Distribution of Resource Use in an Informal Learning Environment: Using Sensor Technologies to Bring Geography Indoors

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Abstract

Indoor spaces have become increasingly prevalent in human lives. While scholarship in other fields has studied the relationship between humans and the indoors, it has not been readily investigated in Geography. This study draws from prior research in Building Design, Managerial Science, and Education to examine the relationship between building users and resources in indoor spaces. To better understand how users seek resources in an indoor, academic space, this research asks: (1) what spaces and resources do building users value?; and (2) how are their perceptions of value associated with observed measures of occupancy? This research takes place in Goodwin Hall, on the Blacksburg campus of Virginia Polytechnic Institute and State University. This research relies on surveys conducted in 2018 as well as accelerometer data collected in 2018 to examine the relationship between users’ perception and use of resources in informal learning environments. Through quantitative analysis this research tests the ideal free distribution hypothesis. Findings indicate that certain measures of use and value support the ideal free distribution hypothesis. These results help to lay a groundwork for future geographic research in indoor spaces.
Indoor spaces have become increasingly created, used, and occupied by humans. Geography, as a discipline, has traditionally studied the relationship that humans have with their surrounding *outdoor* environments. This research studies how humans interact with their *indoor* environments. Other disciplines, such as Building Design, Managerial Science, and Education have examined how indoor spaces, such as offices and classrooms, can impact human movement, behavior, and choice. Geography is a spatial discipline (observes how variables affect each other over space) and offers a differing lens to view human-indoor relationships. To better understand how users seek resources in an indoor, academic building, this research asks: (1) what spaces and resources do building users value?; and (2) how are their perceptions of value associated with observed measures of occupancy? This research takes place in Goodwin Hall, on the Blacksburg campus of Virginia Polytechnic Institute and State University. This research relies on surveys conducted in 2018 as well accelerometer data, which observes the amount of acceleration created by movement, collected in 2018. The surveys provided measures of how people view indoor work spaces, which, in this research, were areas within a hallway that had tables and chairs, while movement captured by accelerometers provided measures of use. Through quantitative analysis this research tests the ideal free distribution, a hypothesis that argues the number of users in an area will be proportionate to the amount of resources in an area. Findings show that certain measures of use and value support this hypothesis, as more valuable work spaces had more use than less valuable work spaces. Findings from this paper help to provide more insight into how humans interact with indoor spaces and lays the groundwork for future indoor geographic research.
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1. Background and introduction

Indoor spaces are fundamental to many aspects of human endeavor in much of the world. Indoor areas now account for up to 6% of total ice free land area, a total greater area than the flooded grasslands and tropical coniferous forest biomes (Martin et al., 2015). The amount of indoor space has rapidly grown, as has the time inhabitants spend within it (Martin et al., 2015). In Manhattan alone, there are 113 more square kilometers of floor space than outdoor space (Martin et al., 2015). Americans spend approximately 87% of their time in an indoor setting (Klepeis et al., 2001). Indoor space is an essential part of humans’ lives, yet geographers, who frequently study the relationship between humans and their environments, have rarely examined this relationship (Biehler et al., 2010).

Scholarship on building use can be found outside of the discipline of Geography. Building Design and Managerial Science have each investigated how indoor spaces affect humans’ socially (Baird, 2010; Haynes, 2007). Studies in these fields have found that the design of buildings, and spaces within buildings, impact workers’ satisfaction and productivity (Ilozor et al., 2002). Along with impacting individual productivity, the design of indoor space can also serve as a driver to increase collaboration between users (McElroy & Morrow, 2010). Studies in these disciplines have often examined the economic impact that indoor spaces have on workers’ success, viewing the design of indoor spaces as a driving variable that acts on its users (Byrd, 2016).

The importance of indoor space has also been examined in educational research. Research in this discipline is interested in the effect academic spaces have on users’ success (Cleveland & Fisher, 2014). Academic spaces can be divided into formal and informal learning environments (Choi & Jacobs, 2011). Formal learning environments are areas where teaching typically occurs, such as classrooms, while informal learning environments include areas such as hallways and lobbies, where learning occurs at the discretion of the learner (Choi & Jacobs, 2011). Learning environments are spaces that contain a variety of resources, and an increase in the quantity of resources correlates with improved user success (Whiteside et al. 2010; Brooks, 2011).

This research draws parallels between resources in learning environments and outdoor natural resources. Both spaces are areas where users have the ability to seek and use resources.
Research in geography has historically examined the relation between humans and their environment (Zimmer, 2017). This study aims to continue that tradition in a new environment. Few studies have examined an “ecosystem” of informal learning environments with diverse spaces and users. Geography is well positioned to address this. Given the lack of geographic research on how humans interact with indoor environments, this study aims to fill that gap in the literature by examining how users seek resources and organize themselves within a large, mixed use academic building. This research will seek to answer two main research questions: (RQ 1) What spaces and resources do users value?; and (RQ 2) How are users’ perceptions of value associated with observed measures of occupancy?

2. Theoretical overview

2.1 Conceptual framework: human-environment interactions

To examine how people interact with environments at the indoor scale, this study draws from prior literature that studied human-environment interactions. Human-environment interaction is a geographical lens that examines the spatial and temporal relationship between people and their environments (Castree et al., 2013). Geographers have historically studied how humans interact with the natural environment by investigating the physical relationship between humans, the natural environment, and the social processes that arise from that relationship (Bird, 2015). Although rooted in geography, researchers from other disciplines have investigated the relationship between users and the design of indoor space. The impact the built environment has on users has been studied within the fields of Building Design (Byrd, 2016), Managerial Sciences (Sailer et al., 2015), and Education (Cleveland & Fisher, 2014).

2.2 Built environment

Within the built environment, researchers in Building Design and Managerial Sciences have investigated the physical and social impact of how humans interact with indoor workspaces. Building design research has examined how the architectural design of a building affects users’ satisfaction and productivity (Baird, 2010). Managerial Science research scales this down to the interior level, and studies how shaping the physical environment, through interior design, affects the social environment of workers (Haynes, 2007).
Prior research in Building Design has examined how architecture can positively or negatively affect its users (Byrd, 2016). Building design, including lighting, heating technologies, and building construction affect energy efficiency and user comfort (Mortensen et al., 2017; Hansen et al., 2017). A recent study has found that the shape and natural lighting of the building correlates with the success of users working within the building, with users experiencing higher levels of satisfaction within buildings that have more natural lighting (Bailey et al., 2018). Other studies have further scaled down the area of research from the architectural design of an office building to the interior design of an office.

Researchers in Managerial Sciences have examined how the interior design of office spaces affect workplace productivity (Haynes, 2007). The design, capacity, and resources available within a work environment relate to workers’ satisfaction with their workplace (Sailer et al., 2015). Spatial changes within workplaces can further affect managers’ success as well (Skogland & Hansen, 2017). Ilozor et al. (2002) found a correlation between the physical properties of office environments and workers’ performances, finding that environments with more shared spaces led to higher worker productivity. McElroy and Morrow (2010) expanded on this by finding an increase in collaboration with Midwestern office employees when their work environment was reconfigured to be more open. While office spaces can be reconfigured to improve employees’ satisfaction and productivity, they are often designed without employees’ considerations in mind (Peterson & Beard, 2004).

The social environment of workspaces, defined as the “relationships, groups, and social processes that exist among individuals” (Kepper et al., 2019), can also affect user productivity and satisfaction. Prior research has examined how the social behavior of workers relates to interior office design. In some cases, worker satisfaction decreased and stress levels increased as offices moved from traditional to more open designs (Brennan et al., 2002). In other cases, shared, open spaces within an office resulted in users moving and communicating more frequently than they had in a traditional office layout (Sugiyama et al., 2018). Different reactions to distinct office layouts can be attributed to the demographics of users within the workplace. Haynes et al. (2017) found both female workers and older workers to have a significantly more positive perception of their office when an open layout was implemented, due to the increase of socialization.
2.3 Educational environment

Within educational research on human-environment interactions, studies have focused on learning environments (Cleveland & Fisher, 2014). Learning environments are spaces where people learn, either through the facilitation of learning, such as a classroom, or on their own, such as a museum or library (Choi & Jacobs, 2011). The quality and quantity of resources in these spaces can impact the success of users of learning environments (Burke, 2015). Research has examined the design of learning environments, including how the physical layout of resources can impact the quality of the environment (Whiteside et al., 2010)

Learning environments can be divided into formal and informal spaces (Choi & Jacobs, 2011). Formal learning environments are areas where learning is planned and scheduled to occur, such as an office or a classroom. Informal learning environments are places where learning is not scheduled to occur, but can happen organically, such as a library, a museum, a hallway, or a lobby (Choi & Jacobs, 2011). Students’ perceptions of learning environments can relate to their academic success. Lizzio et al. (2002) found that students in more favorable learning environments developed a deeper understanding of their studies. Although learning environments have traditionally been thought of as social environments in educational research (Lizzio et al., 2002), more recent studies argue that learning environments can also be viewed as physical spaces. Brooks (2011) and Whiteside et al. (2010) both maintain that learning environments with an increased number of physical resources, such as larger tables and more shared LCD screens, led to students outperforming expectations.

Learning environments contain both physical and social resources. In formal learning environments, resources are often social and occur in the interactions the user has with those who are facilitating their learning, such as teachers and peers (Burke, 2015). In informal learning environments, resources are often physical objects, such as chairs, tables, or available space for one to work independently or in a group (Choi & Jacobs, 2011). Both informal and formal learning environments can affect self-efficacy and are often positively associated with participation in activities that promote self-development (Choi & Jacobs, 2011).

Much of the research on informal learning environments has focused on libraries and museums (De Backer et al., 2014; Andrews et al., 2015). There was a large increase in the number of museums during the 20th and 21st centuries and curators helped to identify them as educational spaces (Crowley et al., 2014). Curators within museums provide expertise, serving as
educational staff to assist the visitor with information (Simon, 2010). Museums help to facilitate self-learning by providing resources, such as brochures, plaques, exhibits, and videos (De Backer et al., 2014). Libraries have traditionally been a place for informal learning in both universities and public spaces (Walton & Mathews, 2013). While paper books have been traditional resources in libraries, new research has examined that additional digital resources, such as computers and digital books, which were found to improve the ease of access to information (Walton & Mathews, 2013). The physical design of libraries also affects how users interact with their space (McKee, 2010). A study in Denmark found a library to be more accommodating to informal learning by transforming a reference area into a learning commons, allowing for groups of users to collaborate (Larsen, 2010).

2.4 Sensor-based methodologies

Researchers in geography have used accelerometers to better understand patterns of movement in several contexts. For example, accelerometers have been used to study the physical activity of livestock (Robert et al., 2009) and humans (Bell et al., 2015). By using accelerometers, researchers have been able to determine activity levels of the subjects they are studying (Robert et al., 2009; Baek et al., 2015). When combining this data with other sensor technologies, such as GPS, researchers are able to compile more complete datasets providing information on the level of activity that has occurred in specific areas (Baek et al., 2015). Bell et al. (2015) incorporated accelerometer data with social data and found that levels of activity correlate with peoples’ perceptions of place.

Museum learning environment research has used sensors to estimate the effectiveness of designs (Mygind & Bentson, 2017). Klein (1993, p.785) noted that visitors in museums “vote with their feet”, implying that the more time spent at an exhibit displayed increased interest from visitors. To validate the use of sensors to track visitor movement, Moussouri and Roussos (2014) tracked museum visitors’ Wi-Fi connection from their mobile device to investigate the time individuals were spending in exhibit rooms. They applied this method in multiple case studies to test which museum rooms people spent more time in. Yoshimura et al. (2014) used a similar method by setting up Bluetooth sensors, connected to visitors’ mobile devices in the doorways of museums, allowing them to track visitors’ time spent in rooms and their path through the museum. Both studies found that sensors can be used to accurately track museum visitors’
movement throughout the museum and time spent at particular exhibits.

While common methodologies used in studying academic learning environments includes interviews, expert walkthroughs and surveys (Leaman et al., 2010), there are other studies that look at the potential of quantitative measures gathered from remote sensing (Bradley et al., 2017; Su et al., 2014; Fortenbacher et al., 2019). Bradley et al. (2017) discuss the potential of using sensor-based technologies to measure the location and use of resources within informal learning environments. Accelerometers, Bluetooth beacons, and force sensitive resistors can be used to potentially analyze the amount of time resources were used, the movement and relocation of the resources, and the intensity of the use. The process of creating resource-rich and technology-rich facilities is “in its infancy” (Cleveland & Fisher, 2014). Still, there has been research using sensor-based methods to further the discussion on the efficacy of these environments. Su et al., (2014) used facial detection sensors and artificial intelligence in order to track students’ concentration in classrooms, finding that levels of engagement could be measured with the use of sensors. Similarly, Fortenbacher et al. (2019) used a combination of sensor wristbands, tablets, and monitors to analyze the relationship between motion data and cognitive states of learners, finding that motion data can be a successful predictor of engagement. In a review of sensor-based methodology in education, Schneider et al. (2015) found 51 that different sensor methods have been used to further learning in an educational setting. Accelerometers, Bluetooth, cameras, infrared cameras, microphones, and sonar were all found to be noninvasive sensors that can be used in furthering educational research.

2.5 Gaps and opportunities

This research aims to apply a geographic lens to examine how humans interact with their environment at the indoor scale. Existing research in Building Sciences, Managerial Sciences, and Educational Research has studied human-environment interactions at the indoor scale, but opportunities remain. Geography focuses on patterns on processes and how those interpolate, and is a well suited discipline to examine this relationship at the indoor scale.
3. Study design

3.1 Guiding hypothesis and conceptual framework

This research views an academic building as being analogous to a natural environment. Both places contain resources which users seek to obtain. Distinct places where resources are clustered together is being defined as a ‘patch’. To examine how users’ perceptions of patches associate with patterns of use, this study tests a hypothesis that resource value and use follow an ideal free distribution (IFD). IFD is a resource depletion model used to examine both wildlife and human movements (Winterhalder et al., 2010). The model states that the number of individuals in a given area (i.e., patch) is proportionate to the quality and quantity of resources within those areas (Tregenza, 1995).

Figure 1 shows a conceptual model of the IFD. Value, the Y axis, represents the quality and quantity of resources within a patch. Number of individuals, the X axis, refers to the total number of individuals in each patch. The numbers above the graphed points, ranging from 1 through 12, represent the order in which an individual occupies the patch. The first 6 individuals occupy Patch B. The 7th individual then occupies Patch A, as an unoccupied Patch A has more value than Patch B does with 6 other occupants. Figure 1 conceptualizes the IFD hypothesis by showing individuals occupying whichever patch has the highest value relative to the total amount of occupants. A patch with higher value will be occupied first and will have more occupants than
lesser patches. This theory assumes that users distribute themselves in the most ideal way. Patches, patch value, and patch use are three necessary variables for testing this theory. This research tests if resource use in informal learning environments within an academic building adhere to an IFD.

Figure 2. A conceptual rendering of patch areas within the study environment

Figure 2 shows a conceptual rendering of the study environment, where users of a building group themselves into different areas in pursuit of resources. The building is seen as an ecosystem with diverse users and spaces. Users have the freedom to distribute themselves throughout the building in an ideal manner.

3.2 Strategies for testing IFD hypothesis

Correlation of patch value and use:

Studies have tested the IFD by examining the relation of patch use and patch value by examining correlations (Moritz et al., 2013; Beckmann and Berger, 2003; Walhström & Kjellander, 1995). Theoretically, patches with a higher value will have more users in them than lower-value patches. This can be seen in the theoretical model, Figure 1. Patch B, the higher
valued patch, consistently contains more occupants than the lower valued Patch A. A strong positive correlation with patch use and patch value suggests that the user of a space follows an IFD (Moritz et al., 2013).

**Order of occupancy:**

An alternative strategy for testing the IFD is examining the order of patch occupancy (Moritz et al., 2013; Winterhalder et al., 2010). The IFD model states that users will *first* seek to occupy the most ideal patch. Lesser patches will start to become occupied when the most ideal patch becomes overcrowded (Tregenza, 1995). To observe this, this study examines the amount of acceleration occurring in each patch at the start of the day. Support for the IFD hypothesis would be indicated by the highest rated patches have activity in them first.

### 3.3 Study area and population

This study was conducted in Goodwin Hall, on the Blacksburg campus of Virginia Polytechnic Institute and State University (Virginia Tech), which is well suited for this type of research. First, the building is instrumented with 241 accelerometers, attached to 136 sensor mounts, which measure acceleration on the second, third, and fourth floors. The distribution and number of accelerometers allow for measures of acceleration to be collected throughout large portions of the building. Second, the building contains numerous patches that serve as informal learning environments. A diversity of spaces containing varied resources provides a range of contexts within which path value can be measured. These spaces within Goodwin Hall are all open access and individuals are free to find their ideal patch. The variety of resources within these informal learning environments allows for an in-depth study of which resources and spaces students perceive to be the most useful.

This study’s population is limited to users of Goodwin Hall - who include undergraduate and graduate students. The population of Goodwin Hall contains predominately engineering students but is open to students in any major. The informal learning environments, where this research is focused, are primarily used by undergraduate students. Users of informal learning environments use these spaces for class work, individual and group work, and leisure.
4. Methods

4.1 Data collection

4.1.1 Qualitative: semi-structured interviews of building users

To begin to address each of the research questions (Pg. 4), I conducted semi-structured interviews (N=50) in October, 2019 to identify students’ perception and use of informal learning environments in Goodwin Hall and to define resources and patches. I used an opportunistic sampling method to recruit students to participate in semi-structured interviews within the building. I asked questions regarding: (1) how often spaces are used within Goodwin Hall; (2) which areas students preferred to work in and spots which students tried to avoid; (3) if students preferred to work in the same area; (4) which factors led the student to work in the specific informal learning environment; and (5) demographics, including peoples’ gender identity, academic year, and major (Appendix A).
4.1.2 Quantitative: structured survey

To examine the relationship between respondents’ perceived value of patches and actual use of patches, as measured by accelerometers, I constructed a survey to distribute to users of Goodwin Hall. I acquired respondents for the survey through a convenience sampling method. Fliers with a QR code and a web address were placed on tables and chairs in each of the
patches. I distributed fliers in Goodwin Hall from November 5\textsuperscript{th} through the 16\textsuperscript{th}, 2018. A total of 257 individuals started the survey and 201 completed it. The survey solicited information about respondents’ perceptions and uses of learning environments within Goodwin Hall, along with basic demographic information. Regarding perceptions of learning environments, the survey had questions asking respondents to rank pre-existing lists of two categories: (1) preferred resources; and (2) preferred patches. The survey also asked respondents to indicate what type of work they do in these environments and how frequently they use them. The survey included questions about the respondents’ academic year, academic college, and gender identity (Appendix B).

4.2 Data analyses

4.2.1 Qualitative analysis

I used the semi-structured interviews to examine students' perceptions of informal learning environments within Goodwin Hall, including patches and resources. Inductive coding focused on identifying resources within informal learning environments, identifying patches within Goodwin Hall, and identifying different types of patches. Insights from content analysis of the interviews informed the design of the structured survey.

4.2.2 Quantitative analysis

Descriptive statistics (RQ1):

To examine patch preference for different student types (RQ1) I calculated basic descriptive statistics of survey data. The survey responses were used to calculate the patch preference stratified by participants’ gender, academic year, and workstyle preference.

Ideal free distribution (RQ2):

Testing the IFD hypothesis requires measures of both patch value and patch use (Tregenza, 1995). To examine how users’ perception of space related to their use of space, the IFD hypothesis was tested in two separate ways: examining correlations and observing the order of occupancy.
**Patch value:**

Calculating patch value is a necessary step in testing the IFD (Moritz, 2013; Tregenza, 1995). Patch value was determined in three different ways. First, *direct* survey patch ranking was calculated. This ranking directly reflected survey respondents’ rankings of patches. Second, *derived* resource ranking was calculated. This measure of patch value reflects the product of the values of resources in a patch. Third, resources per capita was found. This measure of patch value divides the derived resource ranking by the total user capacity of the patch.

Direct survey patch rankings and patch rankings from direct resource rankings were both numbered by respondents from most to least favorable. Participants in the survey were not required to rank every patch or resource, resulting in a varying number of rankings. Participants were able to rank up to ten total patches, A-J, and five resources; windows, whiteboards, upholstered chairs, tables, and outlets. For example, respondent A may have only ranked seven out of ten patches and three out of five resources. Respondent B may have ranked ten out of ten patches and four out of five resources. Participants ranking numbers of variables creates a problem of comparing different rankings. Respondent A may have ranked patch E their second most favorable out of their seven ranked while Participant B may have ranked E as their third most favorable out of their ten ranked.

To compare these, (Smith et al., 2001) suggested using uniform intervals between ranked variables on an indexed scale from 0 to 1. For example, a participant who ranked all ten patches would have their highest rated patch result in a value of 1, their second highest rated patch result in a value of .9, and each following patch resulting in a value .1 less than the patch ranked above it. A participant who ranked five patches would have their highest rated patch result in a value of 1, their second highest ranked patch result in a value of .8, and each following patch would result in a value .2 less than the patch ranked above it. This interval is defined for each response as 1/n, where n is the number of patches ranked by respondent i. An individual patch-ranking index value \( P_{ix} \), for patch x of a rank p for the n number of patches ranked by respondent i. Thus:

\[
P_{ix} = 1 - (P_{ix} - 1)/(n_i)
\]

This sets each respondent’s highest ranked item to \( P_{ix} = 1 \), and the lowest ranked item to \( 1/n_i \), or one interval up from 0. All items not ranked by the respondent were given a null value.
The first measure of patch value, direct survey patch ranking, was calculated by taking the average value of all respondents’ uniform patch rank interval. This process resulted in each patch having a value between 0-1. Patches closer to one have a higher patch value than patches closer to 0.

The second measure of patch value, derived resource ranking, was calculated in two steps. First, the total amount of resources in each patch was found. Second, the average value of each respondents’ uniform resource rank interval was multiplied by the amount of each resource in a given patch. This gave larger patches with more resources a higher ranking than smaller patches with fewer resources.

The third measure of patch value, resource ranking per capita, was found by dividing the derived resource ranking by the capacity of the given patch. Capacity was found by totaling the number of seats in each patch. This adjusted the derived resource ranking by accounting for the amount of individuals that could be in each patch.

Table 1. Measures of, and methods for calculating patch value

<table>
<thead>
<tr>
<th>Measure of patch value</th>
<th>Method of calculating patch value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Direct Survey Patch Ranking</td>
<td>Average patch ranking</td>
</tr>
<tr>
<td>2. Derived Resource Ranking</td>
<td>Product of average resource ranking</td>
</tr>
<tr>
<td>3. Per Capita Ranking</td>
<td>Resource ranking per patch capacity</td>
</tr>
</tbody>
</table>

Patch use:

Patch use was determined by using the accelerometers located within Goodwin Hall. Accelerometers estimate the amount of movement occurring in an area (Westerterp, 1999; Karantonis et al., 2006). This strategy assumes that the amount of movement within an area is an indicator of use. Accelerometers are located within the floors below patches. Accelerometer data were collected one week per month, from September 2019 to November 2019, from 6:00 to 20:00 Monday through Friday. The root mean square (RMS) of acceleration was found. Accelerometer data were collected and processed using Matlab software.
Table 2. Accelerometer Collection Dates

<table>
<thead>
<tr>
<th>Month</th>
<th>Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>September</td>
<td>12-18</td>
</tr>
<tr>
<td>October</td>
<td>08-12</td>
</tr>
<tr>
<td>November</td>
<td>15-19</td>
</tr>
</tbody>
</table>

Average value of acceleration

Accelerometer data were analyzed at two time scales: daily and weekly. The means of RMS of acceleration for each day over the collection period were calculated to find daily averages for each patch. For example, the Monday data for each week was combined to produce a single value for Monday acceleration per patch. The same process was repeated for Tuesday through Friday. The means of each week of acceleration were averaged to get weekly averages of patches. The daily averages provide average movement over each day of the collection period while the weekly averages provide the total average of acceleration.

Peaks in acceleration

An additional strategy to analyze accelerometer data is to “count peaks”. Peaks are defined as a data point that has a higher value of acceleration than the data point immediately before and after it. Peaks were analyzed in daily and weekly averages. Peaks were counted over five minute intervals, providing 168 time intervals, per day, per patch. Averages of peaks were taken for each time interval. Means were found for each corresponding day over the collection period, resulting in average peak values for Monday through Friday. Weekly averages were found by taking the mean value of peaks from each week in the collection period. Peaks of acceleration were counted in Microsoft Excel.

Analyses:

Correlations

Correlations were calculated to identify the relationship between patch value and patch use. The structured survey provided patch value during a collection time that did not directly align with the collection period of patch use. However, perceived value was solicited in the general sense. Patch use was analyzed on a daily and weekly scale because single moments in
time could not be matched with survey results. Correlations were calculated for three measures of patch value: (1) ‘direct’ survey patch rankings; (2) ‘derived’ patch rankings from direct survey resource rankings; and (3) resource rankings ‘per capita’; and two measures of patch use: (1) peaks; and (2) RMS; over six measures of time: (1) weekly average, and (2) five daily averages (Monday through Friday). Table 3 illustrates how correlations were calculated for different combinations of patch value and patch use.

Table 3. Visual representation of the data being calculated for correlations

<table>
<thead>
<tr>
<th>Patch Use</th>
<th>Patch Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
</tr>
<tr>
<td>RMS</td>
<td></td>
</tr>
<tr>
<td>Peaks</td>
<td></td>
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</tbody>
</table>

This resulted in twelve correlation coefficients for each measure of patch value and thirty-six total correlation coefficients. The P value was set at .05 for significance.

Order of occupancy

A final strategy to test the IFD involved examining the order of occupancy. I examined this by comparing the RMS in acceleration in different patches beginning at 6:00 AM. RMS data were averaged at three different time scales: (1) semester average, (2) Monday, Wednesday, Friday average, and (3) Tuesday and Thursday average. Accelerometer data were normalized by setting each dataset’s 6:00 AM value to 0 to account for variable baselines within each accelerometer. Accelerometer data were further divided by splitting the data into patch types (isolated hallways, public hallways, and lobbies) and into different floors (second floor, third floor, and fourth floor).

5. Findings

5.1 Qualitative analysis

5.1.1 Defining patches and resources
Findings from semi-structured interviews (n=50) identified what users perceived as a patch, which patches they found to be similar, and what resources they look for when deciding which patch to use.

Participants were informed that patches were being defined as work areas that were spatially distinct from other patches. Users of these spaces grouped like areas by privacy and size, resulting in me defining ten patches, A-J, within Goodwin Hall (see figure 3). Semi-structured interviews also provided insight into which patches participants found to be similar or distinct. Participants would discuss what they look for in an area and which other areas within Goodwin Hall had similar characteristics. This lead to me creating groupings of patches into larger patch type categories; (1) isolated hallways; (2) public hallways; and (3) lobbies. Isolated hallways were defined as areas without heavy foot traffic and were limited to fewer participants per patch than public hallways and lobbies. Patches D, G, and J were classified as private hallways. Public hallways were defined as areas that expanded to a further extent than private hallways, these areas were more compatible for group work and experienced more foot traffic. Patches A, C, E, and H were classified as public hallways. Lobbies were places with larger tables, couches, and chairs, and had a higher user capacity than other areas. Patches B, F, and I were classified as lobbies. Figure 4 displays all patches in Goodwin Hall and which patch type they belong to. Red represents public hallways, green represents private hallways, and blue represents lobbies.
Participants described resources as being anything within informal learning environments that were useful to them. Whiteboards, windows, upholstered chairs, tables, and outlets were identified as resources by participants of the semi-structured interviews. Resources varied throughout informal learning environments. Participants valued resources differently, i.e., whiteboards would be important to some interviewees and would not be used whatsoever by others.

5.2 Quantitative analysis

5.2.1 Patch users’ demographics, preferences, and tendencies

To identify how users’ perceptions of patch types varied in Goodwin Hall (RQ1) (i.e. lobbies, isolated hallways, and public hallways), survey responses were stratified (Table 4). The survey collected information on respondents’ gender, academic year, work frequency, and workstyle preference. The number and percentage of each demographics’ patch preference is displayed in Table 4.
Table 4. Most valued patch type by respondents’ characteristics

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Lobbies</th>
<th>Isolated Hallways</th>
<th>Public Hallways</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
<td>196 (100%)</td>
<td>83 (42%)</td>
<td>76 (39%)</td>
<td>37 (19%)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>106 (100%)</td>
<td>44 (42%)</td>
<td>44 (42%)</td>
<td>18 (17%)</td>
</tr>
<tr>
<td>Female</td>
<td>90 (100%)</td>
<td>39 (43%)</td>
<td>32 (36%)</td>
<td>19 (21%)</td>
</tr>
<tr>
<td><strong>Academic Year</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First Year</td>
<td>28 (100%)</td>
<td>12 (43%)</td>
<td>13 (46%)</td>
<td>3 (11%)</td>
</tr>
<tr>
<td>Second Year</td>
<td>30 (100%)</td>
<td>14 (47%)</td>
<td>7 (23%)</td>
<td>9 (30%)</td>
</tr>
<tr>
<td>Third Year</td>
<td>60 (100%)</td>
<td>24 (40%)</td>
<td>27 (45%)</td>
<td>9 (15%)</td>
</tr>
<tr>
<td>Fourth Year</td>
<td>59 (100%)</td>
<td>22 (37%)</td>
<td>26 (44%)</td>
<td>11 (19%)</td>
</tr>
<tr>
<td>Graduate Student</td>
<td>19 (100%)</td>
<td>11 (58%)</td>
<td>3 (16%)</td>
<td>5 (26%)</td>
</tr>
<tr>
<td><strong>Work Frequency, Per Week</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One Day</td>
<td>85 (100%)</td>
<td>43 (51%)</td>
<td>28 (33%)</td>
<td>14 (16%)</td>
</tr>
<tr>
<td>Two Days</td>
<td>46 (100%)</td>
<td>19 (41%)</td>
<td>22 (48%)</td>
<td>5 (11%)</td>
</tr>
<tr>
<td>Three Days</td>
<td>35 (100%)</td>
<td>14 (40%)</td>
<td>16 (46%)</td>
<td>5 (14%)</td>
</tr>
<tr>
<td>Four Or More Days</td>
<td>30 (100%)</td>
<td>7 (23%)</td>
<td>10 (33%)</td>
<td>13 (43%)</td>
</tr>
<tr>
<td><strong>Workstyle Preference</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mostly Alone</td>
<td>77 (100%)</td>
<td>36 (47%)</td>
<td>21 (27%)</td>
<td>20 (26%)</td>
</tr>
<tr>
<td>Mix Of Both</td>
<td>94 (100%)</td>
<td>36 (38%)</td>
<td>47 (50%)</td>
<td>11 (12%)</td>
</tr>
<tr>
<td>Mostly Group</td>
<td>25 (100%)</td>
<td>11 (44%)</td>
<td>8 (32%)</td>
<td>6 (24%)</td>
</tr>
</tbody>
</table>

5.2.2 Finding Patch Value

Three measures of patch value were identified by collecting data on participants’ rankings of patches and resources from the survey (Table 5). Table 6 shows the rankings and values of patches that were used for analyses. Patches A, B, and C were located on the first floor and did not have any accelerometer data available to them and were omitted (Table 6). The values associated with each patch were found through participants’ ranking of patches, resources, and the amount of resources available per person, per patch.
Table 5. Respondent rank order for the three measurements of patch value: Direct, Derived, and Per Capita. Note: Lobbies (B, F, I), Public Hallways (A, C, E, H), Private Hallways (J, G, D)

<table>
<thead>
<tr>
<th>Rank order</th>
<th>Direct</th>
<th>Derived</th>
<th>Per Capita</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B</td>
<td>B</td>
<td>D</td>
</tr>
<tr>
<td>2</td>
<td>E</td>
<td>E</td>
<td>G</td>
</tr>
<tr>
<td>3</td>
<td>D</td>
<td>G</td>
<td>H</td>
</tr>
<tr>
<td>4</td>
<td>A</td>
<td>F</td>
<td>J</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>C</td>
<td>I</td>
</tr>
<tr>
<td>6</td>
<td>C</td>
<td>J</td>
<td>B</td>
</tr>
<tr>
<td>7</td>
<td>H</td>
<td>I</td>
<td>E</td>
</tr>
<tr>
<td>8</td>
<td>G</td>
<td>D</td>
<td>F</td>
</tr>
<tr>
<td>9</td>
<td>I</td>
<td>A</td>
<td>A</td>
</tr>
<tr>
<td>10</td>
<td>J</td>
<td>H</td>
<td>C</td>
</tr>
</tbody>
</table>
Table 6. Respondent rank order and value for the three measurements of patch value: Direct, Derived, and per Capita, omitting patches on the first floor

<table>
<thead>
<tr>
<th>Rank order</th>
<th>Direct Ranking</th>
<th>Direct (Values)</th>
<th>Derived Ranking</th>
<th>Derived (Values)</th>
<th>Per Capita Ranking</th>
<th>Patch Capacity</th>
<th>Per Capita (Values)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>E</td>
<td>0.47</td>
<td>E</td>
<td>26.76</td>
<td>D</td>
<td>3</td>
<td>2.50</td>
</tr>
<tr>
<td>2</td>
<td>D</td>
<td>0.46</td>
<td>G</td>
<td>15.00</td>
<td>G</td>
<td>7</td>
<td>2.14</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>0.41</td>
<td>F</td>
<td>14.00</td>
<td>H</td>
<td>3</td>
<td>2.07</td>
</tr>
<tr>
<td>4</td>
<td>H</td>
<td>0.38</td>
<td>J</td>
<td>11.00</td>
<td>J</td>
<td>6</td>
<td>1.83</td>
</tr>
<tr>
<td>5</td>
<td>G</td>
<td>0.37</td>
<td>I</td>
<td>7.90</td>
<td>I</td>
<td>6</td>
<td>1.32</td>
</tr>
<tr>
<td>6</td>
<td>I</td>
<td>0.32</td>
<td>D</td>
<td>7.50</td>
<td>E</td>
<td>22</td>
<td>1.22</td>
</tr>
<tr>
<td>7</td>
<td>J</td>
<td>0.24</td>
<td>H</td>
<td>6.20</td>
<td>F</td>
<td>12</td>
<td>1.17</td>
</tr>
</tbody>
</table>

5.3 Ideal free distribution

5.3.1 Correlation of patch value and patch use

Linear correlation coefficients were tested for three measures of patch value at daily and weekly time scales in order to test the relationship between patch value and patch use. Patch value data was found through the structured survey while averages of acceleration, processed as peaks and RMS, were used for patch use. Table 7 shows the correlation coefficient and significance between direct patch value and patch use. Table 8 shows the correlation between derived patch value and patch use. Table 9 shows the correlation between per capita patch value and patch use. A positive correlation between patch value and patch use would show that users are using more valuable patches more than less valuable patches, supporting my IFD hypothesis.
Table 7. Linear correlation coefficients between ‘Direct’ patch value and two measures of acceleration (Peaks and RMS) per patch* during three one-week periods during the Fall 2018 semester

<table>
<thead>
<tr>
<th>Time period</th>
<th>Peaks coefficient</th>
<th>Peaks P</th>
<th>RMS coefficient</th>
<th>RMS p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekly</td>
<td>-0.611</td>
<td>0.0033**</td>
<td>0.433</td>
<td>0.3314</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mondays</td>
<td>0.224</td>
<td>0.3290</td>
<td>0.439</td>
<td>0.4429</td>
</tr>
<tr>
<td>Tuesdays</td>
<td>-0.262</td>
<td>0.2513</td>
<td>0.109</td>
<td>0.8164</td>
</tr>
<tr>
<td>Wednesdays</td>
<td>-0.199</td>
<td>0.3872</td>
<td>0.241</td>
<td>0.6034</td>
</tr>
<tr>
<td>Thursdays</td>
<td>0.062</td>
<td>0.7895</td>
<td>0.644</td>
<td>0.1186</td>
</tr>
<tr>
<td>Fridays</td>
<td>-0.098</td>
<td>0.6726</td>
<td>0.452</td>
<td>0.3091</td>
</tr>
</tbody>
</table>

*Acceleration was found from accelerometers located under each patch. Acceleration for patches with multiple accelerometers was found by taking the mean acceleration values from the corresponding accelerometers.

Table 7 shows no significant correlations between patch use and value.
Table 8. Linear correlation coefficients between ‘Derived’ patch value and two measures of acceleration (Peaks and RMS) per patch* during three one-week periods during the Fall 2018 semester

<table>
<thead>
<tr>
<th>Time period</th>
<th>Peaks coefficient</th>
<th>p</th>
<th>RMS coefficient</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekly</td>
<td>0.335</td>
<td>0.1377</td>
<td>0.506</td>
<td>0.1418</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mondays</td>
<td>-0.086</td>
<td>0.7109</td>
<td>0.757</td>
<td>0.0490*</td>
</tr>
<tr>
<td>Tuesdays</td>
<td>-0.597</td>
<td>0.0043**</td>
<td>0.328</td>
<td>0.4723</td>
</tr>
<tr>
<td>Wednesdays</td>
<td>-0.512</td>
<td>0.0177*</td>
<td>0.407</td>
<td>0.3654</td>
</tr>
<tr>
<td>Thursdays</td>
<td>-0.326</td>
<td>0.1492</td>
<td>0.644</td>
<td>0.1186</td>
</tr>
<tr>
<td>Fridays</td>
<td>-0.499</td>
<td>0.0213*</td>
<td>0.187</td>
<td>0.6875</td>
</tr>
</tbody>
</table>

*Acceleration was found from accelerometers located under each patch. Acceleration for patches with multiple accelerometers was found by taking the mean acceleration values from the corresponding accelerometers.

Table 8 shows four significant correlations between patch use and derived patch value. All significant correlations with peaks and value are negative. The single significant correlation with RMS and derived patch value are positive.
Table 9. Linear correlation coefficients between ‘Per Capita’ patch value and two measures of acceleration (Peaks and RMS) per patch* during three one-week periods during the Fall 2018 semester

<table>
<thead>
<tr>
<th>Time period</th>
<th>Peaks coefficient</th>
<th>p</th>
<th>RMS coefficient</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekly</td>
<td>0.589</td>
<td>0.0050**</td>
<td>-0.142</td>
<td>0.7616</td>
</tr>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mondays</td>
<td>0.547</td>
<td>0.0103*</td>
<td>-0.115</td>
<td>0.8056</td>
</tr>
<tr>
<td>Tuesdays</td>
<td>0.634</td>
<td>0.0002**</td>
<td>-0.028</td>
<td>0.9516</td>
</tr>
<tr>
<td>Wednesdays</td>
<td>0.622</td>
<td>0.0026*</td>
<td>0.457</td>
<td>0.3021</td>
</tr>
<tr>
<td>Thursdays</td>
<td>0.497</td>
<td>0.0219*</td>
<td>-0.038</td>
<td>0.9348</td>
</tr>
<tr>
<td>Fridays</td>
<td>0.542</td>
<td>0.0111*</td>
<td>0.229</td>
<td>0.6208</td>
</tr>
</tbody>
</table>

*Acceleration was found from accelerometers located under each patch. Acceleration for patches with multiple accelerometers was found by taking the mean acceleration values from the corresponding accelerometers.

Table 9 shows six significant correlations, all of which occurred between peaks and per capita patch value. All significant correlations are also positive.

Taken together, these findings above suggest that: (1) Peaks may be a more important measure than RMS for this type of analysis, (2) per capita measures of use are more strongly supportive of the IFD hypothesis, and (3) evidence for an IFD exist at daily and weekly scales.

5.3.2 Order of occupancy

To further test if students’ patterns of use resembles an IFD, this research identifies the order in which patches were occupied. Order of occupancy was examined in multiple ways. Figures 5a, 5b, and 5c examine each patch. Figures 6a, 6b, and 6c examine each floor, Figures 7a, 7b, and 7c examine each patch type. Figures 5a, 6a, and 7a examine weekly averages of data from 6:00 to 9:00, charting the first movements to occur in Goodwin Hall. Figures 5b, 5c, 6b, 6c, 7b, and 7c display grouped daily averages of acceleration from 6:00 to 15:00, displaying how acceleration changes during class exchanges.
Figure 5a. Order of occupancy by individual patch. Normalized average amount of acceleration for per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals.
Figure 5b. Order of occupancy by individual patch, Monday, Wednesday, and Friday.
Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals. Vertical red lines represent the time at which class exchanges start.
Figure 5c. Order of occupancy by individual patch, Tuesday and Thursday. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals. Vertical red lines represent the time at which class exchanges start.

Graphing the acceleration of movement in each patch provides insight into the order in which each patch is occupied. Figures 5a, 5b, and 5c all show patches F, E, D, and G having higher amounts of acceleration than the other patches. In each figure, patches I and J, located on the fourth floor, have a lower amount of acceleration than the other patches. Spikes in acceleration, among all patches, can be seen during class exchanges in Figure 5b, but this spike in acceleration tends to happen in between class exchanges in Figure 5c.
Figure 6a. Order of occupancy by floor. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals.
Figure 6b. Order of occupancy by floor, Monday, Wednesday, and Friday. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals. Vertical red lines represent the time at which class exchanges start.
Figure 6c. Order of occupancy by floor, Tuesday and Thursday. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals. Vertical red lines represent the time at which class exchanges start.

Analyzing the order of occupation by floor results in similar patterns for Figures 6a, 6b, and 6c. The second and third floors have higher measures of acceleration than the fourth floor. This aligns with the observational analysis of Figures 5a, 5b, and 5c, as the patches with lesser amounts of movement, I and J, are on the fourth floor. Peaks in acceleration during class exchanges are visible on Tuesday and Thursday (Figure 6c) while peaks in acceleration occur in between class exchanges on Monday, Wednesday, and Friday (Figure 6b).
Figure 7a. Order of occupancy by patch type. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals.
Figure 7b. Order of occupancy by patch type, Monday, Wednesday, and Friday. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals. Vertical red lines represent the time at which class exchanges start.
Figure 7c. Order of occupancy by patch type, Tuesday and Thursday. Normalized average amount of acceleration per patch during the Fall 2018 semester. Data were collected for three one-week periods over three months. Values were averaged over 5 minute intervals. Vertical red lines represent the time at which class exchanges start.

Graphing acceleration of each patch type helps to identify that isolated hallways’ and public hallways’ levels of acceleration are tightly related. Lobbies have a higher variance of use, as their acceleration moves to higher peaks at a quicker rate (Figures 7b, 7c). Class exchanges do not seem to consistently align with peaks in movement on Mondays, Wednesdays, and Fridays (Figure 7b) or on Tuesdays and Thursdays (Figure 7c).

6. Discussion

This project tested an IFD hypothesis using multiple measures of perceived value and use. Taken together, my analyses provide some support for this hypothesis. Specifically, per
capita measures of patch value were significantly correlated with peaks in acceleration at both weekly and daily time scales. This research provides two main contributions; (1) this research found that users’ direct perceptions of patches did not align with their use, and (2) this research shows the potential benefits of interdisciplinary research between Geography, Education, and Mechanical Engineering.

6.1 Ideal free distribution – correlations

Correlations of per capita patch value and peaks in acceleration were positive and significant for all six time measures tested (Table 9). This specific analysis was the only analysis that supported the IFD hypothesis. This suggests that: (1) users seek out patches where they are able to ensure the most amount of resources will be available, and (2) that resources per capita is the best way to discern patch value in a setting like this. Per capita patch value was also the least direct measure, as direct patch value reflected users’ immediate perceptions of patches and derived patch value reflected users’ immediate perceptions of resources. This suggests that students actual use of informal learning environments may not align with their perceived value of space.

Direct patch rankings and derived patch rankings were either insignificantly or negatively correlated with patch use. Regarding direct patch rankings, a lack of support for an IFD hypothesis could simply be due to students’ perceptions of patches not being aligned with their actual use of patches. Derived patch rankings not supporting an IFD could be due to how the measure reflected the total amount of resources in an area and not account for how many resources each user could expect to obtain. Both of these measures of value suggest a difference between perceived value and actual use.

6.2 Ideal free distribution – order of occupancy

Graphing the accelerometer data for patches, floors, and patch type shows that stratifying the data by different “day groups”, (e.g. Monday, Wednesday, and Friday, or Tuesday and Thursday) does not appear to greatly affect the use of the patches. Different groupings of patches, such as by floor, support the IFD when compared to different measures of use. When examining the order of occupation of patches (Figure 5a), F, G, and E being the first three patches occupied aligns well with ‘derived’ patch rank (Table 6). Examining the order of occupation by floor displays that the use of the second and third and floors are tightly related and
noticeably higher than the use of the fourth floor (Figure 6a). Ranking patches by floor eliminates the possibility of directly relating the data to any measure of patch value. Examining the order of occupation by patch type (e.g. private hallway, public hallway, and lobby) showed private patches being occupied first, followed by public patches and then lobbies (Figure 7a). Despite isolation, occupants seemed to pursue isolated hallways at a higher rate than other patch types. Although not tightly aligned with any one of the three patch value measurements, this order is loosely, but not significantly, aligned with the ranked order of ‘per capita’ patches.

Patches I and J, located on the fourth floor, consistently had the lowest levels of acceleration (Figure 5a). Similarly, the fourth floor also had the lowest levels of acceleration (Figure 6a). When entering an unoccupied building users tended to use the patches on the second and third floor. This suggests that the extra time and effort it would take to get to the fourth floor was a deterrent to users. Lower levels of use for patches I and J could also be due there being no classes on the fourth floor, like there are on the second and third floors, placing these patches further away from an upcoming class users may have. Patches I and J were ranked as the least valuable patch by the direct rankings, but were in the middle of the rankings for derived resource value and per capita value.

6.3 Patch type preferences

Stratifying users’ highest ranked patch by demographics and use characteristics provided insight into which type of informal learning environments users perceived to be the most favorable. Table 4 shows that users mostly prefer lobbies or isolated hallways to public hallways. Patches A, C, E, and H were classified as public hallways. User demographics do not affect patch type preference. While previous research has shown females to benefit more from public and open informal work environments (Haynes et al., 2017), there are more males in STEM, and more males responded to the survey, which could account for this difference (Turner et al., 2019). Users of informal learning environments within Goodwin Hall are typically composed of third and fourth year students, students who work alone or in a mixture of alone and in a group, and frequent these spaces one to two days a week.
6.4 Voting with their feet

Few measures of patch use aligned with measures of patch value. ‘Per capita’ patch value and peaks in acceleration were significantly correlated and supported an IFD. The two other measures of patch value were either not significantly correlated with patch use or were inversely related with patch use. Examining order of occupation by patch, the most precise version of this analysis, best aligned with ‘derived’ patch value, which is focused on resources irrespective of density concerns. Neither analysis that examined the use of every patch showed that ‘direct’ patch value aligned with an IFD. Students’ direct perception of learning environments was not aligned with their use.

Previous research in informal learning environments have noted the importance of users “voting with their feet” (Klein 1993, p.785). Although other studies have shown that the amount of use of an area is an indicator of the users’ perception of it (Yoshimura et al., 2014), this research found that users of informal learning environments perceived patches differently than they used them. There is no support for an IFD when examining ‘direct’ patch value. However, there is support for users adhering to an ideal free distribution when patch value was found by the total amount of resources in a patch (Figure 5a) and the per capita accessibility to these resources (Table 9). The importance of resources for users of informal learning environments has been shown in educational research (Brooks 2011; Whiteside et al., 2010). Students sought out spaces where resources were most available to them.

6.5 Interdisciplinary contributions

This research drew from Geographic, Educational, and Mechanical Engineering theories and methods. The IFD, a model that tests resource use distribution spatially, aligns well with Geographic research. Education Research provided an understanding of the study environment, and I worked with mechanical engineers to provide context for accelerometer use and data collection. Learning environments have used accelerometers, along with other sensors, to gauge the effectiveness of the environment (Bradley et al., 2017; Su et al., 2014; Fortenbacher et al., 2019). This research contributed a spatial lens to the research, providing insight into the distribution of use of learning environments. Accelerometers have often been used to measure physical activity of humans (Migueles et al., 2017) and structural vibration (Sabato et al., 2016), but have not often been used to examine the spatial distribution of users. Using accelerometers in
other disciplines, such as Geography and Education, could provide insight into new possibilities for data collection, and in return, provide insight into new use cases for these instruments by mechanical engineers.

6.6 Limitations

This research’s biggest limitation was in measuring patch use. Accelerometers provided consistent data for the amount of acceleration occurring in a given patch at a given time. However, acceleration requires movement. High levels of acceleration in a patch could be due to users of Goodwin Hall walking past a patch without using it. A person sitting in an isolated patch would create less acceleration to be measured than students walking past that patch. Observing if acceleration was due to users or people passing by would require a level of observation that this research could not provide. Future research could address this limitation by using multiple methods of remote sensing.
References


Sailer, K; Pomeroy, R; Haslem, R; (2015) Data-driven design — Using data on human behaviour and spatial configuration to inform better workplace design Corporate Real Estate Journal, 4 (3) 249 – 262


Appendix A: Semi-structured survey template

**Study Area Preferences in Informal Learning Environments**

The purpose of this interview is to learn your opinions about study areas in Goodwin Hall. This is part of a study being conducted by Timothy Baird (tbaird@vt.edu 540-231-5116) and Mark Villarreal (villarmd@vt.edu 540-931-6050). The results will be used to examine the perceived value and physical use of informal learning environments and will be included in a masters thesis and potentially research publications. Eligibility is limited to individuals 18 years old or older. Your participation will include this one time interview. Your participation is voluntary and confidential. You have the right withdraw at anytime or not answer any question. This interview should take approximately 7 minutes. Should you have any questions or concerns about the study’s conduct or your rights as a research subject, or need to report a research-related injury or event, you may contact VT IRB Chair, Dr. David M Moore at moored@vt.edu or (540) 231-4991

Today’s Date: ______________________

Do you consent to this interview?     YES     NO

Are you 18 or older?     YES     NO

Academic major resides in the following college:
___College of Agriculture and Life Sciences
___College of Architecture and Urban Studies
___College of Business
___College of Engineering
___College of Liberal Arts and Human Sciences
___College of Natural Resources and Environment
___College of Science
___University Studies
What is your current academic standing?
___ First Year
___ Second Year
___ Third Year
___ Fourth Year
___ Masters Student
___ Doctoral Student
___ Other

What is your gender identity?
___ Female
___ Male
___ Other

I am interested in your use of informal learning spaces. This can be any hallway, common area,
or space that is outside of a classroom or a laboratory.

How did you make the decision to work in this spot today?

Do you normally work in this spot?
What other spots do you like to do work in Goodwin?

Appendix B: Formal survey template

Perception of Space in Goodwin Hall

The purpose of this survey is to learn how students at Virginia Tech use public areas in Goodwin Hall. This study is being conducted by Timothy Baird (tbaird@vt.edu, 540-231-5116), a professor in Geography, and Mark Villarreal (villarmd@vt.edu, 540-931-6050), a student in Geography. Results of this study will be used to examine the perceived value and physical use of informal learning environments. In addition, results will be included in a Master's thesis and additional research publications. Your participation is limited to this survey. Participation is
voluntary. You can withdraw from this study at any time and you reserve the right to refuse to answer any question. This survey should take you approximately 11 minutes to complete. Should you have any questions or concerns about the study’s conduct or your rights as a research subject, or need to report a research-related injury or event, you may contact VT IRB at 540-31-3732, or irb@vt.edu.

Your initials document your consent to take part in this research.

Are you 18 or older?

☐ Yes

☐ No
My academic major resides in:

- Agriculture and Life Sciences
- Architecture and Urban Studies
- Business
- Engineering
- Liberal Arts and Human Sciences
- Natural Resources and Environment
- Science
- University Studies
My current academic standing is:

- [ ] First Year
- [ ] Second Year
- [ ] Third Year
- [ ] Fourth Year
- [ ] Masters Student
- [ ] Doctoral Student
- [ ] Other

I identify as:

- [ ] Male
- [ ] Female
- [ ] Other ______________________________________________

The purpose of this study is to examine student use and perception of non-classroom spaces within Goodwin Hall. These spaces include all public spaces such as lobbies and hallways.
1. I use Goodwin Hall for activities other than attending a class (e.g., homework, studying, group meetings).

   - Yes
   - No

2. If so, generally how often?

   - One day per week
   - Two days per week
   - Three days per week
   - Four days per week
   - Five days per week
   - Six days per week
   - Seven days per week
3. When working in Goodwin Hall, do you **normally** work as an individual, or in a group? Select the number that best corresponds with your work habits

<table>
<thead>
<tr>
<th>Only as an individual (1)</th>
<th>2</th>
<th>3</th>
<th>Same amount of both (4)</th>
<th>5</th>
<th>6</th>
<th>Only as a group (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4. When choosing a place to work in Goodwin Hall, which floor do you prefer? Please rank from 1 (most preferable) to 4 (least preferable). Drag and drop responses to rank

_____ First Floor
_____ Second Floor
_____ Third Floor
_____ Fourth Floor
5. When choosing a place to work in in Goodwin Hall, which characteristics do you prefer?

Assume that a place to sit is a given. Please rank from 1 (most important) to 7 (least important).

Drag and drop responses to rank

_____ Window
_____ Whiteboard
_____ Upholstered chair
_____ Table
_____ Outlet
_____ Distant from other features, quiet (bathrooms, water fountains, meeting area)
_____ Close proximity to other features, noisy (bathrooms, water fountains, meeting area)

Below are maps of the first, second, third, and fourth floors of Goodwin Hall. The circles and letters represent distinct spaces where students are likely to perform out-of-classroom activities. A description of the workspaces can be found above each image.

1st floor:
A: Windowsills along the hallway across from the lecture hall
B: Lobby directly across from the main entrance, located in the back of the first floor
C: Windowsills and chairs to along the hallway to the right of where the main entrance is

2nd floor:
D: Hallway with work spaces at each end of it, windows overlook Stanger Street
E: Hallway to the right of the elevator, wraps around the restrooms. Windows overlook Perry Street.

3rd floor:
F: Third floor lobby
G: Hallway with work spaces at each end of it, windows overlook Stanger Street
H: Hallway to the right of the elevator, wraps around the restrooms. Windows overlook Perry Street.
4th floor:
I: Fourth floor lobby, ping pong table
J: Hallway with work spaces at each end of it, windows overlook Stanger Street
6. Please list the spaces (A-J) in Goodwin Hall that you prefer to perform out-of-classroom activities in, assuming all spaces are available


7. Please rank your top 5 spaces to perform out-of-classroom activities in Goodwin Hall from the list you made above (your first letter listed will be the most ideal area).


8. Does the space that you prefer vary depending on the work that you're doing?

    - Yes
    - No


9. If so, how?


10. Does the space that you prefer vary depending on the time of day?

- Yes
- No

11. If so, how?

________________________________________________________________

12. Does the space that you prefer vary depending on the day of the week?

- Yes
- No

13. If so, how?

________________________________________________________________

14. To fill out this table, please think about what days and times you perform out-of-classroom activities in Goodwin Hall, and which floor (1-4) is the most ideal to work in for that time.
Please put the corresponding floor (1-4) into the times and days which you do activities outside of the classroom in Goodwin

<table>
<thead>
<tr>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
<th>Saturday</th>
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<tr>
<td>AM</td>
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<td>PM</td>
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</tbody>
</table>

If you wish to be entered into the raffle, please enter your email address below

__________________________________________________________________________

__________________________________________________________________________

Thank you!