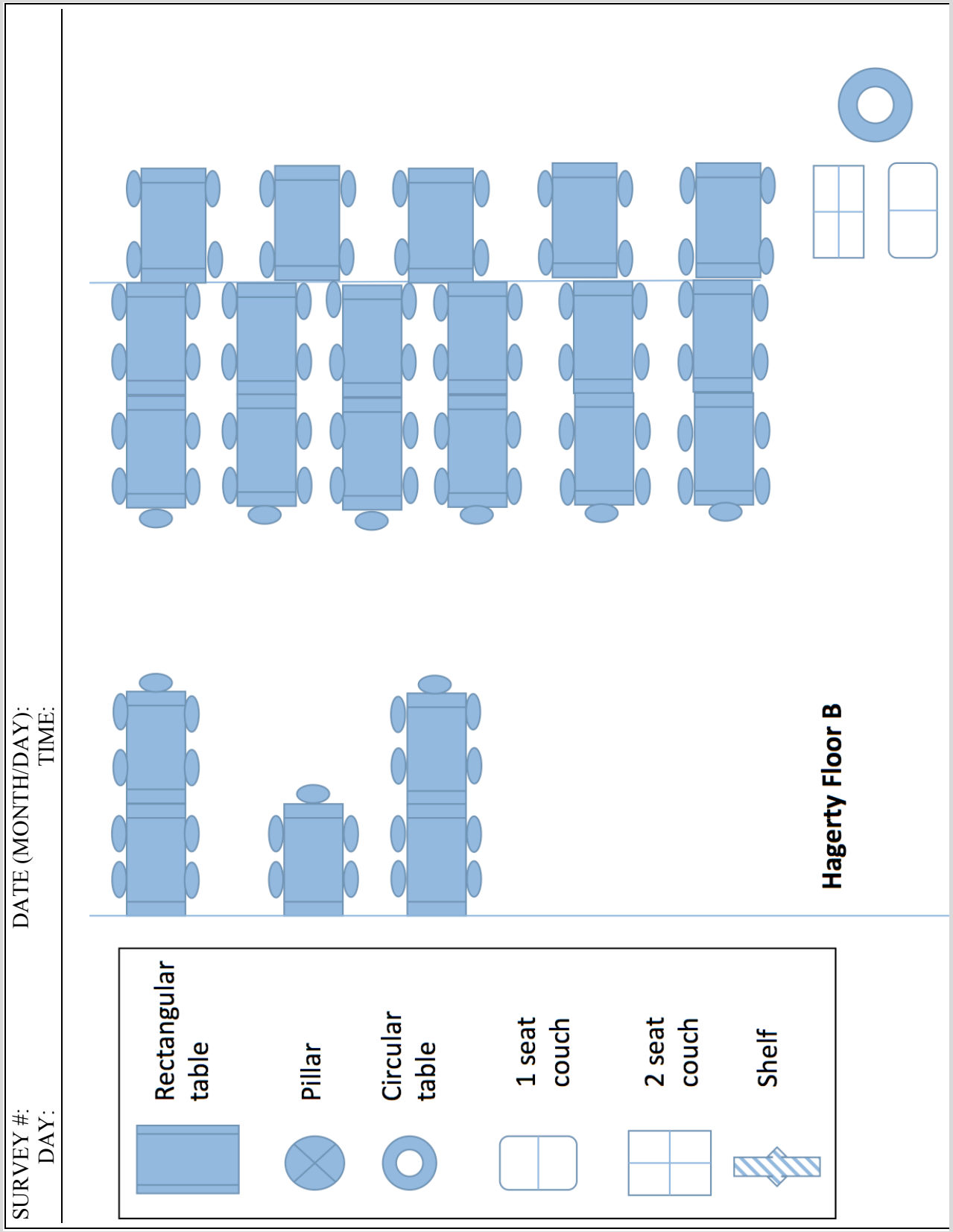
HL1 Camera
Hagerty Floor B

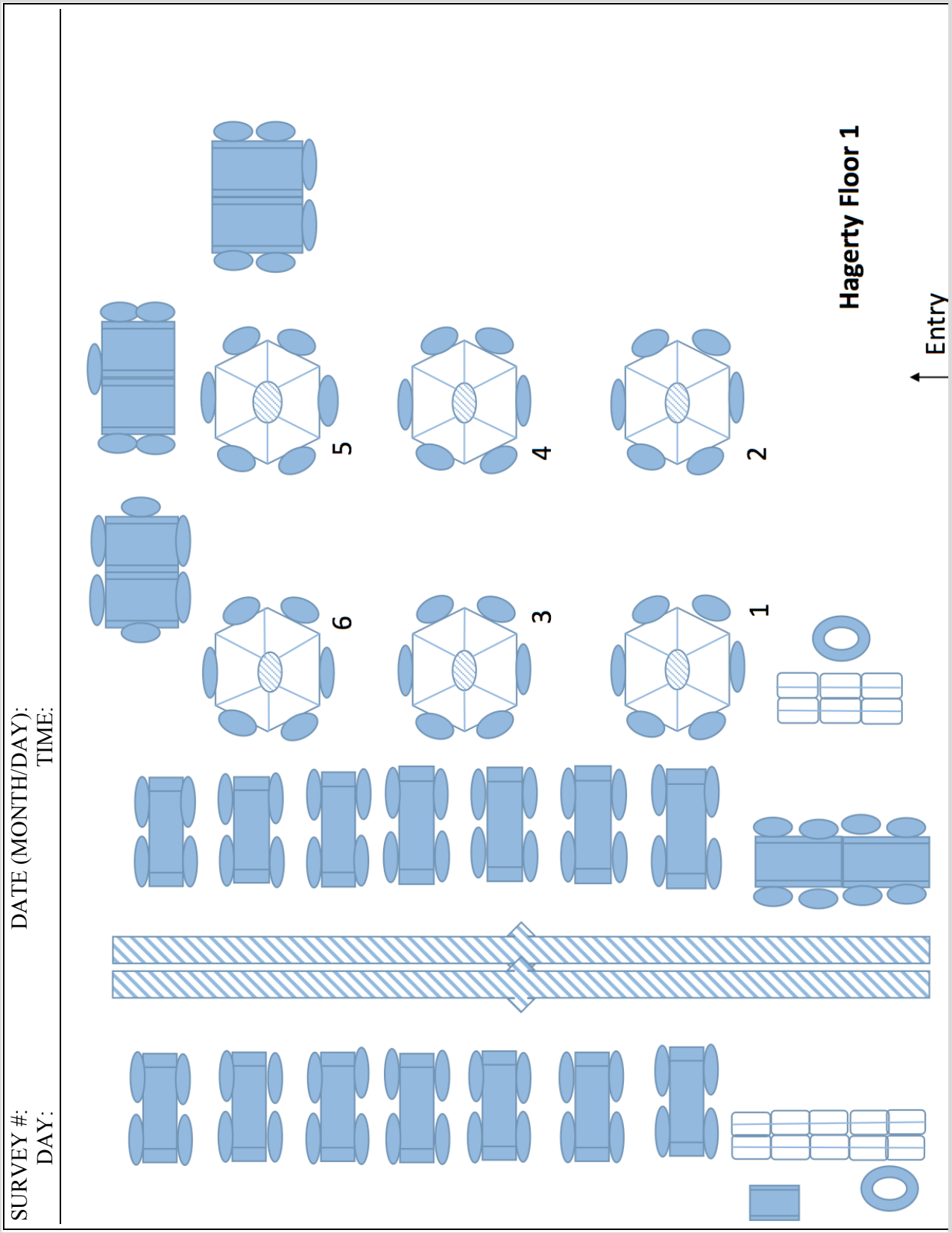


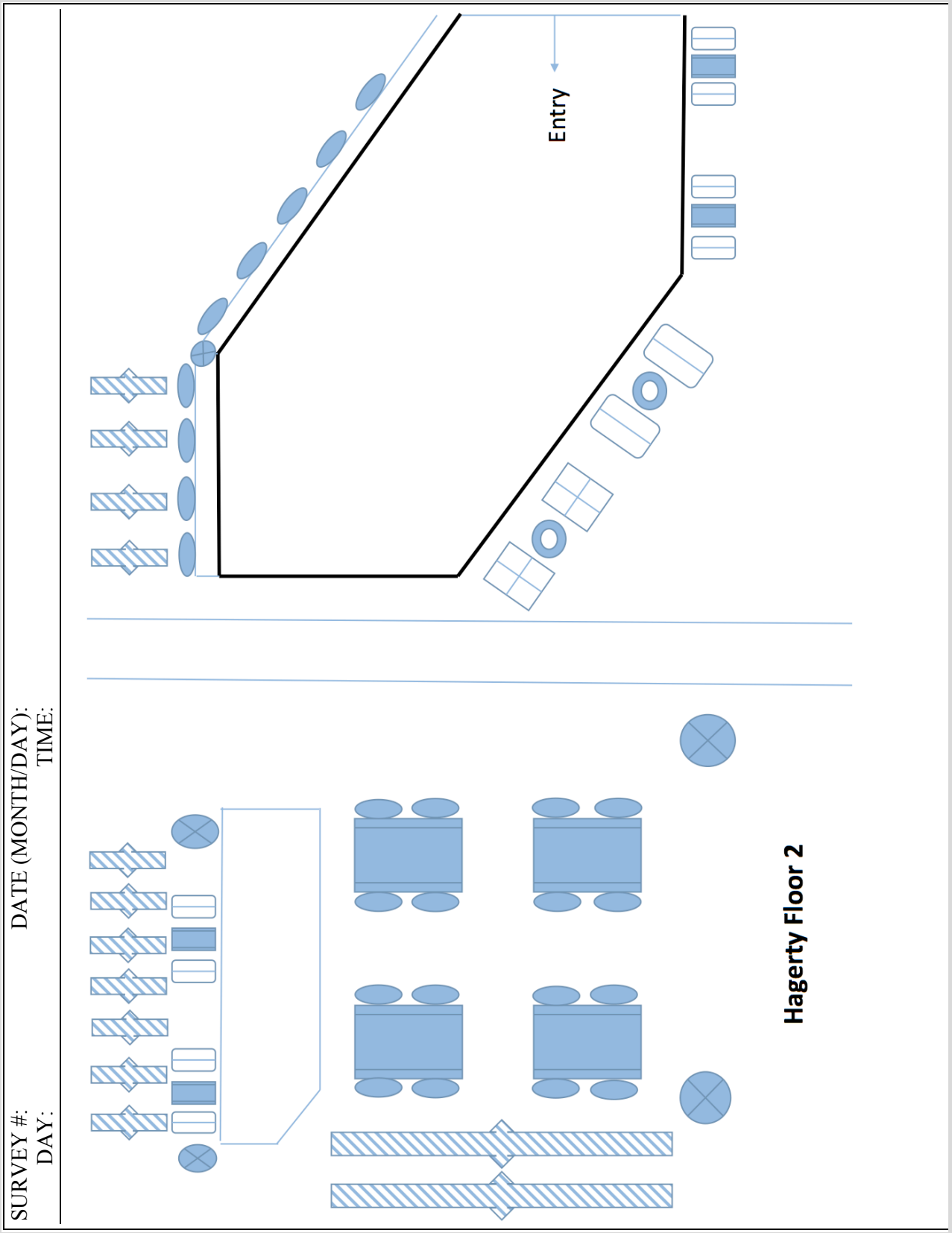
HL2 Camera
Hagerty Floor 1

HL3 Camera
Hagerty Floor 2

The areas that we are interested in are the shaded areas in each of the three maps above. Each of the shaded areas represents the approximate field of view of a camera.


SURVEY #:
DAY:
DATE (MONTH/DAY):
TIME:
Rectangular table
Pillar
Circular table
1 seat couch
2 seat couch
Shelf
Hagerty Floor B


SURVEY #:
DAY:
DATE (MONTH/DAY):
TIME:
Hagerty Floor 1
Entry
1
2
3
4
5
6


SURVEY #:
DAY:
DATE (MONTH/DAY):
TIME:
Entry
Hagerty Floor 2

LEARNING SPACES SURVEY

INSTRUCTIONS FOR SURVEY TAKERS

This survey will gather data on the ways in which users use different learning spaces on the Drexel campus. Each copy of this document contains the survey sheets and two consent forms.[1] The full survey should take about 15-20 minutes to complete.

- Select a research subject, and introduce yourself:
  - *Hello. Would you like to take part in a survey to help improve campus learning spaces?*
- If the answer is yes, sign and date the consent forms.
- Give the subject the consent forms. Instruct the subject to:
  - read the consent form
  - initial and sign the two copies
  - return one copy to the researcher
- Read the following introduction to the subject.

Hello. My name is '_____.' I am:

- *a faculty member at the College of Computing and Informatics at Drexel*
- *a student research assistant at Drexel University*

I am conducting research into how users use learning spaces on the Drexel campus. The aim is to improve these learning spaces. Your participation is voluntary; you can answer as many or as few of the questions as you wish, and you can stop at any time without penalty. Participating in this survey signifies your understanding that the data may be used for research purposes. Do you have any questions before we begin?

- If the answer is 'Yes,' answer the questions.
- If the answer is 'No,' begin the survey.

Please answer the following questions about yourself, and about what you think of Drexel learning spaces services. If you are interested in possibly being contacted in the future about your replies, please supply a contact name and email. Thank you.

- Carry out the survey.
- Collect the survey.
- Thank the subject.

If you have any questions, please contact [survey coordinator name, survey coordinator email]

[1] Note: Consent forms are not included in the version of the survey included with this Report.

SURVEY QUESTIONS

1	**Student status** ☐ Undergrad ☐ Combined BS/MS ☐ Masters ☐ Doctoral Department/College:_____ Program or Major (if declared):_____ ☐ Full-time ☐ Other **How many years have you been at Drexel?** ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 More than 6:_____
2	**Gender** ☐ Male ☐ Female ☐ I'd prefer not to say
3	**Age** ☐ 18-20 ☐ 21-23 ☐ 24-26 ☐ 27-30 ☐ 31-35 Over 35:_____ ☐ I'd prefer not to say
4	**Where do you live** ☐ Off campus ☐ On campus (not fraternity/sorority house) ☐ Fraternity/sorority house ☐ Other
	Are you an international student or foreign national? ☐ Yes ☐ No ☐ I'd prefer not to say

	If two or more people are present: Who are you with and why? For example: Are you studying with a group on a common project? With friends, but working on different projects? Working alone?
	Why did you choose to sit in this particular place? For example: is this one of your favorite places? Or was you favorite place taken? Were you meeting friends? Did you just need somewhere to sit, without preference?
	Could you tell us in detail what you are doing here, and how you are accomplishing it? For example: I'm writing a paper for class, and I need to refer to some books. – I'm working on a project, and I need somewhere quiet to study and spread out my notes. – I need somewhere where I can sit down and use the Internet for a while.

	What technology (hardware/software) are you currently using? For example, laptop, smartphone, tablet? Word processor, browser. spreadsheet, PDF reader? How many apps do you have open? What are you using them for? How many tabs do you have open on your browser?
	How would you describe this particular place? You can say anything you want. For example: Where is this place? What is the furniture like? Is it crowded/noisy/quiet? What is the lighting like? etc. **Is there anything you would change?**

We would like to ask you some questions about how well this space suits your needs. Please mark your response on the scale below.

1. This space helps me work alone on class assignments

Disagree						Agree
1	2	3	4	5	6	7

2. This space helps me work with other students on class assignments

Disagree						Agree
1	2	3	4	5	6	7

3. This space helps me work alone on class assignments, but in proximity to students working in the same way

Disagree						Agree
1	2	3	4	5	6	7

4. This space helps me discuss my work with other students

Disagree						Agree
1	2	3	4	5	6	7

5. This space helps me work on a paper or project that requires integrating ideas or information from various sources

Disagree						Agree
1	2	3	4	5	6	7

6. I know where to find assistance in this space

Disagree						Agree
1	2	3	4	5	6	7

	We would like to photograph and sketch this space, make a list of the objects in it, and record the locations of any people studying here. We may ask you some follow-up questions, and record your responses. Is this okay? We will not show any faces in the photographs, although we may ask for you to leave your hands in view. ☐ Hagerty Library ☐ LeBow common space/atrium ☐ Hahnnemann Medical Library [This space for survey taker's notes]
7	**If necessary, would you be interested to take part in a further follow-up interview?** ☐ Yes ☐ No If yes, please provide your contact information, in case we have any further questions. Name: _____ Email: _____

Thank you for your participation. Please return this survey to the survey taker.

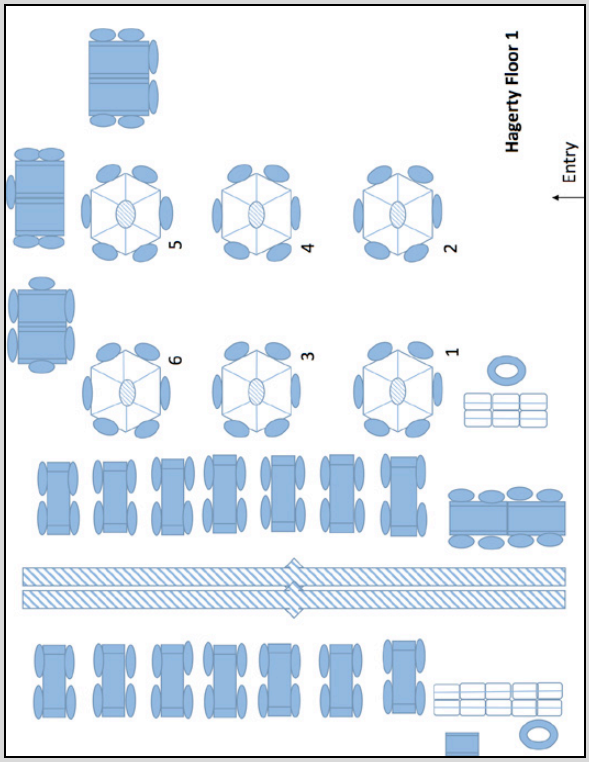
Survey taker: _____

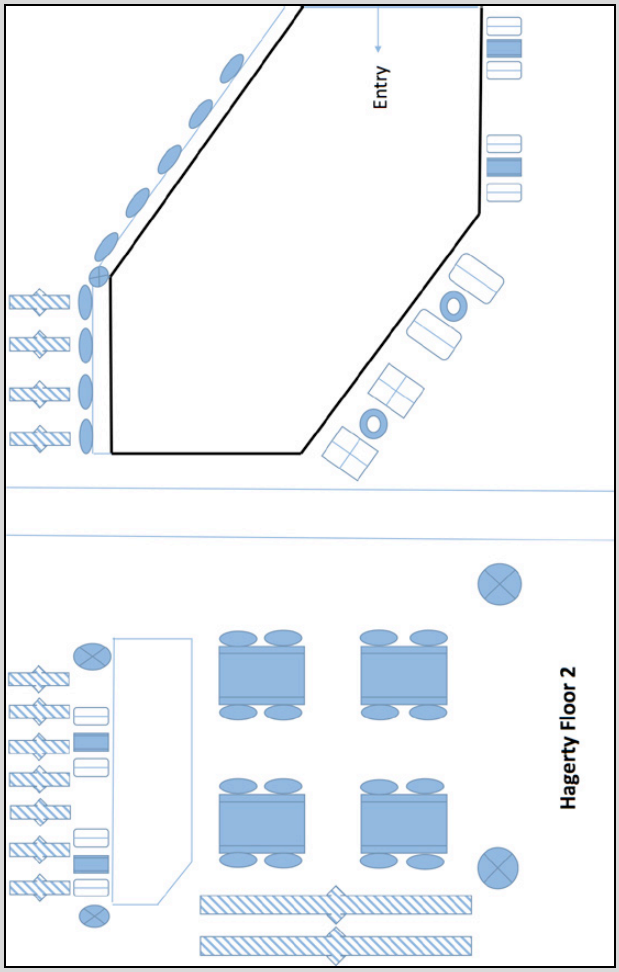
Date _____

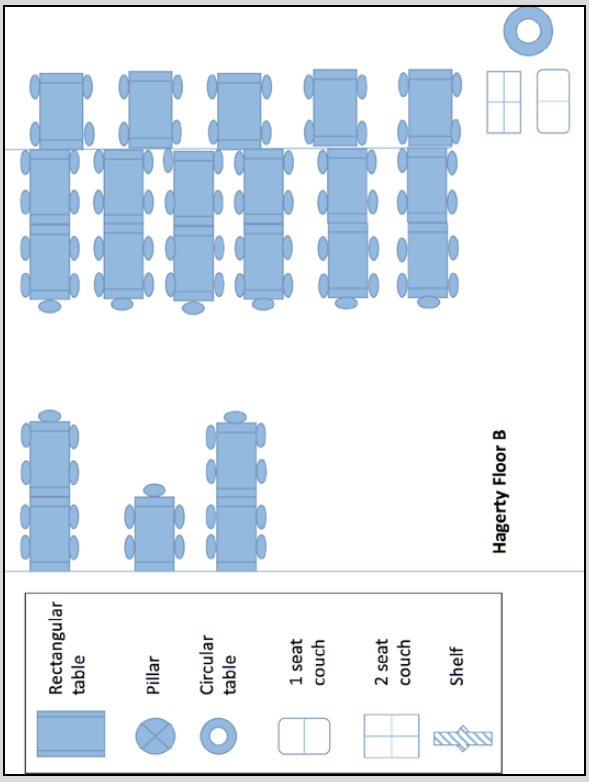
Day _____ Time _____

Location: please indicate on the following page where the survey was carried out.

Comments:


Hagerty Floor 1
Entry
5
4
2
6
3
1


Entry
Hagerty Floor 2


Hagerty Floor B
Rectangular table
Pillar
Circular table
1 seat couch
2 seat couch
Shelf

Appendix 6: Recording Index

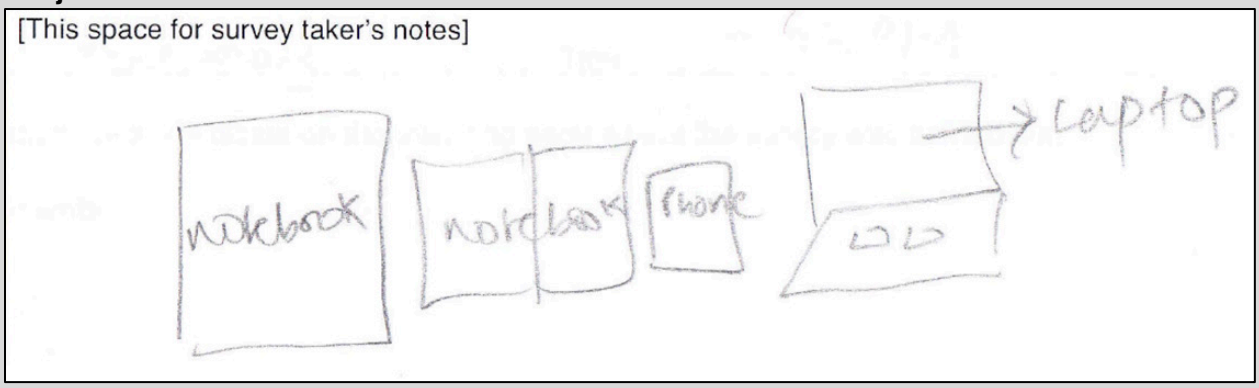
Location			Q1	Q2	Q3	Total
Hagerty Library	HL1	Controls	12	52		64
	HL2	Controls	30	63	48	141
	HL3	Controls	12	61		73
	HL2a	Cases			23	23
	HL2b	Cases			1	1
	HL2d	Cases			1	1
	HL2e	Cases			36	36
	HL2f	Cases			34	34
	HL2g	Cases			9	9
	HL2ga	Cases			18	18
	HL2h	Cases			1	1
	HL2i	Cases			2	2
	HL2j	Cases			2	2
Learning Terrace	LT0	Cases			5	5
	LT1	Cases			2	2
LeBow School of Business	LB	v			2	2
	PL	Cases			2	2

Grand Totals			
Q1	Q2	Q3	Total
54	176	186	416

Appendix 7: Sample Student Survey

Examples of desk sketches carried out by the survey taker.

Subject 003.



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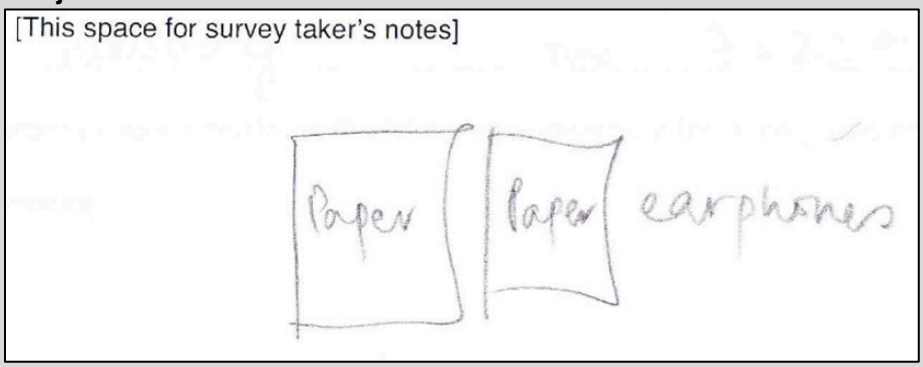

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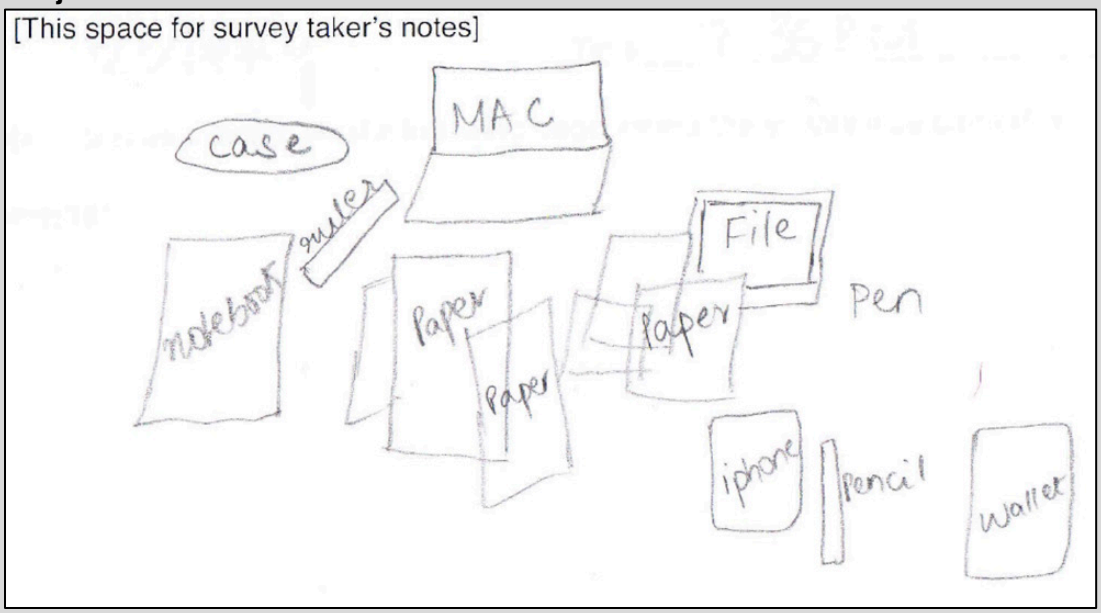

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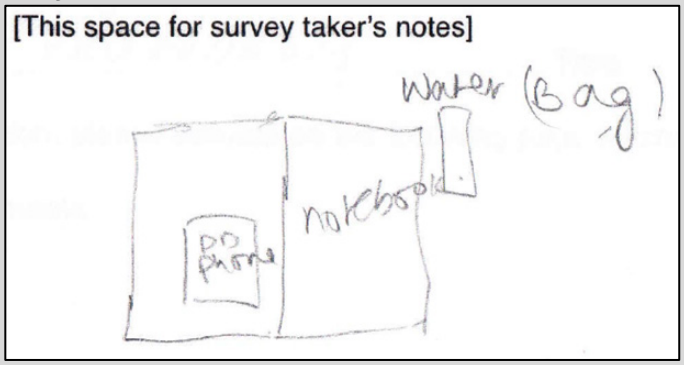

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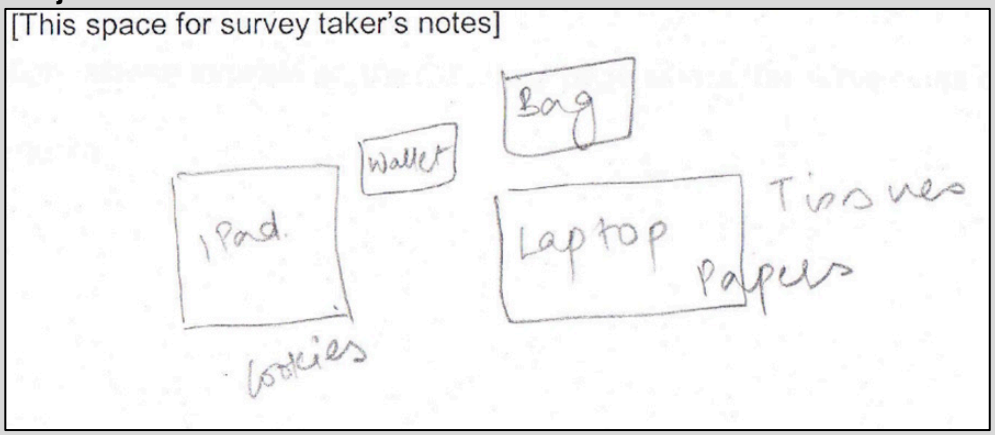

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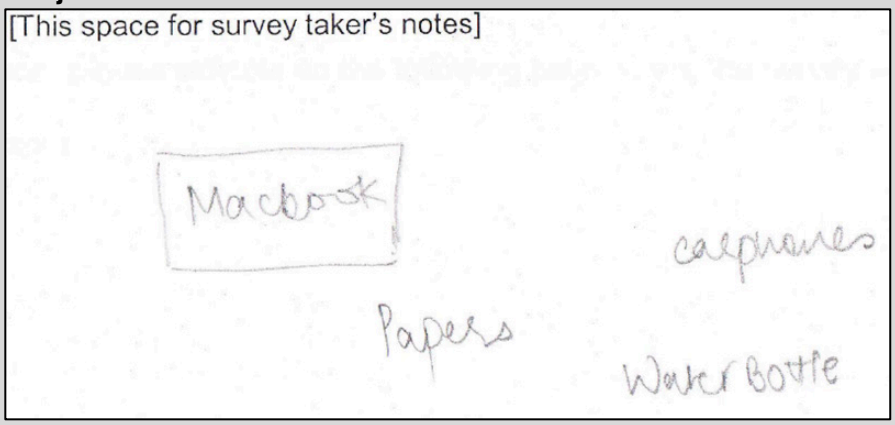

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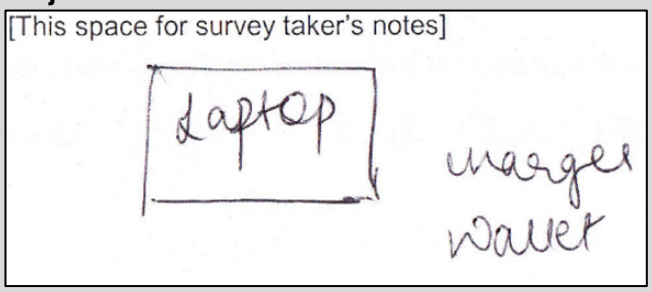

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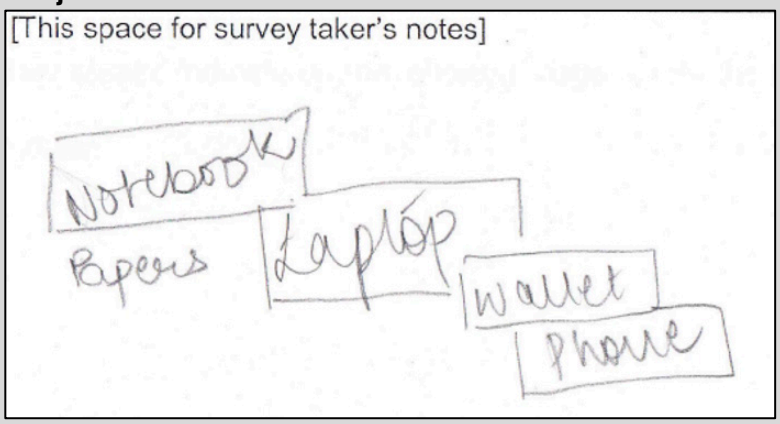

Appendix 8: Project Expense Summary

Direct Project expenses:

Supply Cost [purchase of iphones, camera mounts]	$955
Personnel Cost [Graduate and undergraduate student labor]	$10,785
Total direct cost	$11,740

We appreciate the generous funding and support received from the Society for College and University Planning through the award of the 2014–15 M.Perry Chapman Prize of $10,000 and the contribution of $1,740 from the Drexel University Libraries to cover a portion of the student labor costs.

Additional non-reimbursed, indirect costs of this project over the year included the research team's time (over 1,200 hours), SCUP staff time to create and maintain the project blog and other communication venues for the Chapman Prize, and the Drexel University Libraries staff time to recruit and manage student labor and administer the prize.