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ARTICLE

# Shared space and resource use within a building environment: An indoor geography

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**Abstract**

Indoor spaces are essential to most humans' lives. Furthermore, in many cases, buildings are shared indoor environments that contain diverse people and resources. Spatial patterns of use are important but under-examined aspects of human-building interactions. This study leverages perspectives from human-environment geography and mechanical engineering to examine spatial patterns of use within a network of shared indoor spaces in an academic building at a research university in the United States. Here we ask: (1) What spaces and resources do building users value? and (2) How are values associated with observed measures of use? We hypothesise that spatial patterns of use follow an ideal free distribution (IFD), a common ecological model of resource use. To test this, we define measures of value and use derived from mixed qualitative ($n = 50$) and survey-based social data ($n = 196$) and data from a building-based system of accelerometers. Our analyses provide some support for the IFD hypothesis. We discuss the implications of this finding and potential new avenues for geographic research in shared indoor environments.

**KEYWORDS**

accelerometers, human-building interactions, human-environment geography, ideal free distribution, mixed-methods, United States

## 1 | INTRODUCTION

Throughout the world, indoor environments are central to human endeavour. Americans alone spend approximately 87% of their lives indoors (Klepeis et al., 2001). Furthermore, indoor environments are widespread, with estimates of the global extent of commercial and residential buildings ranging from 0.5% (Martin et al., 2015) to 1.3% (Kitzes et al., 2007) of total ice-free land area, comprising a footprint similar to that of Earth's smaller biomes like flooded grasslands and tropical coniferous forests (Martin et al., 2015). And whereas these biomes are shrinking, indoor environments are growing rapidly (UN, 2019).

Given the importance of indoor spaces, scholars and practitioners should think creatively about how these complex human-built environments work. Geography, especially, can offer new ways of conceptualising and examining these spaces.

This study leverages geographic perspectives, especially human-environment geography, to examine a shared indoor environment. Correspondingly, we draw parallels between indoor environments and outdoor ones. Geography has a long tradition of research on human-environment interactions (Barrows, 1923; Grossman, 1977; Zimmerer, 2010), but few studies have discussed shared *indoor* environments as types of ecosystems with certain patterns of use. Here, we embrace this view to address two research questions involving a network of informal learning spaces within a large academic building on a university campus in the United States: (RQ1) What spaces and resources do building users value? and (RQ2) How are users' perceptions of value associated with observed measures of use? To address these, we integrate social science and remote-sensing strategies within an instrumented building that contains a network of informal learning spaces.

## 2 | THEORETICAL BACKGROUND

While our study departs considerably from other geographic scholarship on indoor spaces, both conceptually and methodologically, below we outline broad scholarly trends in the discipline.

### 2.1 | Geography and indoor environments

Geographic research examining indoor spaces has grown recently, especially studies using GIS and remote sensing strategies (Chen & Clarke, 2020; Teixeira et al., 2021). However, the earliest geographic scholarship of these spaces, which applied more behavioural and humanistic approaches (Golledge & Stimson, 1997), sought to improve upon the prevailing assumptions of rational, optimising actors by better understanding how diverse individuals interpreted spatial information and made decisions, especially related to wayfinding, symbolism and meaning (Devlin, 2014; Gesler, 2003; Goss, 1988; Hopkins, 1990).

More recently, geographic analyses of indoor spaces have focused on applying geospatial tools and epistemologies to better understand patterns of human behaviour. Spurred by the rapid growth of cities and buildings around the world, geographers have turned their attention to the mapping, navigation and analysis of indoor environments. In their systematic review of the scholarship on indoor environments and geographical information systems, Teixeira et al. (2021) identified and characterised five main research themes: management, geospatial analysis, positioning, data acquisition and spatial data models. Management studies have focused on network analysis (Kwan & Lee, 2005) and related optimum path analyses (Scholz & Schabus, 2017). Studies of indoor positioning systems have tracked individuals' movements through improved mobile-phone based position systems (Ai et al., 2020) and incorporated volunteered geographic information to improve location-based services (Goetz & Zipf, 2011). GIS-based studies have examined human-robot interactions, often in concert with the simultaneous localisation and mapping (SLAM) algorithm (Będkowski et al., 2016). Last, research on indoor spatial data models has largely focused on models for emergency response (Lee, 2007; Tashakkori et al., 2015). Importantly, Teixeira et al. (2021) note that the use of GIS in indoor spaces in still emerging.

With the pivot from horizontal landscapes to vertical buildings, a major challenge has been moving from two- to three-dimensional models of physical space (Jamali et al., 2017). In their review of advances in indoor cartography, Chen and Clarke (2020) credit indoor positioning systems (IPSs) with having the greatest impact on the development of advanced indoor mapping. With the assistance of IPSs, much of the recent cartographic literature has focused on issues of access and wayfinding. Scholars have also worked to improve building design by using geographic modelling and analysis tools to audit floor plans and improved accessibility (Dao & Thill, 2018). Some have developed strategies to leverage floor plans to produce more accurate indoor mapping and modelling (Wu et al., 2021). And others have sought to improve models of indoor space by better accounting for moveable and immovable objects that affect navigation (Diakité & Zlatanova, 2018).

### 2.2 | Gaps, opportunities and human-environment geography

Broadly, studies have tended to see buildings as spatial projects, rather than ecological systems. Furthermore, few studies have focused on building-based resources, which occupants may be seeking. Accordingly, opportunities exist to leverage geography's longstanding interest in human-environment interactions, along with new technologies, to examine patchy, connected, shared, informal, building-scale indoor environments, containing valuable resources—criteria that increasingly characterise educational, commercial and corporate spaces (Jens & Gregg, 2021). This exploratory study embraces this opportunity to better understand the spatial distribution of building users across a network of informal learning spaces in a shared indoor environment.

## 3 | STUDY DESIGN

### 3.1 | Conceptual framework and the ideal free distribution hypothesis

This study views buildings as a type of ecosystem. They contain diverse spaces, or 'patches', distributed across floors, which have valuable resources sought by occupants. And while users, typically students in our case, are diverse, embodying a range of identities and activities, their resources needs are quite similar, often centred on space, furniture and electricity.

To examine how building users' perceptions of the value of diverse spaces, or patches, are associated with observed use, we test a hypothesis that value and use follow an ideal free distribution (IFD). IFD is a simple spatial ecological model of optimal foraging, and a common component of other models of the relationship between behaviour and population dynamics in ecosystems (Fretwell & Lucas, 1970; Sutherland, 1996; Sutherland et al., 1988). The model is based on four basic assumptions: (1) patches have values associated with the level of resources they each contain; (2) individuals are *free* to move to the patch with the highest value; (3) individuals know the value of each patch so that they can choose the *ideal* one; and (4) as the number of individuals in a patch increases, the value decreases. When these assumptions are met, the theory predicts that individuals will distribute themselves across patches in a way that no individual can capture more value by moving to a different patch.

Despite its origins in behavioural ecology, support for the IFD model has been found in studies of human decisions, movements, settlement and population density in a variety of contexts, including rangelands where mobile pastoralists seek high-quality forage (Behnke et al., 2011; Moritz et al., 2014; Scholte et al., 2006), fisheries where fishing vessels seek to maximise catch-per-unit-efforts (Gillis et al., 1993), observational and experimental psychological studies where subjects seek to maximise payouts (Disma et al., 2011; Kraft & Baum, 2001; Sokolowski et al., 1999; Sokolowski & Tonneau, 2004), and archaeological studies of human settlement and development (Kennett & Winterhalder, 2006; Miller & Carmody, 2022; Weitzel & Codding, 2022; Winterhalder et al., 2010). Even research that failed to support the IFD hypothesis has noted its usefulness as a heuristic with the potential to inform efficient resource management (Abernethy et al., 2007).

Figure 1 presents a common graphical representation of the IFD model. *Patch value*, located on the *Y*-axis, represents the quality and quantity of resources within a patch. *Patch use*, located on the *X*-axis, refers broadly to the level of resource use within the patch, which is driven by the number of individuals and their levels of activity (adapted from Weitzel & Codding, 2022). The curves represent two patches, A and B, where patch A is more valuable than patch B. Seeking the best resources for their activities, individuals would enter patch A first (i), and as use increased, either through the addition of individuals or the intensification of activities, value would decrease until the value of patch A (ii) was equal to the value of patch B with no individuals/use (iii).

Studies have tested the IFD hypothesis in various contexts by correlating patch value and use (Beckmann & Berger, 2003; Disma et al., 2011; Gillis et al., 1993; Moritz et al., 2014; Walhström & Kjellander, 1995). With this strategy, higher value patches are expected to have greater use in them than lower-value patches. Correspondingly, a significant positive correlation between patch value and use, across a sample of patches, suggests that patch use follows an IFD (Moritz et al., 2014).

## 4 | METHODS

### 4.1 | Study area and population

This study was conducted on the campus of a large, public research-intensive university in an academic building well suited for this type of research. The building contains various types of academic space, including classrooms and

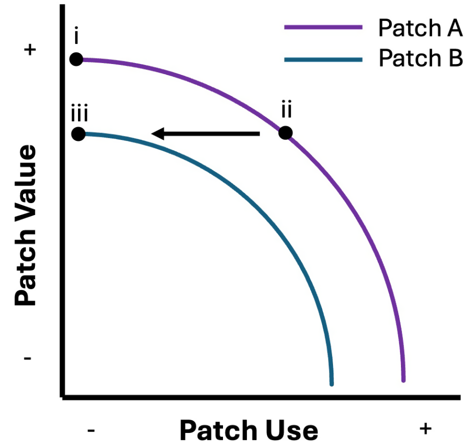


FIGURE 1 Conceptual model of an ideal free distribution, adapted from Weitzel and Codding (2022).

laboratories. It also contains several informal study lounges and other spaces where anyone can work. Importantly, the building is instrumented with 241 accelerometers, attached to 136 sensor mounts throughout the building. (In this paper, we use the terms accelerometers and sensors interchangeably.) Located on key support structures in the ceilings, the sensors measure acceleration on the building's second, third and fourth floors. This acceleration is movement of the floor itself and sensitive enough to measure human footsteps and other movement (Alajlouni & Tarazaga, 2019). Last, individuals are free to move around the building in search of these spaces, which are open access.

The study population is limited to users of the building, who primarily include undergraduate and graduate students. Furthermore, the building predominantly serves engineering students but is open to students of any major, and multiple non-engineering courses are taught in the building.

Figure 2 presents a conceptual rendering of the informal study spaces in the building, including the resources within these spaces, and the sensing technologies (i.e., accelerometers) deployed throughout the building. Here, building users seek patches with resources. In this way the building can be seen as a type of ecosystem, which contains diverse spaces, resources and users who are able to move freely.

## 4.2 | Data collection

### 4.2.1 | Qualitative social data—semi-structured interviews of building users

To begin to understand what patches and resources building users value (RQ1), we conducted semi-structured interviews ($n = 50$) in October 2018 to identify building users' perceptions and use of study areas, and to define resources and patches. We used an opportunistic sampling strategy to recruit building users to participate in interviews. Questions included: (1) how often the respondent used spaces within the building; (2) which spaces they preferred and/or avoided; and (3) what factors they look for in spaces. Insights from these interviews were then integrated with direct observations of the locations, and of accelerometer distribution. Taken together, these factors offered support for the identification of 10 discrete patches throughout the building that people are free to use. Figure 3 presents the locations of these patches, labelled A–J, across four floors. These patches were not arbitrarily determined, but represent recognisably discrete study areas, separated by hallways devoid of seating. Accordingly, we don't believe our patches suffer from the uncertain geographic context problem (Kwan, 2012). Ultimately, these observations, along with insights from our semi-structured interviews, informed the design of a structured survey of building users, with the goal of approximating patch value.

### 4.2.2 | Quantitative social data—structured survey

To approximate patch value, we designed a survey to identify respondents' perceptions of patches and the resources within patches. Specifically, the survey asked respondents to rank, from most to least preferred, a pre-existing list of patches (i.e., A–J) and a separate list of resources, identified through the semi-structured interviews. It also asked respondents to indicate how they use these spaces, how frequently they use them, and standard demographic information (i.e., gender, academic

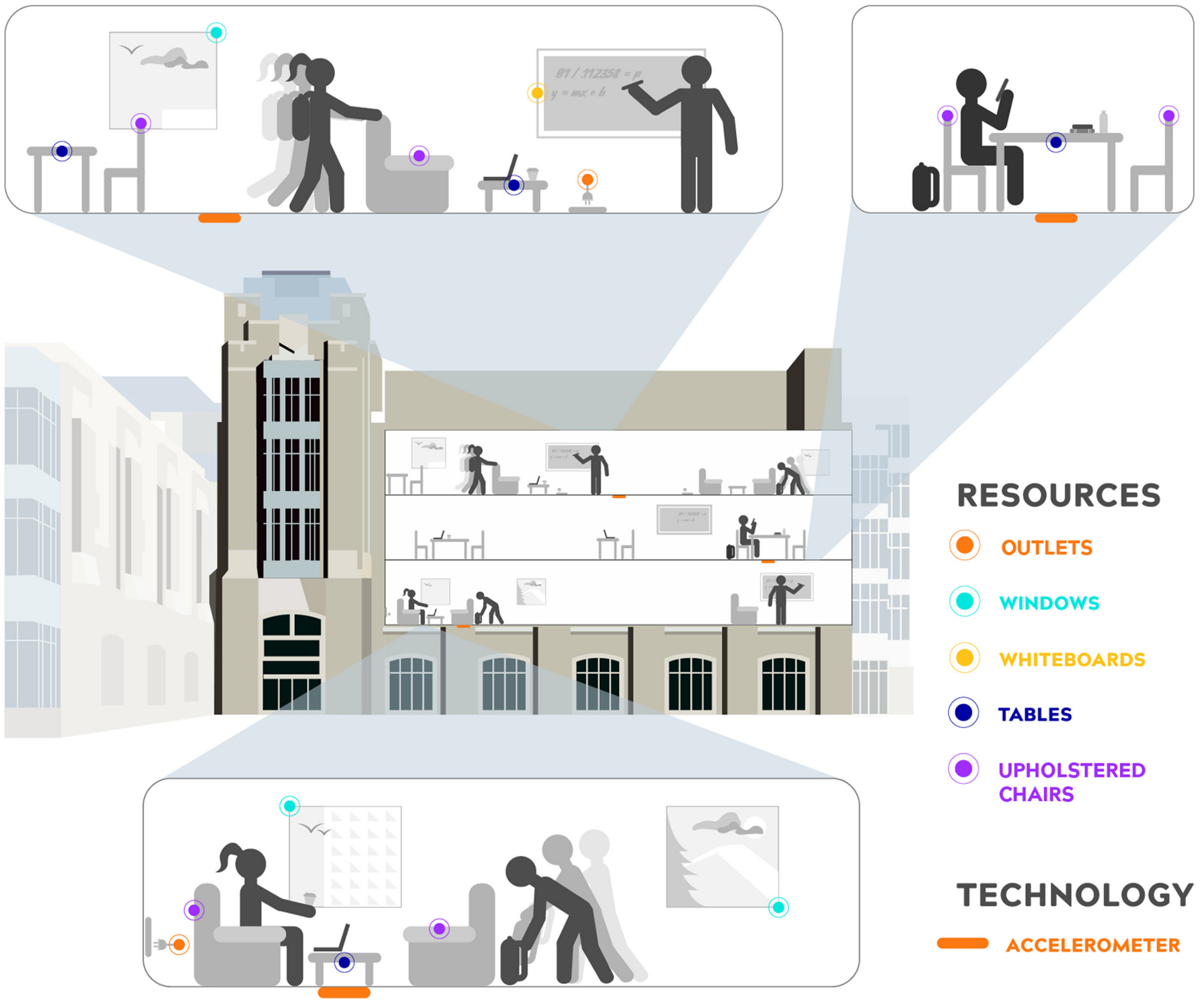


**FIGURE 2** Conceptual rendering of patches, resources and accelerometers in the study area.

year, major). In November 2018, we distributed fliers advertising the survey throughout the building's study patches. Two hundred and fifty-seven individuals started the short survey and 201 completed it, a 78% completion rate.

## 4.3 | Data analyses

### 4.3.1 | Social data—qualitative analyses

We inductively coded the content of semi-structured interviews to: (1) identify discrete patches in the building; and (2) identify what resources respondents valued within patches.

### 4.3.2 | Social data—quantitative analyses—patch value

To identify patch and resource preferences (RQ1), we calculated basic descriptive statistics of survey data. To test our IFD hypothesis (RQ2), we analysed data on patch value (i.e., survey data) and patch use (i.e., accelerometer data) by correlating mean patch value and accelerator-derived patch use.

Where prior social studies of IFDs have relied on comparatively objective measures of value including rangeland forage quality (Moritz et al., 2014), fish catch (Gillis et al., 1993), elevation (Miller & Carmody, 2022) and money (Disma et al., 2011; Kraft & Baum, 2001), we determined patch value in three related but distinct ways, using mean measures of survey respondents' preferences for patches and resources, which we labelled: *direct*, *derived*, and *per capita*. First, we created the *direct value* ranking from survey data of respondents' direct rankings of patches. Second, we calculated the *derived value* ranking from survey data of respondents' direct ranking of resources. For each patch, we counted the number of resources, stratified by type (e.g., two upholstered chairs, one table, one outlet, etc.), and multiplied each number by the mean value of that resource type as determined by survey data. We then summed the products to generate a single value for the patch. Third, we calculated *per capita value* by dividing the *derived value* by the patch's user capacity, which we determined by counting the available seating in the patch.

Calculating these patch rankings required multiple steps. First, we designed our survey, which presented the 10 patches noted above (see Figure 3) and six important resources identified through our semi-structured interviews: tables, electrical outlets, whiteboards, windows, upholstered chairs, and other seats. We asked survey respondents to rank each list (i.e., patches and resources) from most to least preferable. However, we did not explicitly instruct respondents to rank *every* item on each list. We did this so that respondents wouldn't feel forced to rank items that were not relevant to them, which we believed would undermine the quality of the data.

To compare these, we created an index where each respondent's rankings where standardised, with uniform intervals between ranked items, on a scale from 0 to 1 (Baird et al., 2009). The interval between ranked items for each survey is defined as $1/n_i$, where $n_i$ is the number of patches (or resources) ranked by respondent $i$. A respondent patch-ranking index value $P_{ix}$, for patch $x$ of rank $p$ for the $n$ number of patches ranked by respondent $i$ is 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 assigned the value of 0. We used this approach to calculate a patch-ranking index value and a resource-ranking index value for each survey respondent.

For our first patch value measure, *direct value*, we calculated the average of all respondents' patch-ranking index values for each patch. This process resulted in each patch having a value between 0 and 1.

We calculated our second patch value measure, *derived value*, in three steps. First, we calculated the average of all respondents' resource-ranking index values for each resource (as described above). Second, we counted the total number of each type of resource in each patch. Third, for each patch, we multiplied the number of each resource in the patch by the average resource-ranking index value calculated in the first step. This gave larger patches with more resources a higher ranking that smaller patches with fewer resources.

We calculated our third patch value measure, *per capita value*, by dividing the *derived value* ranking for each patch by the seating capacity of that patch. This adjusted our *derived value* measure by accounting for the number of individuals who could use the patch at the same time.

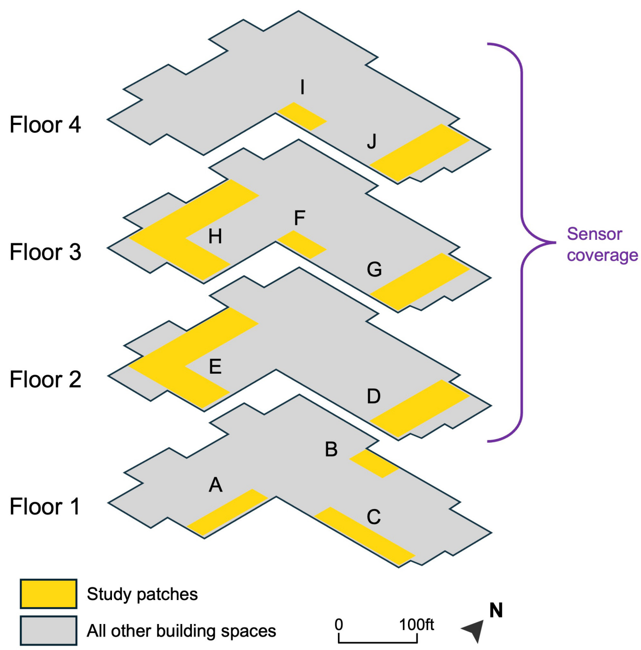


FIGURE 3 Patches in building (A–J).

TABLE 1 Patch value measures and methods of calculating.

| Patch value measure | Method of calculating |
|---|---|
| Direct value | Survey rankings of patches used to create patch-rank index values for each respondent. Mean patch-rank index value calculated for each patch. |
| Derived value | Survey rankings of resources used to create resource-rank index values for each respondent. Mean resources-rank index value calculated for each resource, multiplied by number of resources in each patch. |
| Per capita value | *Derived value* divided by seating capacity of the patch. |

Ultimately, this approach to determining value contrasts with other approaches, as noted above, but leverages local knowledge and perceptions systematically to generate a single measure of value for each measurement type for each patch. Table 1 presents our three different measures of patch value and summarises our methodological approach to calculate each measure.

#### 4.3.3 | Spatial data analyses—patch use

To measure patch use, we used accelerometers installed in the study building. Accelerometers are a type of sensor that measures acceleration. Correspondingly, we assert that the amount of acceleration (of the floor in our case) in an area is a reasonable proxy for movement and ultimately patch use, especially over longer time periods. Data from these sensors were collected for three 1-week periods between September and November 2018, between the hours of 6:00 and 20:00, Monday through Friday. Accelerometer data were collected and processed using Matlab. Because raw accelerometer data include positive and negative values that have a mean of 0 (oscillation around 0), we converted the data to the root mean square (RMS) of each second of acceleration to facilitate analyses (Crandall & Mark, 2014). This standard analytical approach constitutes a statistical measure of the magnitude of acceleration for each 1-s interval, reflecting the amount of activity in that interval. The 1-s RMS data were analysed using two strategies, described below: (1) average value of RMS acceleration; and (2) peaks in RMS acceleration.

#### 4.3.4 | Average value of RMS acceleration

Our first approach to analysing acceleration data was to simply calculate the average RMS value for each patch for a defined period. We calculated average RMS at two time scales: daily and weekly. In addition, daily and weekly averages were calculated across each of the sampling periods. For example, data from each of the Mondays were averaged to produce a single acceleration value for Monday for each patch. This same strategy was repeated for Tuesday through Friday. Similarly, we calculated a single weekly mean for each patch by averaging across each of the sampling periods. Ultimately, the daily averages provide a measure of average RMS acceleration for each patch over each day type (e.g., Monday, Tuesday, etc.) while the weekly average provides total average RMS acceleration for a synthetic week.

#### 4.3.5 | Peaks in acceleration

Our second approach to analysing the RMS acceleration was to 'count peaks'. A peak is defined here as a data point that has a value 10% higher than the data point immediately before it and a value higher than the point immediately after it. This approach serves as a threshold, which omits peaks caused by normal low-level fluctuations in acceleration even when humans are not present. We counted peaks over 5-min intervals, which yielded 168 time intervals, per day, per patch. We then calculated averages of these intervals at daily and weekly time scales to produce week and weekday means across the entire sampling period.

#### 4.3.6 | Analysis of patch value and patch use

To examine the relationship between patch value and patch use (RQ2), we calculated correlation coefficients of our different measures of each variable. This included three measures of patch value (i.e., *direct*, *derived*, and *per capita*) and two measures of patch use (i.e., *RMS* and *peaks*). For each of the six combinations, we calculated correlation coefficients for six measures of time: (1) one weekly average; and (2) five daily averages (i.e., Monday through Friday). Again, patch use was measured with accelerometers located beneath each patch, mounted on support structures in the sub-flooring. In cases where a patch was located above multiple accelerometers, we calculated a mean acceleration value to use in our analyses.

Importantly, our structured survey solicited respondents' general perceptions of patch and resource value, not their specific perceptions of value during the periods of accelerometer data collection. Accordingly, survey results cannot be matched with accelerometer data.

# 5 | FINDINGS

## 5.1 | Qualitative analysis

### 5.1.1 | Defining patches and resources

Our findings from 50 semi-structured interviews with building users highlight what areas they perceive as patches, which patches are similar, and what resources they look for when deciding which patch to use. Interview respondents also identified important resources they look for when seeking a place to work. Resources could be anything within a space that would be useful to them. Seats, outlets, tables, windows, whiteboards and upholstered chairs were all identified as important resources. Table 2 presents the number of these resources in each patch.

And as expected, respondents valued resources differently, with certain items valued highly by some and not valued by others. As noted above, we used insights from these interviews to design a structured survey of building users. After excluding five surveys due to missing data, our final sample size was 196. Table 3 presents our survey respondents' basic characteristics. Notably, women represented 46% of our sample, despite the reality that women are underrepresented in engineering fields (Trapani & Hale, 2022). Also, over 70% of respondents were third-year students or higher, strengthening the likelihood that they had strong knowledge of the building, its patches and its resources.

## 5.2 | Quantitative analyses

### 5.2.1 | Finding patch value

We used survey respondents' patch and resource rankings to create three measures of average patch rank. *Direct*, *derived* and *per capita* measures are described above. Table 4 shows these patch rankings and nominal values for each mean measure of patch value, excluding first floor patches, which do not contain accelerometers, as noted in section 4.1.

**TABLE 2** Number of resources in study patches. (See Figure 3 for patch locations).

| Patch | Seats (all types) | Outlets | Tables | Windows (yes/no) | Whiteboards | Upholstered chairs |
|---|---|---|---|---|---|---|
| A | 8[a] | 4 | 0 | Yes | 0 | 2 |
| B | 30 | 6 | 11 | Yes | 0 | 4 |
| C | 10[a] | 2 | 0 | Yes | 2 | 2 |
| D | 3 | 3 | 0 | Yes | 3 | 3 |
| E | 22 | 9 | 6 | Yes/No | 8 | 6 |
| F | 12 | 2 | 2 | Yes | 0 | 8 |
| G | 7 | 2 | 2 | Yes | 5 | 4 |
| H | 3 | 2 | 0 | Yes | 12 | 3 |
| I | 6 | 2 | 0 | Yes | 0 | 6 |
| J | 6 | 1 | 2 | Yes | 3 | 0 |

[a]Non-upholstered seats are bench-style window seats.

**TABLE 3** Survey respondents' gender and academic year.

| Characteristics | *n* (%) |
|---|---|
| Gender | |
| Male | 106 (54) |
| Female | 90 (46) |
| Academic year | |
| First | 28 (14) |
| Second | 30 (15) |
| Third | 60 (31) |
| Fourth | 59 (30) |
| Graduate student | 19 (10) |
| Total | 196 (100) |

**TABLE 4** Patch rank for each patch value measure, including nominal values (floors 2–4). (See Figure 3 for patch locations).

| | Patch value measure | | |
|---|---|---|---|
| Patch rank | Direct (nom. value) | Derived (nom. value) | Per capita (nom. value) |
| 1 | E (0.47) | E (26.8) | D (2.50) |
| 2 | D (0.46) | G (15.0) | G (2.14) |
| 3 | F (0.41) | F (14.0) | H (2.07) |
| 4 | H (0.38) | J (11.0) | J (1.83) |
| 5 | G (0.37) | I (7.9) | I (1.32) |
| 6 | I (0.32) | D (7.5) | E (1.22) |
| 7 | J (0.24) | H (6.2) | F (1.17) |

## 5.3 | Testing the IFD hypothesis

### 5.3.1 | Correlating patch value and patch use

To test our IFD hypothesis (RQ2), we calculated Pearson correlation coefficients (i.e., linear) for each measure of patch value and patch use at weekly and daily time scales. We examined nominal measures (i.e., not ranks) of patch value, where the highest nominal value is associated with the highest rank (1). Table 5 presents our findings. It reports correlation coefficients and *p*-values for each measure of patch use (*RMS* and *peaks*) and patch value (*direct*, *derived* and *per capita*) for each period (weekly and daily). Ultimately, a positive correlation between patch value and patch use supports our IFD hypothesis by showing that patches perceived as more valuable have higher measures of acceleration than less valued patches (i.e., lower rank). However, given our small number of patches, degrees of freedom are limited, and significance difficult to achieve. As is common, given these types of limitations, we report on significance where $p < 0.10$.

For *direct value*, neither measure of patch use was significantly correlated. For *derived value*, we found a significant positive correlation with *RMS* acceleration for Mondays, which indicates that as patch value increases, so does patch use. *Peaks* values were not significantly correlated. For *per capita* value, *peaks* were significantly positively correlated for each time category except Thursdays. Correlations were significant at the $p < 0.10$ level for the weekly time scale, as well as Tuesdays, Wednesdays and Fridays. The correlation on Mondays was significant at the $p < 0.05$ level. *RMS* values were not significantly correlated.

Taken together, these findings indicate that: (1) per capita measures of resource preferences may offer a better estimation of patch value than direct rankings of patches or resources; (2) counting peaks may be a better strategy than RMS for using accelerometer data to estimate patch use; and (3) our analysis of *per capita* measures of patch value and *peaks* measures of patch use offer support for the IFD hypothesis across time scales.

**TABLE 5** Linear correlation coefficients and *p*-values for each *patch value* (direct, derived and per capita) and *patch use* (RMS and peaks) measured at weekly and daily time scales.

| | Direct value | | Derived value | | Per capita value | |
|---|---|---|---|---|---|---|
| | RMS | Peaks | RMS | Peaks | RMS | Peaks |
| Time scale | Coefficient (*p*-value) | Coefficient (*p*-value) | Coefficient (*p*-value) | Coefficient (*p*-value) | Coefficient (*p*-value) | Coefficient (*p*-value) |
| Weekly | 0.433 (0.331) | 0.485 (0.270) | 0.506 (0.142) | −0.340 (0.456) | −0.142 (0.762) | 0.737 (0.059)* |
| Daily | | | | | | |
| Mondays | 0.439 (0.443) | 0.282 (0.540) | 0.757 (0.049)** | −0.365 (0.421) | −0.115 (0.806) | 0.847 (0.016)** |
| Tuesdays | 0.109 (0.816) | 0.531 (0.220) | 0.328 (0.472) | −0.103 (0.826) | −0.028 (0.952) | 0.743 (0.056)* |
| Wednesdays | 0.241 (0.603) | 0.401 (0.372) | 0.407 (0.365) | −0.317 (0.488) | 0.457 (0.302) | 0.695 (0.083)* |
| Thursdays | 0.644 (0.119) | 0.562 (0.190) | 0.644 (0.119) | 0.037 (0.937) | −0.038 (0.935) | 0.487 (0.267) |
| Fridays | 0.452 (0.309) | 0.500 (0.253) | 0.187 (0.688) | −0.257 (0.578) | 0.229 (0.621) | 0.715 (0.071)* |

*$p < 0.10$. **$p < 0.05$.

## 6 | DISCUSSION

In this paper, we have presented our efforts to define and examine spatially explicit patch and resource use within a shared indoor environment on a university campus. Specifically, we tested the IFD hypothesis using mixed social methodologies alongside a form of remote sensing provided by building-based accelerometers. We have operationalised this approach by defining and justifying: (1) multiple discrete patches within a shared indoor environment where people are free to use the resources therein; (2) multiple measures of patch value grounded in human perceptions; and (3) multiple measures of patch use afforded by accelerometer data recorded in a highly instrumented building. Ultimately, our findings provide some support for the hypothesis that resource use within the study area follows an IFD, specifically that patch value, defined by resources per capita, was positively and significantly associated with patch use, as defined by peaks in accelerometer data, at both weekly and daily time scales.

This primary conclusion raises multiple issues worth discussing. First, our measurement decisions and significant findings indicate a path forward for future research of shared indoor environments. Second, buildingscapes remain frontiers with opportunities for geography. And third, interdisciplinarity is valuable for charting new geographic paths. But first, we discuss some limitations of our study.

### 6.1 | Study limitations

Given the novel and exploratory nature of this study, we faced multiple limitations. First, accelerometers, which afforded continuous (and discrete) sensing through most of the building for the entirety of the study periods, do not provide counts of individual building users. IFD, however, is often discussed in terms of the numbers of individuals in patches. In response, we assert that *use* density may, in some cases, be more important than *population* density. With study lounges, for example, two people could be quietly reading and moving little in one lounge, while another two, working collaboratively in an identical lounge, could have several materials spread out (books, devices, etc.), be talking loudly, and moving back and forth between a desk and white board. With the second scenario, a newcomer may perceive higher patch use, and lower patch value compared with the first scenario, even though the number of individuals is the same. For this reason, we believe our use of accelerometer data is reasonable.

Yet, a further limitation is that accelerometer coverage does not extend to the first floor in our building, a challenge determined by the structure of the building itself. While this limitation is not optimal, the first-floor patches were quite different than patches on the other floors in multiple ways, specifically: (1) patches A and C contain primarily window bench seating, the only in the building; and (2) patch B contains the highest density seating in the building by far. Perhaps most importantly, because the first floor contains the building's entrances, primary lobby, lecture hall and coffee shop, traffic is much, much greater than on the other floors. For these reasons, excluding the first floor for IFD analyses is practical and arguably rational.

Another concern is that the IFD, which is premised on competition between individuals for resources, is poorly matched to our case because fixed seating precludes competition, except where only one seat is available. This, however, assumes that individuals are indifferent to sitting immediately adjacent to a stranger versus sitting further away. Our experience from this, and a related project in a university building, has been that students often will not 'invade the space' of someone else, even when a seat is available in their favourite patch. People put some premium on a spatial buffer, which indicates that increasing measures of use (e.g., increased population or use intensity) do degrade the patch for others. As such, we believe that the conditions in our study are suitable to apply the IFD model.

This spatial buffering example raises additional concerns, which may be limitations of our study and/or insights about the assumptions of the IFD. First, there may be simple patch-leaving rules, as others have observed (Griffen, 2009; Sokolowski et al., 1999), like minimising crowding or noise, that shape individuals' behaviours, and that we were unable to incorporate in our measures of value and use. Second, the IFD assumption that patch values are objective and known to all is problematic in many cases, including our own. Our case is also complicated by the presence of different types of resources across different patches, whereas in other human studies of IFD, measurable resources are singularly defined. We address these challenges by: (1) assuming that individual preferences vary; and (2) measuring *value* in different ways by averaging measures taken from a large social survey. Last, by measuring *use* over three 1-week periods across the semester, we believe that we capture a wide range of behaviours, including patch-entering and patch-leaving scenarios.

## 6.2 | Support for the IFD hypothesis

Given these limitations, we approached the IFD model as a guiding heuristic and evaluated multiple measures of patch value (i.e., *direct*, *derived* and *per capita*) and patch use (e.g., *RMS* and *peaks*), casting a wide net. Ultimately, we found some support for the IFD hypothesis, which sheds light on human-building interactions in a shared indoor environment. Specifically, Pearson correlations of *per capita value* and acceleration *peaks* were positive and moderately significant at weekly and most daily time scales, despite a small sample of patches. This approach, which others have used to examine human mobility and resource use (Disma et al., 2011; Gillis et al., 1993; Moritz et al., 2014), provides support for IFD and is consistent with Birdsall's geographic maxim that *resources are desired* (2003). Notably, value measured either by respondents' direct rankings of patches or resources was not significantly associated with use. Instead, occupants, even at small spatial and temporal scales, maximise value by settling in spaces where per capita resources are highest.

Figure 4 presents the rank order of patches using *per capita value*, which was significantly associated with observed patch use. It shows a likely path that the average survey respondent would take to maximise value. They would begin

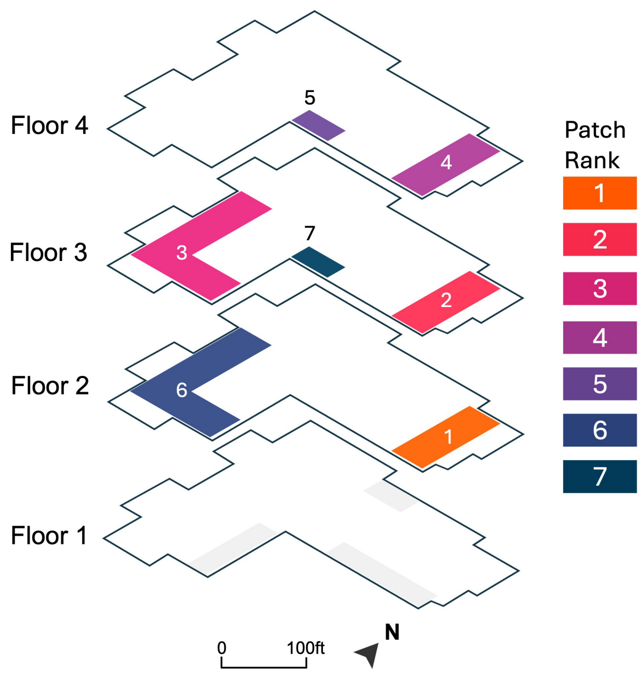


**FIGURE 4** Patch rank using *per capita value* measure.

their search on the east patch of the second floor, and if suitable space was not available there, they would go up a floor checking on two spaces, the east then west, before moving to the fourth and evaluating two more. If these spaces were full, they would return to the second and third floors, respectively, to evaluate their last two preferences. Notably, the top four ranked patches each offer abundant space, good windows, suitable outlets, and perhaps most importantly, few seating options. In contrast, the least 'valuable' spaces have the highest seating densities, suggesting that building users value personal space.

Our findings suggest that humans seek resources and distinguish between small differences. Furthermore, while our conceptual approach contrasts starkly with research on buildings in behavioural geography and environmental psychology, which has largely been concerned with wayfinding (Devlin, 2014), our findings may contribute to this scholarship by providing a case study of an indoor space that individuals visit frequently (i.e., a campus building) as opposed to occasionally, like an airport (Raubal et al., 1997) or a shopping mall (Dogu & Erkip, 2000). Importantly, different spatial perceptions and patterns may emerge in these different types of space. Ultimately, the value of the IFD model lies in its simplicity—and scholars should take care not to conflate theoretical ecological models with the reality of human-environment systems. Last, while our study focused on a network of shared, informal workspaces in a university setting, these spatial attributes are increasingly characteristic of professional spaces across sectors (Jens & Gregg, 2021).

### 6.3 | Buildingscapes are frontiers

Despite geographic work spanning decades, buildingscapes remain curious frontiers. Insights from this study point to two especially robust opportunities for indoor geography: (1) attention to open access and common property systems; and (2) improved object tracking.

By applying the IFD model, as a type of heuristic, our hope was to begin a broader theoretical discussion about shared indoor environments that may be broadly familiar and engaging to human geographers especially, namely how dynamics surrounding open access systems, common property regimes, and the tragedy of the commons are evident indoors (Giordano, 2003; Ostrom, 1990). Our findings offer support for the idea that the study area is a self-organising system, where diverse individuals and groups have open access to space and resources. Subsequent research, however, could go further by examining where tragedy strikes (Hardin, 1968) in shared indoor environments (e.g., how power dynamics shape disparate access or perceived access to space according to gender, race, ethnicity or disability statuses) or how informal and formal rules can emerge over time.

One of the shortcomings of this study is that our accelerometer data, while useful, effectively preclude tracking of individuals. Instead, we rely on weeks of aggregated data to approximate patch use density, but better sensing tools could afford smaller scale observations. Lidar especially holds great promise for indoor settings, where point cloud data can be used to track individuals and objects while maintaining research subjects' anonymity (Flack, 2024; Karki, 2024). Last, buildings offer great potential for conducting experiments, including maintaining controls and adjusting conditions. Future research should leverage this opportunity.

### 6.4 | Interdisciplinarity and geography

This study diverges from prior geographic studies of indoor spaces, perhaps most evidently by adopting perspectives from human-environment geography, especially its concerns for environmental systems, local knowledge and material resources. Nonetheless, our approach was decidedly interdisciplinary, even opportunistically so. Notably, when co-author PT and his colleagues designed the accelerometer system used in this study, they did not consult geographers. They were not overly concerned about where furniture, or other important resources would be located, or where buildings' users might move and pause. As mechanical engineers, their primary concern was with designing a system that could observe the structural dynamics of the building itself. However, once the system was installed, additional ideas and potential applications emerged. Curious about humans' movements and settlement patterns, as is common for human-environment geographers (Fox et al., 2019), we adopted a pluralistic set of epistemologies to define and examine an under-researched topic that may have useful applications across a number of fields (Miller et al., 2008). This case highlights a common dynamic with interdisciplinary research, which is that it often begins with disciplinary efforts and expands when scholars embrace different perspectives and seek knowledge and techniques from other fields (Baerwald, 2010). Here, we have endeavoured to go a step further by reflecting on how this interdisciplinary exercise can inform our disciplinary efforts going forward.

Day Biehler and Simon argued convincingly in their spectacularly titled paper, 'The great indoors' (2011), that indoor spaces matter to geographers. This echoes Birdsall's geographic maxim (2003) that *everything happens somewhere*. We agree. Buildings may be our best tools to leverage the growing digital revolution, commonly referred to as the Internet of Things (Jia et al., 2019) and combat climate change (Cabeza & Chàfer, 2020). Beyond these clear and present challenges, buildings are simply places where humans live.

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## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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