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BIG DATA AND WORKPLACE MICRO-BEHAVIOURS:

A Closer Inspection Of The Social Behaviour Of Eating and Interacting

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ABSTRACT

Evidence-based design aims to understand human behaviour so that strategic decisions are well-informed when creating a new space. Workplace research to date has provided interesting insights, but has mostly done so on a case-by-case basis. This approach does not yield generalisable patterns, making results problematic to use in an evidence-based design context.

This paper builds upon previous large-scale analysis done by the authors and focuses on two aspects of workplace behaviour – eating and interacting. We aim to understand the nuances of these behaviours, thus we explore them as independent phenomena, separate them into sub-categories and set out to understand the reasons behind these observations.

The examined dataset includes 23 organisations in the UK, with a wide variety of sizes, numbers of floors and buildings. It consists of human activity data collected through direct observation, Visibility Graph Analysis and organisational parameters such as industry and flexibility of desk occupancy.

The first behaviour we focus on – interaction – has already been explored in previous research and has been found to happen primarily in workspace and meeting rooms. In this instance we initially classify interactions according to the activity of the members and the type of space they occur in. The analysis of the second behaviour – eating – revolves around the activities and locations of people at lunchtime. We aim to discover where people choose to eat and how this is affected by the characteristics and availability of eating spaces.

For the two behaviours studied, we examine how each activity relates to the space it is happening in, taking into account a set of spatial and organisational factors. In the first case we test each interaction against proximity to circulation and local visibility of the space, while in the second we examine the popularity of different types of spaces, for example canteens and breakout spaces, against their proximity to workspace and what possibilities of inter-visibility they offer.

This paper provides detailed insights into the phenomena of interacting and eating, and reflects on limitations of traditional statistical analysis. It will also highlight further opportunities for handling these types of big datasets using different techniques such as Principal Component Analysis and machine learning.

KEYWORDS

Workplace, Interaction, Eating, Evidence-based design

1. INTRODUCTION: GENERALISABLE PATTERNS FOR EVIDENCE-BASED DESIGN

Evidence-based design aims to understand human behaviour so that strategic decisions are well-informed when creating a new space. This evidence comes in the form of patterns of human behaviour that are related to the many properties of space and the organisation occupying it. Understanding these patterns would be invaluable to designers, as it would allow them to make informed decisions to drive specific outcomes (e.g. greater collaboration) when creating new workplaces, but there has not been a sufficient amount of data to consistently predict where and how behaviours occur. The problem identified by sociologist Gieryn (2002), i.e. 'scattered empirical evidence' on the relationship between building layout and social interaction, remains unresolved today. In addition, applying research findings in practice has been found problematic. The concerns of confusing practitioners and a potential "misapplication of research findings that become popularised (...) to vastly different organisational contexts" (Heerwagen et al., 2004, p.525) resulting in mixed successes and disruptive behaviours was bemoaned more than 10 years ago.

Two things have changed however in the last decade: firstly, the appetite of architects for evidence-based design practices, and secondly, the availability of larger datasets to reproduce findings, or in fact, search for generalisable patterns.

Online surveys with architects and people who have worked with architects highlighted the general need for evidence-based design, but the lack of tools for this. It was found that 81% of the participating architects wanted to know more about new tools (Outram, 2015) and that 80% perceived a need for evidence in the design process (EBD, 2015). In contrast to these needs, the surveys point out that there is no substantial practice of evidence-based design, with 27% of respondents never having done a post-occupancy evaluation and 40% doing so but not formally capturing the results (Outram, 2015). Moreover, very few review literature as part of normal practice. A general lack of generically valid and thus 'actionable' insights might contribute to that.

Meanwhile, other scientific fields turn their focus towards reproducibility. The advent of big data has allowed for more, and more interesting insights, but has also highlighted inconsistencies when trying to reproduce experiments. From a brief online survey of 1,576 researchers in 2016, Nature magazine found that "More than 70% of researchers have tried and failed to reproduce another scientist's experiments, and more than half have failed to reproduce their own experiments" (Baker, 2016, p.452). The research around human behaviour suffers especially in this regard, with multiple studies following multiple, and at times contradictory, theories, thus resulting in innumerable inconsistencies across them (for a discussion see Watts, 2017).

The aim of the study presented here was to examine multiple cases using a few clearly explained methods typically used in the literature. If the lack of consistent results in previous research was driven by the lack of sufficient amounts of data to be examined, then we should be able to identify patterns of human behaviour in this dataset. If on the other hand, the larger

dataset yielded similarly inconclusive results then other methods need to be tested that can take confounding factors into account more systematically.

Given that we are looking for generalised patterns that hold across all types and sizes of office spaces, the methods were initially applied across the whole dataset. They were then extended to focus on other properties of the dataset. We split the dataset in two ways, across industries and specific projects (where applicable) allowing us to examine the many differences between the cases or industries. This deeper analysis highlighted the nuances of the metrics we examined as well as the limits of the methods applied.

The paper is structured as follows: the next section is a review of existing research around the subject of human behaviour in the office and the various efforts, methods and metrics to understand it. A section will follow on the properties of the dataset used and a description of the metrics used in this analysis. The next three sections describe the analysis of the behaviours, the first two at the top-level, and the last digging into more detail. The last two sections discuss the overall conclusion from this analysis and the future direction this research intends to follow.

2. LITERATURE REVIEW: HUMAN BEHAVIOURS IN WORKPLACES

Workplace research to date has tried to frame the problem of understanding social processes and behaviours initially through purely psychological studies (Sundstrom, 1987) and latterly through empirical methods that take the properties of the workspace into account (Allen and Fustfeld, 1975). The emergence of Space Syntax (Hillier and Hanson, 1984) has given researchers theories and methods to analyse space in more systematic ways, some of which could be used to understand human behaviour in the workplace. Since then, a rich research field has emerged and multiple studies have created new metrics and methods to understand how interaction is affected by barriers (Hatch, 1987), the role of attractors such as photocopiers and water-coolers (Fayard and Weeks, 2007), and how face-to-face interactions can be created if paths of workers overlap (Kabo et al., 2015), to name just a few exemplary studies.

Interaction in the workplace was specifically studied by Backhouse and Drew (1992) who suggested that a moving member of staff may be seen as 'available' to initiate an interaction, and thus become 'recruited'. Those recruited may eventually begin an interaction with someone seated and if they continue standing can be seen as 'visiting'. The idea of a 'visiting' behaviour was initially expressed by Penn et al. (1999), as a way to understand how many people are visiting against how many people are inhabiting a space. They used an aggregate metric called 'visiting ratio' defined as the number of people standing to the number of people sitting for a particular area, but only utilised the metric to describe the activity of different floors.

All this research provided interesting insights for each case study examined, but has not shown whether their results can be generalised to other workplaces. One of the main problems identified by Sailer (2010), is the lack of a consistent methodology applied across cases. As each study uses its own methodology to study a few cases, the results identified in the literature stem from a fragmented collective dataset. This approach does not yield generalisable patterns, making results problematic to use in an evidence-based design context. A characteristic study is by Hillier and Grajewski (1990), where the authors examined seven buildings as an example of how Space Syntax methodology can be applied in workplace environments. They used mainly Pearson correlation and found that movement and interaction can be affected by a building's integration, but this only happened in a few samples and not at the dataset as a whole.

3. DATASET AND METRICS

The dataset used in this study was provided by Spacelab, an architectural design and consultancy practice in London, UK, and has already been examined in two previous publications (Koutsolampros et al., 2015; Sailer et al., 2016). It has been collected over the last 6 years with the purpose of providing insights to the inner workings of each client company. The dataset currently includes spatial, social and organisational information as well as observed activity for approximately 50 companies, and continues expanding at a rate of almost ten projects per year.

A partial dataset was used for this study, with cases that were digitised as required for the analysis. It consisted of 20 companies, at 23 sites and across 45 buildings, with a total of 128 floors. The total number of desks in the study was 12,575. The partial dataset included four types of data:

- Visibility Graph Analysis (VGA) at eye-level and with a grid size of 45x45cm. Two VGA metrics were specifically used:
    - Connectivity: The amount of cells another cell can 'see';
    - Metric depth distance: The length (in meters) of the path of fewest turns between two points;
- Functions of space in the form of polygons on the plan;
- Hourly snapshot observations collected by human observers (Vaughan, 2001).

The dataset also contains organisational parameters, of which one was used in this paper: the industry of each organisation. The cases examined were from eight different industries (see table 1): Market research, Architecture, Legal, Financial services, Creative agencies, Technology, Media and Retail.

Industry	Number of desks	Number of cases
Market research	281	1
Architecture	373	2
Legal	507	2
Financial services	723	5
Creative agency	792	3
Technology	854	2
Media	2457	4
Retail	2897	4

Table 1 - Case studies by industry

4. BEHAVIOUR ONE: INTERACTION IN OPEN WORKSPACES

The first behaviour examined was interaction within open workspaces and two different subsets of it were studied, 'Visiting' and 'Chatting'. This examination is an extension of a general micro-behaviour identification carried out in a previous publication by Sailer et al. (2016).

'Visiting' was defined as the interaction between a maximum of three people, where at least one is standing and at least one is sitting at their own desk (as shown in Figure 1), at a maximum distance of a meter and a half (for a discussion on this distance see Lopez de Vallejo, 2010). Chatting was defined as an observed interaction between any number of people, as long as all of them were sitting at their own desks (as shown in Figure 2).

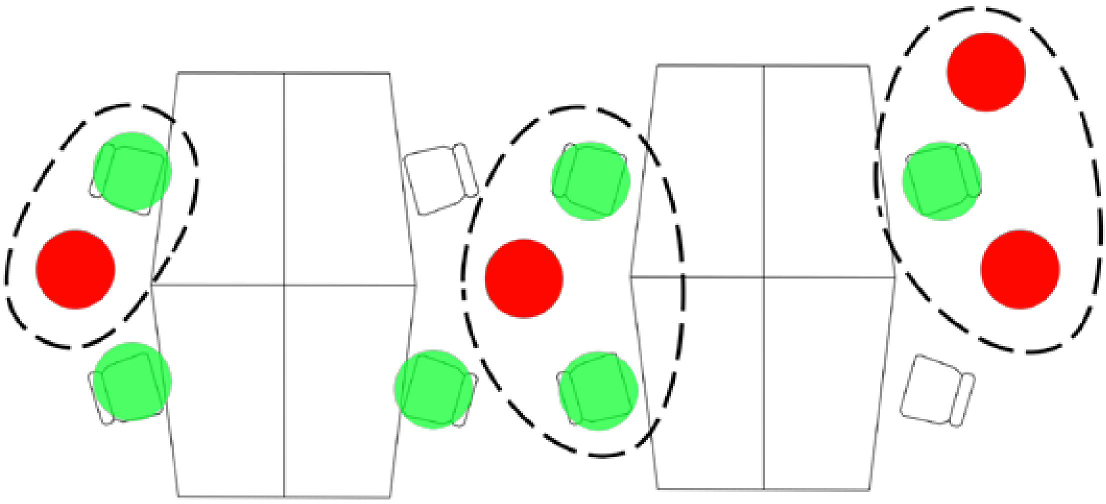

Figure 1 - Visiting interactions. A person standing (red) interacting with a person seated at their own desk (green); two sitting, one standing; and two standing, one sitting.

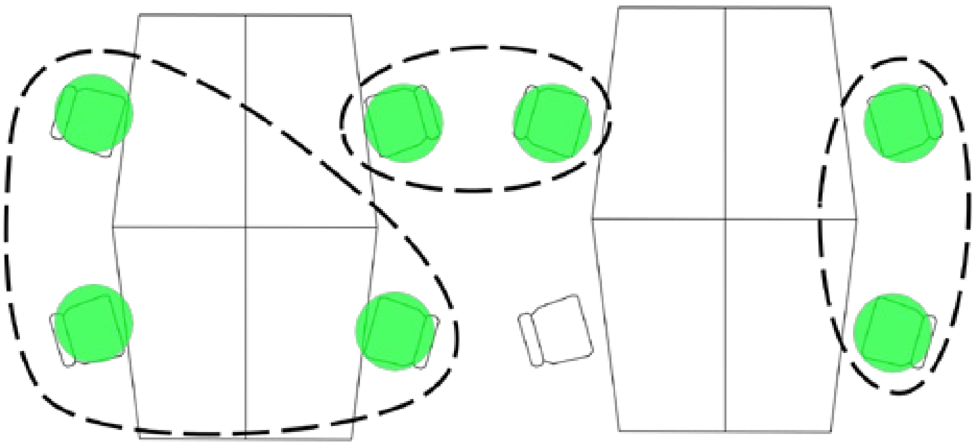

Figure 2 - Chatting interactions. All members of the interaction are seated at their own desk (green).

These interactions were expected to happen under different circumstances. Visiting is a targeted interaction where a pre-existing relationship can be assumed to be the motivation, for example people working together, or having a personal relationship. On the other hand, chatting would almost always be triggered by co-location. Chatting does not exclude conversation about work or personal relationships, especially given the fact that people from the same team are very likely to be placed together. In both cases seats that were never occupied were excluded from the sample because no chance was ever given for interaction. Two different hypotheses were tested for workspace interaction behaviour: 1) Temporary visiting interactions tend to happen in more open spaces and closer to circulation, and 2) Temporary chatting interactions tend to happen in less open spaces and away from circulation. In both hypotheses the input metrics were desk connectivity and visual metric distance from desk to circulation for all cases.

Both hypotheses will now be explained in detail, and then tested against the dataset.

Hypothesis 1: *Temporary visiting interactions tend to happen in more open spaces and closer to circulation.*

Regarding hypothesis 1, the assumption was that availability plays a major role in the selection of desks for such targeted interactions. A person sitting in a more visible desk has more chances to see and be seen by others, and is thus more likely to 'recruit' passers-by into an interaction (Backhouse and Drew, 1992). Therefore, the first parameter examined was connectivity, i.e. the ability to see others locally. The same can be said for the desk's distance to circulation. A desk closer to circulation is closer to the main funnel for movement and is thus easier to reach by many people passing by. Although not examined here, the main difference between the two is that connectivity would be expected to trigger more interactions with co-workers who sit in the same room (i.e. from the same department), while distance to circulation is more likely to attract interactions from people from other departments who just happened to pass by.

Three output metrics were examined: A) whether a seat was visited at all, B) how many times it was visited, and C) the amount of times visited grouped into categories. The rationale behind C is to examine if there are thresholds to how many times people are visited. If for example a desk is visited very frequently (for example on more than 4 rounds) one could argue that this is the typical mode of operation of the person or team. On the other hand, desks visited 1-3 times are more likely to be random interactions triggered by 'recruitment'. The size of the sample was 8,884 observations of desks.

Two t-tests were carried out, one for how connectivity and one for how distance to circulation differed for desks that were visited in comparison to those that were not. None yielded significant results (p-value: 0.64 and 0.14 respectively). Four ANOVA tests were also carried out to test for significant differences in connectivity and distance to circulation for the number of times visiting occurred (as discrete count and grouped) (see Figure 3).

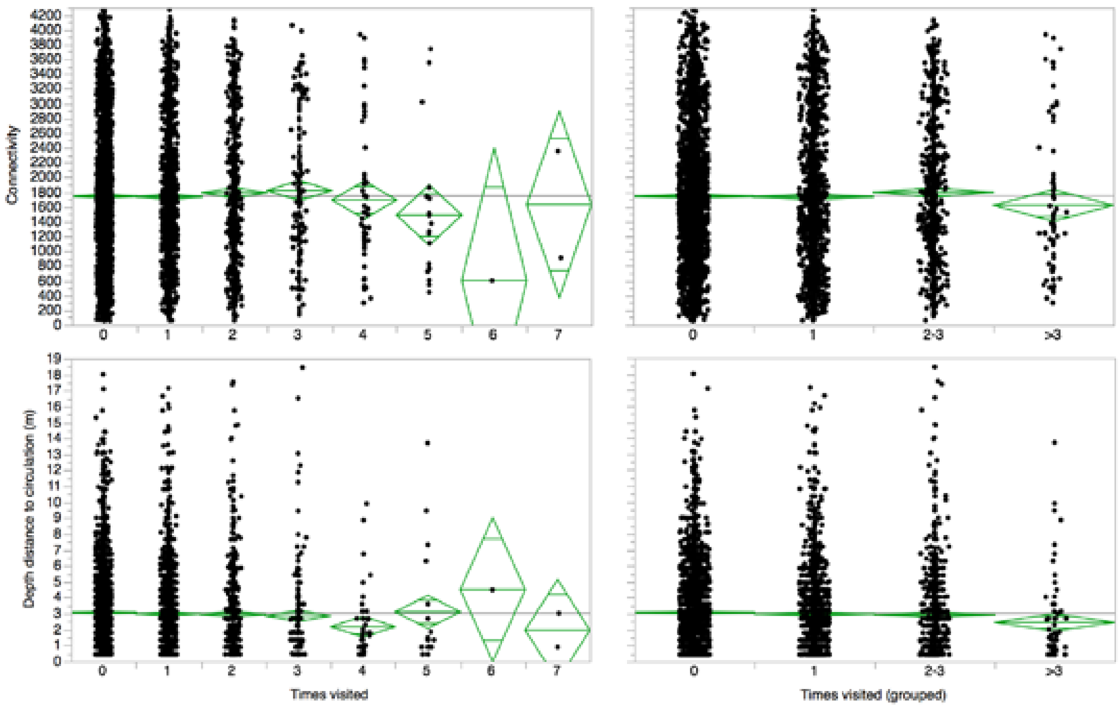

Figure 3 - Times visited count and grouped VS connectivity and distance to circulation

The results were inconclusive for all tests, yielding non-significant results. The relevant p-values and size of effects (R2) were:

- Times visited VS connectivity: R2 = 0.000, p-value = 0.5110
- Times visited VS depth distance: R2 = 0.001, p-value = 0.1363
- Times visited (grouped) VS connectivity: R2 = 0.002, p-value = 0.0539
- Times visited (grouped) VS depth distance: R2 = 0.001, p-value = 0.2002

Therefore, connectivity and distance to circulation are not, by themselves, factors that affect the number of times a desk is visited.

The second hypothesis deals with the second subset, 'chatting' interactions.

Hypothesis 2: *Temporary chatting interactions tend to happen in less open spaces and away from circulation.*

Three metrics were examined to verify or falsify this hypothesis: A) whether a person on a seat was observed to chat at all, B) how many times this happened, and C) the number of times happened categorised. The grouping is once again a way to distinguish cases where chatting is a normal mode of operation, for example due to an unusually cohesive relationship between the members and thus not the product of random encounters. The size of the sample was 8,884 observations of desks, as in the previous analysis.

Two t-tests were carried out, one for how connectivity and one for how distance to circulation differed for desks that saw chatting in comparison to those that did not. None yielded significant results (p-value: 0.702 and 0.2873 respectively).

Four ANOVA tests were also carried out to test the combinations between the input and output variables (see Figure 4).

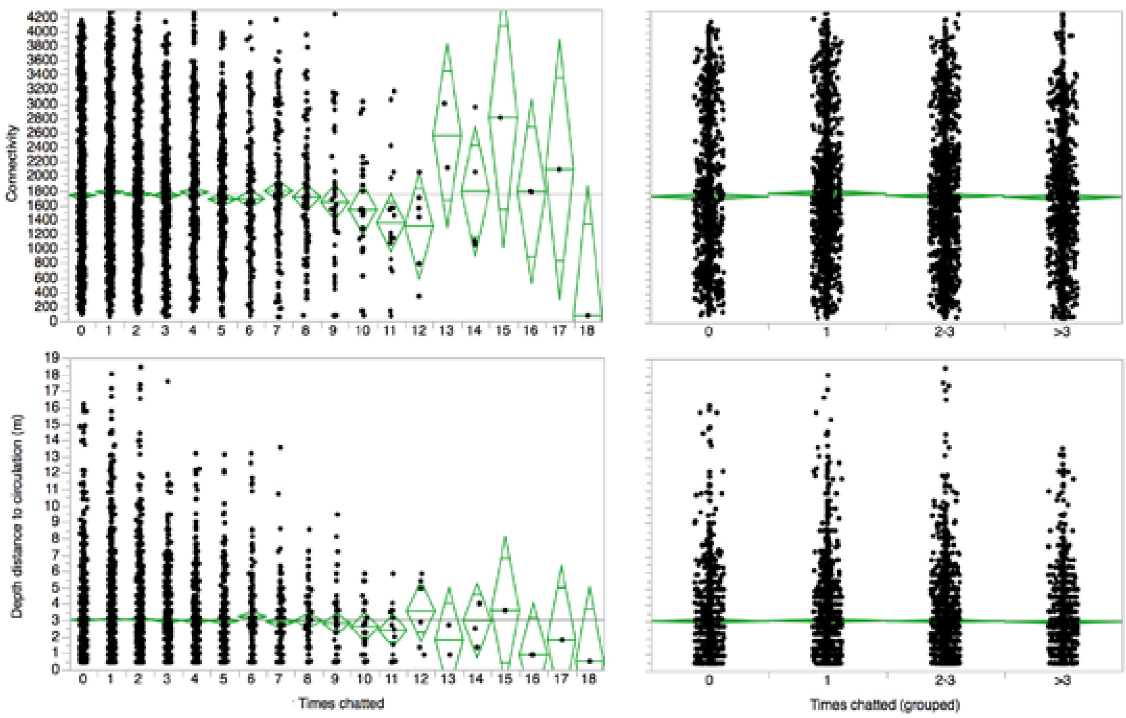

Figure 4 - Times chatted count and grouped VS connectivity and distance to circulation

All results were inconclusive, yielding non-significant results. The relevant p-values and R2 were:

- Times chatted VS connectivity: R2 = 0.003, p-value = 0.2505
- Times chatted VS depth distance: R2 = 0.001, p-value = 0.8764
- Times chatted (grouped) VS connectivity: R2 = 0.001, p-value = 0.2318
- Times chatted (grouped) VS depth distance: R2 = 0.000, p-value = 0.7766

Both hypotheses 1 and 2 could not have their respective null hypotheses rejected meaning that connectivity or visual depth distance are not alone responsible for fluctuations in the visiting or chatting behaviours, but confounding factors must be found and taken into account. A possible explanation for the lack of significant results in the visiting behaviour could be that a close distance to circulation acts as a recruitment opportunity, but not with the guest staying close to the seat, but instead them causing the host to get up so that they can have a quick meeting elsewhere.

5. BEHAVIOUR TWO: CHOICE OF EATING SPACES

The second studied behaviour dealt with the choices of people, or more specifically what places they chose to go to at lunchtime. Being social spaces, the spaces examined here are likely to be preferred for the amount of people that can be seen there. On the other hand, the selection can be purely utilitarian, i.e. people choosing to go to the closest space to minimise the time and travel needed to get there. Therefore, two more hypotheses were tested: 3) Canteens will experience highest usage rates when they are more visible locally and require less effort to go to, and 4) Break-out spaces will experience highest usage rates when they are more visible locally and require less effort to go to.

Again, both hypotheses will now be explained and tested, one after the other.

Hypothesis 3: *Canteens will experience highest usage rates when they are more visible locally and require less effort to go to.*

For hypothesis 3 the connectivity of each canteen space was tested against its average occupancy. Occupancy was defined as the number of people observed in a lunchtime snapshot divided by the capacity and the number of days of observation. The second metric tested was the average metric distance to get from every seat to any canteen space. The unit of analysis was a site and the total number of observations was 16.

Two correlations were tested (Figure 5) between canteen occupancy and connectivity, and canteen occupancy and average metric distance to desks.

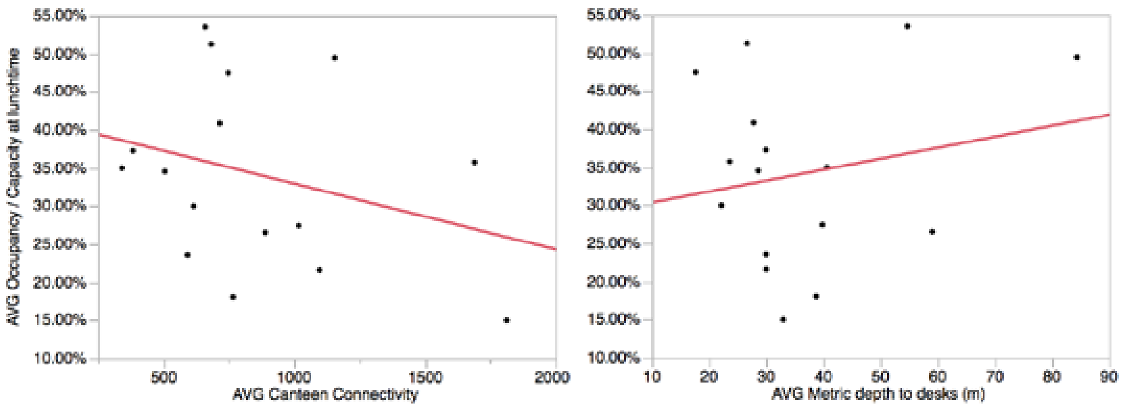

Figure 5 - Canteen occupancy VS Connectivity and Average distance to desks

The tests provided non-significant results:

- Occupancy density versus connectivity: R2 = 0.091, p-value = 0.2554
- Occupancy density versus average metric distance to desks: R2 = 0.0411, p-value = 0.4513

Therefore, no direct relationship could be found between canteen occupancy and connectivity or average distance to desks. The fourth hypothesis asks the same question for break-out spaces:

Hypothesis 4: *Break-out spaces will experience highest usage rates when they are more visible locally and require less effort to go to.*

For this hypothesis, connectivity of each break-out space was tested against the average occupancy density. Occupancy density was defined as the number of people observed in a snapshot when the overall number of people at breakout spaces was highest (i.e. at peak usage, which is lunchtime) divided over the area of said breakout space and averaged over the number of days of observation. The second metric tested was the average distance from the specific breakout space to reach any seat. The unit of analysis is a breakout space and the sample size is 91 spaces.

Two correlations were tested (Figure 6) between break-out occupancy and connectivity, and break-out occupancy and average metric distance to desks.

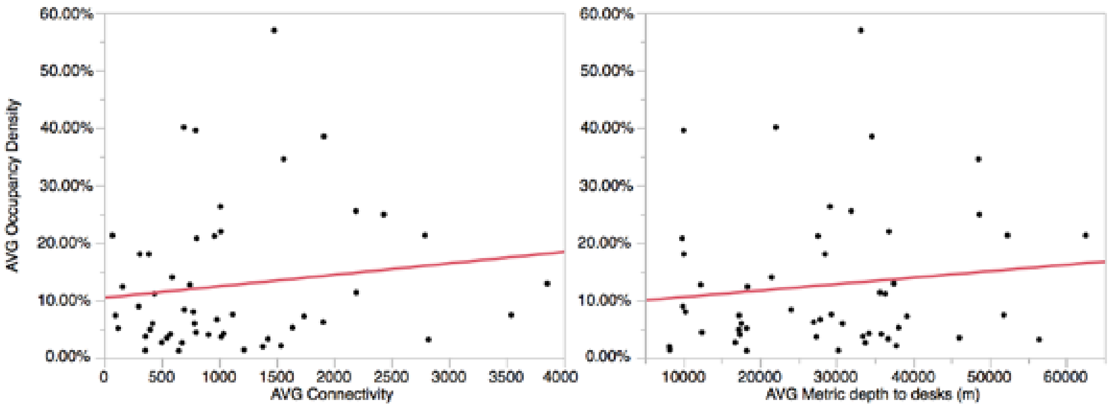

Figure 6 - Break-out space occupancy VS connectivity and average distance to desks

The regressions provided non-significant results:

- Occupancy density versus connectivity: R2 = 0.0235, p-value = 0.1469
- Occupancy density versus average metric distance to desks: R2 = 0.0002, p-value = 0.8821

Hypothesis 4, just as hypothesis 3, yielded non-significant results meaning that connectivity and distance to desks did not alone affect occupancy of an eating space at lunchtime. This is very likely an effect of other factors, such as the quality of the provided food, the availability of external food, inter-team and intra-team communication and the look-and-feel and furniture provision of the canteens. Especially for canteens, this result could also be an effect of the smaller sample we have, since not all the examined companies have canteens, bringing the number of cases down to 16.

6. INTERACTIONS: A CLOSER LOOK

Given that the results were insignificant at the top level, we set out to apply the same methodology taking into account some other parameters, namely the industry each company belongs to. This section will describe the re-focused analysis to take the industry as a grouping parameter into account. The rationale behind this decision is that one may consider that companies in the same industry share the same intrinsic characteristics that allow for the same

patterns of behaviour to emerge. For the last level of the analysis the focus shifted to each site itself. While these shifts essentially created the same problems identified in the literature review (differences in case studies, non-generalisable results) it also created the potential to see the differences between the cases that did present these patterns and those that did not.

The available data comes from companies from eight different industries. With this split, the number of seats per unit of analysis drops considerably to a range from 281 to 2,897 seats. The number of cases per industry is also uneven (see Figure 7); an effect of the way the data was collected.

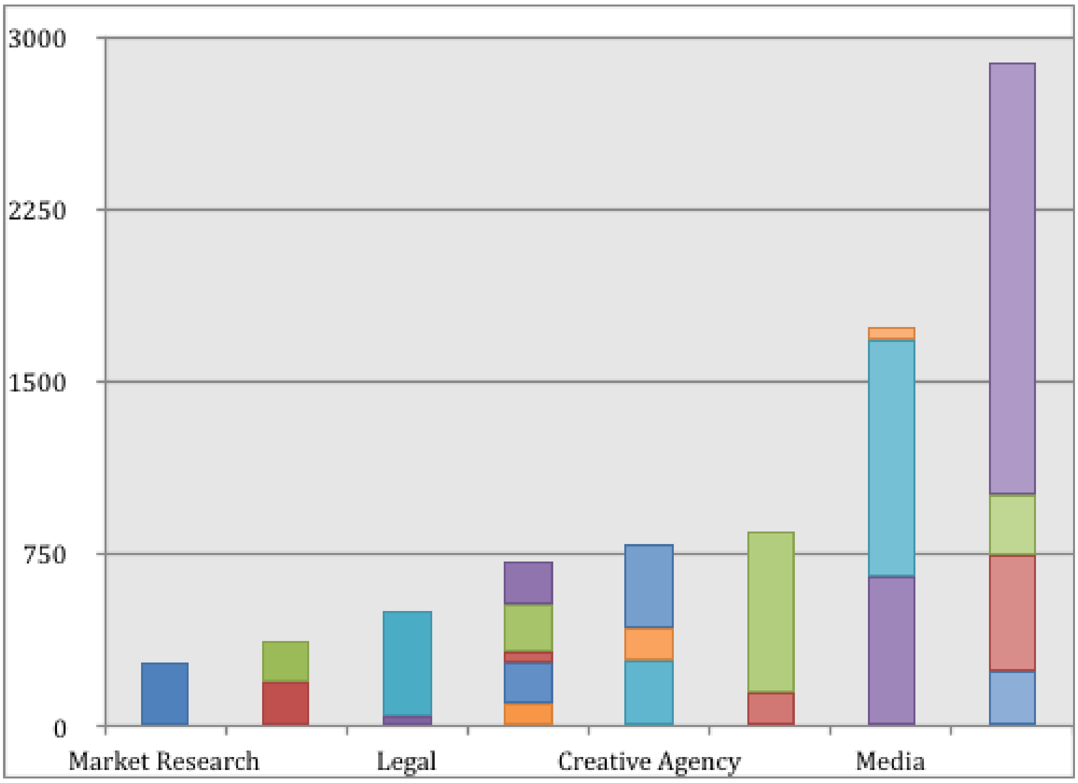

Figure 7 - Number of desks per industry and case

The analysis was carried out for each industry and for each case in the manner described above, starting with a t-Test (Table 2, Table 3) to assess whether seats that were visited were more visible or closer to circulation than the ones not-visited, followed by an ANOVA (Table 4), to examine whether these two metrics had any effect on the times visited.

The t-Test for the visiting behaviour and connectivity (Table 2, left) did yield significant results for five out of eight industries. While Legal, Financial Services, Technology and Media showed visited desks had a higher average connectivity than non-visited desks, the reverse was the case for Retail cases, where visiting tended to be attracted by smaller spaces, i.e. lower connectivity. Two industries (Financial Services and Technology) displayed a negative difference of over 200 grid cells (~40m2) between the non-visited and the visited desks. For these two industries connectivity was also influential in the amount of times a desk was visited (Table 4, left), although the effect was minimal ($R2=0.02$, 0.016). Distance to circulation was not found to significantly affect whether a desk was visited (Table 3, left), or how many times that happened (Table 4, right). In the few cases where the result was significant, the effect was negligible (0.19 metres difference between desks visited or non-visited, or an effect of $R2=0.023$).

Industry	Sample size	Mean 0 (Not visited)	Mean 1 (Visited)	Difference (0-1)	p-value	ID	Sample size	Mean 0 (Not visited)	Mean 1 (Visited)	Difference (0-1)	p-value
Market Research	281	3366	3322	44	0.520	15	281	3366.85	3322.81	44.04	0.521
Architecture	373	1135	1059	76	0.290	21	176	699.26	670.17	29.09	0.015*
						13	197	1591.21	1331.87	259.34	0.018*
Legal	507	664	735	-71	0.02*	4	49	629.44	701.64	-72.19	0.321
						10	458	667.96	739.69	-71.73	0.032*
Financial Services	723	1803	2020	-217	0.003**	6	41	1004.13	995.82	8.32	0.872
						1	97	1357.63	1295.27	62.36	0.473
						5	186	2205.09	2489.00	-283.91	0.048*
						8	195	1400.84	1244.84	156.00	0.076
						7	204	2292.50	2548.62	-256.12	0.007**
Creative Agency	792	1007	969	38	0.290	16	142	506.18	505.54	0.63	0.990
						9	287	852.56	1032.21	-179.65	0.000*
						18	363	1238.52	1285.08	-46.55	0.338
Technology	854	2132	2364	-232	0.004**	11	145	727.19	618.28	108.91	0.063
						17	709	2497.84	2602.28	-104.44	0.178
Media	2457	1667	1734	-67	0.023*	19	59	766.00	751.83	14.17	0.590
						2	658	1502.50	1512.84	-10.34	0.839
						12	1023	1602.21	1602.90	-0.68	0.982
Retail	2897	1988	1898	90	0.008**	3	239	862.44	805.06	57.38	0.304
						20	265	2668.47	2615.89	52.58	0.499
						14	509	1456.83	1454.74	2.09	0.941
						22	1884	2148.32	2124.07	24.25	0.566

Table 2 - Per industry and case t-Tests: Connectivity differences between the desks that were visited and those that were not. Positive significant effects in yellow, negative in red, * significant at the 0.05 level, ** significant at the 0.01 level.

Industry	Sample size	Mean 0 (Not visited)	Mean 1 (Visited)	Difference (0-1)	p-value	ID	Sample size	Mean 0 (Not visited)	Mean 1 (Visited)	Difference (0-1)	p-value
Market Research	281	2.56	2.59	-0.03	0.910	15	281	2.56	2.59	-0.03	0.911
Architecture	373	2.68	2.59	0.09	0.680	21	176	2.49	2.32	0.18	0.508
						13	197	2.89	2.79	0.10	0.769
Legal	507	2.14	1.94	0.20	0.175	4	49	1.03	1.51	-0.48	0.066
						10	458	2.25	2.00	0.25	0.120
Financial Services	723	3.81	4.16	-0.35	0.220	6	41	2.05	2.46	-0.41	0.510
						1	97	2.83	3.78	-0.95	0.423
						5	186	5.48	6.18	-0.70	0.254
						8	195	4.78	4.25	0.54	0.350
						7	204	2.35	2.53	-0.18	0.529
Creative Agency	792	2.60	2.30	0.30	0.055	16	142	3.53	2.67	0.87	0.02*
						9	287	1.63	1.41	0.22	0.134
						18	363	2.98	3.15	-0.17	0.587
Technology	854	3.17	3.57	-0.40	0.081	11	145	2.65	2.42	0.22	0.461
						17	709	3.32	3.73	-0.41	0.109
Media	2457	2.84	2.65	0.19	0.01*	19	59	4.26	4.46	-0.21	0.772
						2	658	3.70	3.50	0.20	0.258
						12	1023	2.32	2.20	0.12	0.128
Retail	2897	3.21	3.05	0.16	0.070	3	239	2.12	2.43	-0.31	0.292
						20	265	3.38	3.11	0.27	0.290
						14	509	2.99	3.00	-0.02	0.924
						22	1884	3.35	3.19	0.16	0.141

Table 3 - Per industry and case t-Tests: Distance to circulation differences between the desks that were visited and those that were not. Positive significant effects in yellow, * significant at the 0.05 level, ** significant at the 0.01 level.

connectivity								distance							
Industry	Sample size	R^2	p-value	ID	Sample size	R^2	p-value	Industry	Sample size	R^2	p-value	ID	Sample size	R^2	p-value
Market Research	281	0.010	0.600	15	281	0.01	0.601	Market Research	281	0.007	0.720	15	281	0.01	0.724
Architecture	373	0.007	0.740	**21**	**176**	**0.04**	**0.032***	Architecture	373	0.009	0.640	21	176	0.00	0.752
				13	197	0.05	0.093					13	197	0.02	0.643
Legal	507	0.020	0.060	4	49	0.09	0.243	Legal	507	0.009	0.600	4	49	0.08	0.269
				10	458	0.02	0.091					10	458	0.01	0.360
Financial Services	**723**	**0.020**	**0.007****	6	41	0.00	0.936	Financial Services	723	0.009	0.240	6	41	0.02	0.734
				1	97	0.01	0.451					1	97	0.01	0.299
				5	186	0.03	0.179					5	186	0.02	0.366
				8	195	0.04	0.101					8	195	0.01	0.790
				7	204	0.05	0.054					7	204	0.02	0.534
Creative Agency	792	0.004	0.640	16	142	0.05	0.219	Creative Agency	792	0.006	0.460	16	142	0.05	0.211
				9	**287**	**0.05**	**0.014***					9	287	0.01	0.671
				18	363	0.01	0.767					18	363	0.00	0.926
Technology	**854**	**0.016**	**0.027***	11	145	0.02	0.481	**Technology**	**854**	**0.023**	**0.003****	11	145	0.03	0.386
				17	709	0.01	0.606					**17**	**709**	**0.02**	**0.003****
Media	2457	0.004	0.057	19	59	0.02	0.888	**Media**	**2457**	**0.006**	**0.017***	19	59	0.12	0.144
				2	658	0.00	0.890					2	658	0.01	0.132
				12	1023	0.00	0.928					12	1023	0.00	0.289
Retail	2897	0.003	0.072	3	239	0.02	0.470	Retail	2897	0.002	0.490	3	239	0.03	0.214
				20	265	0.03	0.083					20	265	0.01	0.436
				14	509	0.01	0.484					14	509	0.01	0.330
				22	1884	0.00	0.737					22	1884	0.00	0.303

Table 4 - ANOVA for times visited VS Connectivity and Distance to circulation. Significant effects in yellow, * significant at the 0.05 level, ** significant at the 0.01 level.

These results imply that in some industries there is a relationship between connectivity and visiting behaviour, specifically that visited seats tend to be in more visible areas. The industries highlighted (Financial Services and Technology) are the ones that are unlikely to prescribe interaction behaviour or have a culture that does. They lie between the strictly professional character of law firms and the noisy information exchange of a creative agency. Therefore, they are more likely to display genuine 'visiting' interactions as those would neither be discouraged nor the normal mode of operation of the firm.

The same analysis was carried out for each site separately. In this case the unit of analysis becomes even smaller, with a range from 41 to 1,600 desks. The aim of this analysis was to identify whether the aforementioned questions can be identified as intrinsic behaviours within the company that are lost when the data is aggregated.

Some parts of the analysis were indeed found to be significant, mostly for the relationship between connectivity and whether a desk was visited or not. The six cases highlighted in 2 (right) are significant at the 0.05 level, but the more interesting observation is that four cases revealed negative differences (i.e. visiting favoured larger spaces with higher average connectivity), whereas two cases showed positive differences (i.e. visited desks were in smaller spaces with lower average connectivity). This points to a fundamental problem of aggregating data into larger datasets, since positive and negative effects will cancel each other out. It also shows very clearly, how the data presented in this paper mirrors the existing state of the art with some effects to be found in some cases, but no generalisable patterns valid across cases and across industries.

In a similar vein, chatting was also examined further, on a per-case and per-industry basis. The initial per-industry t-Tests (see Table 5, left) were slightly less significant overall and showed smaller differences in connectivity (up to 169 cells, ~35m2). Connectivity was found to be a highly significant factor against the number of times chatted (Table 7), but the effect only occurred in four industries and was minimal, never rising above R2=0.06. Distance to circulation (Table 6 and Table 7, right) once again mostly provided insignificant results, or negligible effect sizes and differences.

Industry	Sample size	Mean 0 (Did not chat)	Mean 1 (Did chat)	Difference (0-1)	p-value	ID	Sample size	Mean 0 (Did not chat)	Mean 1 (Did chat)	Difference (0-1)	p-value
Market Research	281	3339	3374	-35	0.560	15	281	3339.39	3374.55	-35.15	0.561
Architecture	373	1134	1081	53	0.464	13	197	1519.72	1441.44	78.28	0.481
						21	176	691.05	687.92	3.13	0.766
Legal	**507**	**731**	**654**	**77**	**0.011***	4	49	588.79	691.09	-102.30	0.192
						10	**458**	**740.16**	**648.61**	**91.54**	**0.005****
Financial Services	**723**	**1753**	**1922**	**-169**	**0.011***	1	97	1375.54	1336.45	39.09	0.454
						5	186	2379.39	2259.90	119.49	0.429
						6	41	1026.11	981.00	45.11	0.216
						7	204	2206.46	2422.91	-216.45	0.063
						8	195	1365.49	1347.49	18.00	0.825
Creative Agency	792	991	996	-5	0.890	9	287	982.86	900.79	82.07	0.192
						16	142	577.35	483.37	93.98	0.093
						18	363	1218.44	1255.12	-36.68	0.509
Technology	854	2327	2180	147	0.082	11	145	704.24	690.11	14.13	0.813
						17	**709**	**2654.45**	**2487.00**	**167.45**	**0.036***
Media	**2457**	**1622**	**1711**	**-89**	**0.026***	**2**	**658**	**1428.56**	**1530.39**	**-101.83**	**0.045***
						12	1023	1564.06	1613.40	-49.34	0.129
						19	59	763.67	762.05	1.62	0.944
Retail	**2897**	**1903**	**1984**	**-81**	**0.019***	3	239	837.85	836.96	0.88	0.989
						14	509	1458.29	1455.03	3.26	0.905
						20	265	2773.04	2620.08	152.97	0.073
						22	**1884**	**2078.06**	**2172.53**	**-94.47**	**0.023***

Table 5 - Per industry and case t-Tests: Connectivity differences between desks that experienced chatting and those that did not. Positive significant effects in yellow, negative in red, * significant at the 0.05 level, ** significant at the 0.01 level.

Industry	Sample size	Mean 0 (Did not chat)	Mean 1 (Did chat)	Difference (0-1)	p-value	ID	Sample size	Mean 0 (Did not chat)	Mean 1 (Did chat)	Difference (0-1)	p-value
Market Research	281	2.52	2.62	-0.1	0.590	15	281	2.52	2.63	-0.11	0.596
Architecture	373	2.76	2.55	0.21	0.346	13	197	2.97	2.73	0.24	0.483
						21	176	2.52	2.36	0.15	0.542
Legal	**507**	**1.87**	**2.25**	**-0.38**	**0.011***	4	49	1.22	1.26	-0.04	0.909
						10	**458**	**1.91**	**2.40**	**-0.48**	**0.002****
Financial Services	723	4.07	3.38	0.69	0.360	1	97	3.69	2.52	1.17	0.074
						5	186	5.13	6.00	-0.87	0.143
						6	41	1.80	2.47	-0.67	0.154
						7	**204**	**1.99**	**2.52**	**-0.53**	**0.049***
						8	195	5.11	4.27	0.84	0.120
Creative Agency	792	2.48	2.51	-0.03	0.870	9	287	1.71	1.51	0.20	0.350
						16	142	2.65	3.27	-0.62	0.155
						18	363	3.10	3.00	0.10	0.768
Technology	854	3.48	3.27	0.21	0.370	11	145	2.66	2.54	0.12	0.724
						17	709	3.64	3.43	0.22	0.415
Media	2457	2.68	2.83	-0.15	0.069	2	658	3.49	3.70	-0.22	0.197
						12	1023	2.20	2.32	-0.12	0.168
						19	59	4.19	4.50	-0.31	0.569
Retail	2897	3.11	3.18	-0.07	0.400	3	239	2.17	2.29	-0.12	0.684
						14	509	2.89	3.04	-0.14	0.431
						20	**265**	**2.67**	**3.38**	**-0.71**	**0.008****
						22	1884	3.31	3.31	0.00	0.963

Table 6 - Per industry and case t-Tests: Distance to circulation differences between desks that experienced chatting and those that did not. Negative significant effects in red, * significant at the 0.05 level, ** significant at the 0.01 level.

connectivity								distance							
Industry	Sample size	R^2	p-value	ID	Sample size	R^2	p-value	Industry	Sample size	R^2	p-value	ID	Sample size	R^2	p-value
Market Research	281	0.011	0.500	15	281	0.012	0.508	Market Research	281	0.019	0.230	15	281	0.020	0.234
Architecture	373	0.01	0.700	21	176	0.030	0.511	Architecture	373	0.02	0.244	21	176	0.025	0.643
				13	197	0.009	0.938					13	197	0.028	0.489
Legal	507	0.02	0.310	4	49	0.188	0.250	**Legal**	**507**	**0.037**	**0.025***	4	49	0.057	0.922
				10	458	0.028	0.161					**10**	**458**	**0.052**	**0.004****
Financial Services	**723**	**0.06**	**0.000****	6	41	0.174	0.067	Financial Services	723	0.009	0.840	6	41	0.120	0.189
				1	97	0.035	0.505					1	97	0.057	0.241
				5	186	0.088	0.129					5	186	0.053	0.558
				8	195	0.057	0.201					8	195	0.037	0.523
				7	**204**	**0.131**	**0.001****					7	204	0.065	0.153
Creative Agency	**792**	**0.05**	**0.000****	16	142	0.074	0.161	Creative Agency	792	0.026	0.120	16	142	0.064	0.253
				9	**287**	**0.136**	**0.000****					9	287	0.052	0.308
				18	363	0.035	0.306					18	363	0.026	0.582
Technology	**854**	**0.03**	**0.003****	11	145	0.058	0.607	Technology	854	0.005	0.930	11	145	0.041	0.838
				17	709	0.027	0.061					17	709	0.006	0.969
Media	**2457**	**0.01**	**0.002****	19	59	0.006	0.839	Media	2457	0.008	0.150	19	59	0.033	0.386
				2	**658**	**0.048**	**0.001****					2	658	0.031	0.058
				12	1023	0.009	0.723					12	1023	0.017	0.187
Retail	2897	0.007	0.111	3	239	0.063	0.056	Retail	2897	0.005	0.422	**3**	**239**	**0.170**	**0.000****
				20	265	0.062	0.170					20	265	0.042	0.526
				14	509	0.014	0.707					14	509	0.014	0.721
				22	1884	0.008	0.354					22	1884	0.002	0.990

Table 7 - ANOVA for times chatted VS Connectivity and Distance to circulation. Significant effects in yellow, * significant at the 0.05 level, ** significant at the 0.01 level.

As previously, tables 5-7 also provide an overview of each case examined with the same methodology. While most cases yielded insignificant results or low effects, three individual cases stand out: IDs 7, 9 and 3. The first two display a p-value below 0.01 and effects of around R2=0.13 when comparing connectivity in relation to the number of times that person chatted, while the last shows a slightly larger effect when comparing distance to circulation and times chatted. Thus, while the effect is small, for the first two cases the amount of visible space did affect how many times someone chatted, while for case 3, it was proximity to circulation that played that role.

These results highlight the pitfalls of small-scale analysis. From a set of 23 case studies, some were found to have significant effects, but overall there appear to be no over-arching patterns as a whole, when split by industry, or even on a case-by-case analysis.

7. CONCLUSION AND FUTURE DEVELOPMENTS

We examined 'visiting' and 'chatting' interactions across the whole dataset, but also within industries and specific cases, and found that local visibility and distance to circulation, on their own, play no major role in the occurrence of these behaviours. We also examined preference of eating spaces across the whole dataset and whether this was affected by local visibility and the average effort to reach each space and found no significant results.

Overall, it is apparent that even with a larger dataset cutting across many companies, buildings and floors, no strong correlations can be extracted between the various spatial metrics and human behaviour. There seem to be confounding factors, some of which are identified here, but also others that will not be visible until deeper examination is performed.

This study pointed to possible confounding factors that could affect the behaviours examined, but has not managed to take them into account systematically. These factors will be examined where possible and incorporated into the analysis to provide a more complete picture. Examples include taking opinions of staff into account for the quality of food at their canteen, identifying whether other eating options are available by looking at the location of the building, or by looking at overall team communication as a factor that affects 'visiting' and 'chatting' interactions.

While the paper at hand is limited in its scope for we only examined two behaviours and three metrics, there are many more workplace parameters that could be investigated. We expect that each parameter affects behaviour in different ways, therefore we intend to test more

metrics against these and more observed behaviours. One such combination to be tested is the relationship of the visiting behaviour to the global integration of the seat. The hypothesis in this case would be that integration positively affects visiting behaviour, given that seats that are easier to reach would invite more people to visit them. The reason this is difficult however, is that overall integration is subject to the intricacies of layout including the size of the building and number of floors, which renders this more complicated for cross-case analysis.

To summarise, this analysis has shown that the traditional methods used to identify patterns of behaviour in workspaces do not necessarily yield significant results when tested across different workspaces. Existing research has used these methods extensively and provided insights with all the aforementioned caveats. While in this study we tested not-previously-examined combinations of metrics, we aim to construct tests in future work that explicitly try to reproduce the results of previous studies. This process will provide clear and definitive answers to whether those insights still hold, and whether patterns can be found across cases. The study by Hillier and Grajewski (1990) will be the first to be examined. It has to be considered though that the study by Hillier and Grajewski examined working practices of the 1980s and the world of work has changed considerably, not least with the advent of electronic communication technologies, the importance of computing and the portability of devices.

Last but not least, we will develop new methodologies in future work. In its current form, only one single parameter was taken into account, although the problem at hand is extremely complex. New methods have to be tested that take into account multiple parameters, since it might be the combination of these parameters that provides a model that can strongly predict activity. These methods could be multivariate regression, Principal Component Analysis and perhaps machine learning methods. In the same spirit, biases such as spatial co-linearity that are inherent to the spatial nature of the dataset will be addressed.

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