Travel Concentration: The effects of attractor-bound movement on workplace activity

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ABSTRACT

Purpose: The purpose of this paper is to explore the effects of office attractors on workplace activity. First, it aims to describe how movement towards different attractors such as canteens and entrances can be approximated in a 2D spatial model, and second, to show how those simulated effects relate to actual observations of movement and interaction.

Theory: Human activity in physical workspace is typically examined from the perspective of the purely geometric properties of the space (i.e. in the field of space syntax), or by other properties of workspaces, such as barriers and distance between workers. Movement in offices however is an activity that is driven by both geometric and non-geometric properties. The non-geometric properties relate to the functional configuration of space (where seats/canteens/meeting rooms are) but the activity itself happens in the real space and it is thus bound by spatial configuration.

Furthermore, while the driver for movement is the need to travel to specific attractors, it is the actual space that allows for secondary effects such as serendipitous interactions to emerge. Thus, it can be expected that a successful approximation of workplace movement will also contribute to understanding interaction, especially that which happens away from spaces programmed for it such as meeting rooms.

This paper examines the two activities of movement and interaction under the hypothesis that a spatial model that properly simulates attractor-bound movement can successfully identify the locations where movement happens, but also provide relevant hints for serendipitous interaction.

Design/methodology/approach: To study this hypothesis, we constructed paths from each seat to a set of three types of attractors, specifically the building entrance, the closest canteen or kitchen and the closest WC. These paths were then transformed to zones of visibility to take into account the surrounding space as well as to allow for interaction to be examined as that activity is unlikely to happen directly on the path. The final result is a metric of travel concentration that measures how likely is it that a space will be seen from those generated paths. The metric is validated against actual observations of movement and interaction in a linear model, tested initially against a large sample of different workplaces (216 floors), but also against two sets of floors, one with high and one with low seat density.

Findings: The new metric fares well against both movement and interaction on the whole sample, but on the two sets of floors the effects are less robust. In high-density floors the main driver of attractor movement is the one generated from outside the floor and to a lesser extent the one that comes from within the floor. In low density floors only interaction is somewhat predictable albeit with a weak effect and only in relation to travel from within the floor. Travel concentration was found to be less effective than the existing Visual Mean Depth metric, however combinations of the two were found, in some cases to yield the best results.

Originality/value: The new metric presented here is a useful simulation of movement in office spaces which can be applied to the analysis of existing spaces, but also provide a way for designers to test against floor plans of new buildings.

Keywords

Workplace analysis, attractor-bound movement, spatial configuration, space syntax, human activity

1 INTRODUCTION

Evidence-based design of workplaces deals, at its core, with the physical properties of office environments as a vehicle to understanding human behaviour. More specifically, the aim of evidence-based design is to understand which properties of workspaces affect human behaviour and how; but also, how this knowledge can be used to design new spaces with potentials for different behaviours to emerge. The need for designing with evidence was highlighted in recent surveys (Outram, 2015; EBD, 2015) with architects and other related professionals noting in particular the lack of tools to carry out such tasks. New tools have indeed started appearing with the increase of computational power, along with analytical units in architectural offices (Denny, 2018), that allow firms to measure and understand organisations and how to design for them. Meanwhile the rise of co-working spaces has allowed companies to gather large datasets for architects to use when designing new spaces (Quito, 2019).

However little predictive power is currently offered by the existing analytical frameworks, especially those within the domain of space syntax. The published research has focused mainly on the development of various distinct methodologies in small samples and with contradictory results (Sailer, 2010). Despite larger samples slowly appearing in newer studies (see for example Hua et al., 2010), there is a systematic neglect to consider functional distributions of points of interest in the workplace, such as the various tea points, printers and watercoolers, which is arguably a reason for the lack of predictability in existing models.

The aim of this paper is to provide a way to measure the effects of these points of interest, by treating them as attractors that generate movement potential through travel towards them. The paper will also aim to link to previous research by comparing the new measurements with existing space syntax metrics and eventually validating the results by testing them against a large sample of activities in 41 workspaces.

2 LITERATURE REVIEW

Research that examined spatial configuration of office spaces as a proxy for understanding human activity can be traced back to the 1970s, with the first examples collating findings from various sources such as newspapers, articles and magazines (Steele, 1973; Sundstrom and Sundstrom, 1986). One of the first studies to rigorously measure properties of space and connect them to human behaviour was by Allen and Fustfeld (1975) where the authors showed that the distances between engineers in seven R&D laboratories significantly affected the communication between them. It was shown for example that a distance of more than 25 to 30 metres between engineers had a negative effect on the probability that those engineers would communicate once a week. A study that instead focused on the properties of surrounding workspace from the perspective of the individual staff member was by Hatch (1987), who tested whether barriers were a hinderance to face-to-face communication, i.e. as interactions which were, at the time, seen as distracting. Hatch found no evidence to support that claim and instead showed that employees in subdivided environments tended to attract more interactions.

Models of higher complexity appeared eventually, primarily within the field of space syntax. In multiple studies Hillier and Grajewski (1990; 1992; 1993) examined seven office spaces in the UK, Scandinavia and the US, employing techniques developed several years earlier for urban spaces and published in the book “The social logic of space” (Hillier and Hanson, 1984). For each of the seven offices the authors created axial maps i.e. linear maps denoting the fewest and longest lines of sight in an office space, but they also captured various activities through observations. The study considered a metric that was also developed for urban systems, ‘integration’ i.e. how integrated (shallow, easy to reach) or segregated (deep, hard to reach) parts of the system were in relation to the whole system. It was found that more integrated buildings as a whole tended to attract more movement, and in some cases interaction (Grajewski, 1992) but it was also shown that most interactions tended to happen at or near workspaces. Later workplace studies focused on different spatial models such as convex spaces (Wineman and Serrato, 1997), but also more detailed ones such as the grid-based Visibility Graph Analysis (Appel-Meulenbroek, 2009).

However, most of these models and techniques treated space as independent of function and did not examine workspace-specific parameters such as targeted movement, despite it being acknowledged as having potentially non-negligible effects on interaction by various researchers (Allen and Fustfeld, 1975; Fayard and Weeks, 2007). Some studies did look at the effects of attractors i.e. by measuring the distances to cellular offices (Serrato and Wineman, 1999) or entrances (Penn et al., 1999), but it wasn’t until a study by Sailer (2007) when a more nuanced approach was undertaken. Sailer specifically simulated paths of staff members of two organisations from their office spaces to various attractors by asking the staff members to pinpoint the places they visited and how often they did so. The author thus demonstrated that when those paths were taken into account along with other existing metrics, predictions about the locations of movement became stronger. An even more detailed approach was attempted in a series of studies by a group of authors (Owen-Smith et al., 2012; Kabo et al., 2013; Kabo et al., 2015) examining two university buildings. In this case a set of paths was created simulating the potential trails of researchers from their cellular office space to various amenities such as toilets, stairs and elevators. When the paths from different researchers overlapped, the common ‘zone’ was treated as a potential for interaction, given that the researchers had a chance of bumping into each other within that zone. The authors showed that path overlaps between researchers tended to create new collaborations in the form of new publications or grant applications.

While the studies by Sailer, Owen-Smith and Kabo introduced the missing ingredient of attractor-led movement and proved that movement and interaction were better predicted in this more nuanced way, they were done on small samples of two organisations each. The studies also used two different underlying spatial models: linear maps (Sailer) and networks of rooms (Owen-Smith, Kabo et al.). These representations allowed the authors to simplify the path generation, however they do not capture much detail of the spatial configuration and are thus more suitable in cases where workspace is clearly delineated in cellular office spaces instead of large open-plan areas.

3 DATA

This study will instead harness a large dataset of office spaces to validate results. This dataset was provided by Spacelab, an architecture and consultancy firm in London, UK, and contains 36 companies also located in the UK. The companies are spread over 41 sites (as some companies have sites in different parts of the country) and 60 buildings. They span 216 floors with a total office area of around 250,000 m^2. These companies belong to eight different industries (shown in figure 1) including retail, media, technology, public sector, and others. The total number of desks in the sample is 37,764.

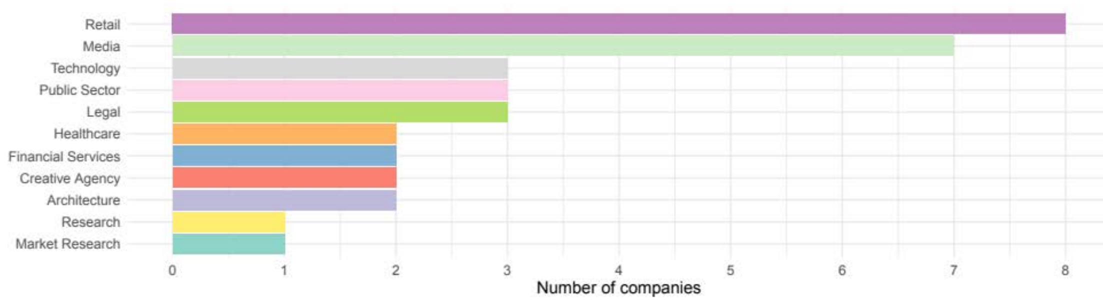


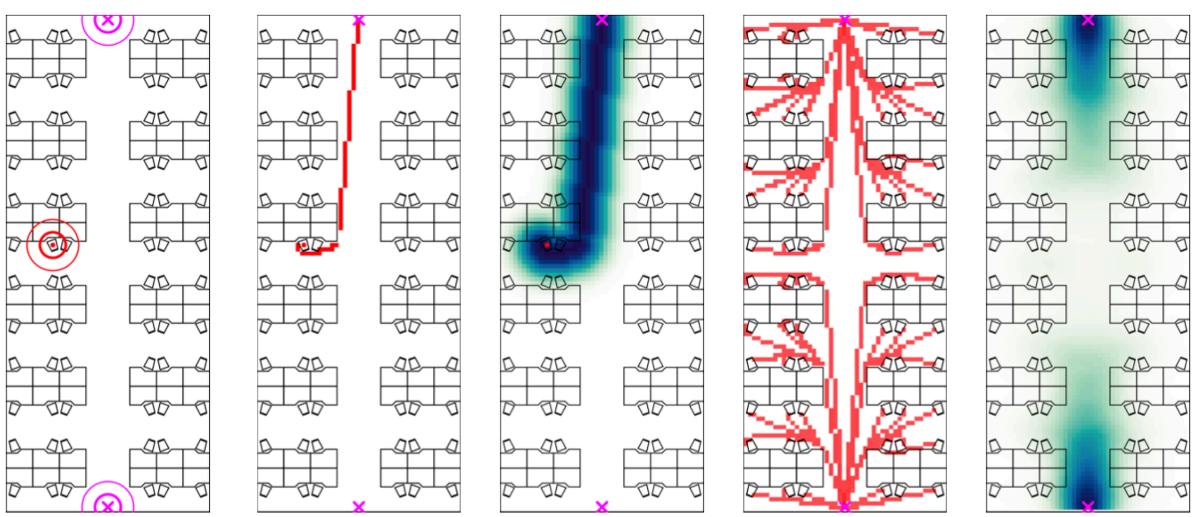
Figure 1: Number of companies per industry.

The dataset contains existing floor plans, Visibility Graph Analysis metrics but also observations of movement and interaction for all workspaces within each company over the period of one week, every hour for eight hours.

4 METHODOLOGY

The underlying representation used for this research was a grid, as this is provided in the context of Visibility Graph Analysis (VGA) a method of geometric spatial analysis within the field of space syntax introduced by Turner et al. (2001) and carried out using the software application depthmapX (Turner, 2001; Varoudis, 2012; depthmapX development team, 2019). While the measure of integration has been transferred from the urban-scale space-syntax analysis to VGA in previous studies, there is currently no equivalent metric capturing attractor-led movement potential for this grid-like representation. To adapt the ideas by Sailer, Owen-Smith and Kabo, three considerations had to be taken into account: origins and destinations, path-generation and path-overlap.

For the first consideration we chose to examine only paths from workspace seats to entrances, toilets and tea points (or canteens). Workspace seats can be thought of as the base for every employee from which most paths will start and end. The three attractor types chosen are the ones that are configurational i.e. their usage is more likely to be dependent on the need to reach them and thus the closest one is more likely to be selected. These are in contrast to other types of attractors such as meeting-rooms or other colleagues which require additional knowledge (i.e. which meeting room each employee attends at which time) for an accurate representation. Path-generation was rather more straightforward to adapt, given that within the field of space syntax various techniques exist for this task. The paths generated were the ones which required the shortest metric distance from seat to attractor. The final consideration, path-overlap required additional elements of the spatial model to adapt. Extant implementations relied on simpler spatial models covering large spaces and rooms but in the case of a grid-like structure the paths generated would be at-most single-cell wide (see for example figure 2b). To properly represent the potential for overlapping movement and co-presence (which allows for interactions to be triggered), a 'zone of visibility' was created around each path simulating all the space that a person travelling on that path could see. Under this assumption the existence of two common zones of visibility could trigger a new interaction, or pinpoint locations where movement is increased especially when those locations are close to the path.



(a) (b) (c) (d) (e)

Figure 2: Generating travel concentration for the same type of attractors (a - attractors marked with a magenta 'X'). From a seat (in red) the closest attractor is chosen and a shortest metric path created towards it from the seat (b). Then, the visible zone is created along that path (c). The zones of the paths from all seats to their closest attractors (d) are accumulated to create the metric Travel Concentration (e).

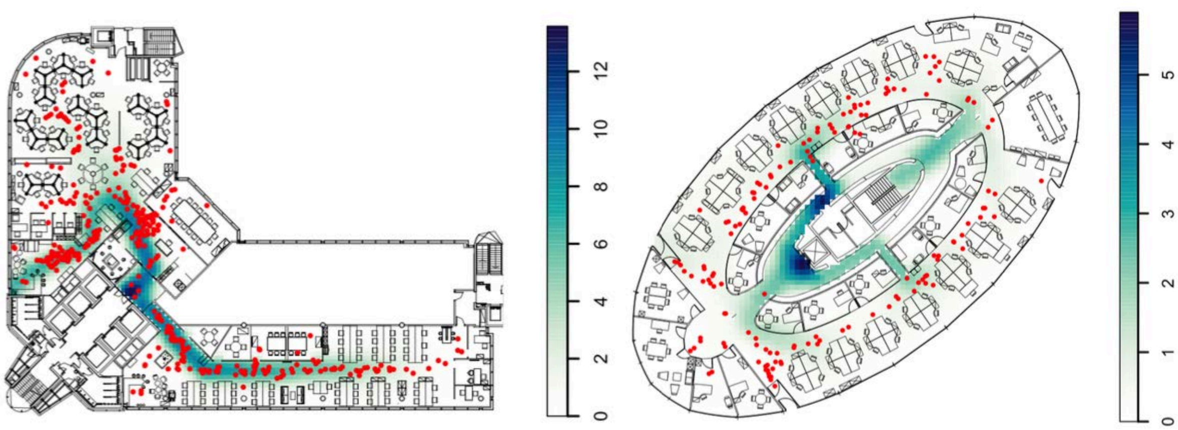
In technical terms, the process has four steps (shown in figure 2) and it is carried out from the perspective of the seat, not the grid cell itself. First, the closest attractor of a specific type is chosen by measuring the metric distance from that seat to all attractors of the same type (fig. 2a) and the shortest metric path on the grid is created from the seat to the attractor (fig. 2b). Obstacles such as furniture are taken into account. For the third step, all the area visible around the path is denoted as a zone of visibility (fig. 2c) that includes all the cells that can be seen when following that path. These cells are then assigned a value using a decay function i.e. one that decreases its value as the distance to the path increases. Finally, the process is carried out for every seat in the office space adding up the closest inverse distance to each path (fig. 2d). The result of this process is a new measurement for each cell, Travel Concentration (fig. 2e), a metric that is essentially a combination of the number of paths on which the cell was visible from, normalised by the distance from each path. Travel Concentration may be expressed using the formula:

$$TravelConcentration = \sum_{p=0}^{n} \frac{e^{\frac{-d(p,c)^2}{2\sigma^2}}}{2\sigma\pi}$$

where c is the cell for which the metric is calculated, p is a single path and d(p, c) the closest distance from the cell centre to the path, assuming they are inter-visible (0 otherwise). The formula is essentially the sum of a convolved gaussian of the path-cell minimum distance with window σ (as it appears in the formula) set to 1, taking into account all the paths from all the seats to the specified attractors.

5 ANALYSIS

Actual samples from the aforementioned dataset show that the method produces convincing results in some cases, but in others it is inadequate. Figure 3 shows two examples with (a) as a convincing case where movement (red dots) is mostly aligned with travel concentration (green/blue shades) and (b) as a non-convincing case where travel concentration appears unrelated to actual movement.



(a) (b)

Figure 3: Travel concentration (shades of green and blue) and movement (red dots) for the ground floor of case 61 (a) and the first floor of case 29 (b).

The new metric was tested against movement and interaction as aggregated for each floor in the whole sample, with the results shown in figure 4, and in comparison, to Visual Mean Depth (normalised for each site). In this and later analyses, floors where travel concentration was zero were removed from the analysis. As expected for travel concentration, movement (R^2 = 0.09) is better predicted than interaction ($R^2 = 0.05$) with the results being highly significant in all cases. Effect sizes are small though, and even smaller than Visual Mean Depth as a metric on its own (movement $R^2 = 0.17$ and interaction $R^2 = 0.10$).

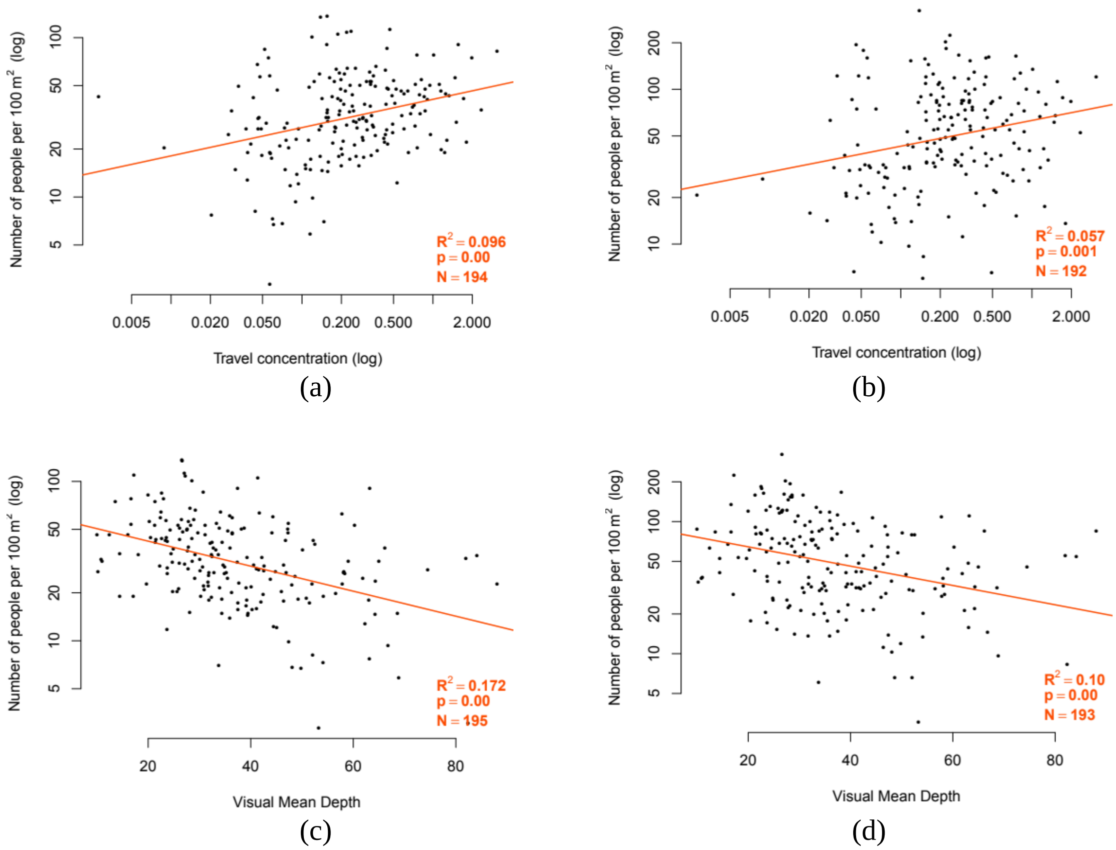
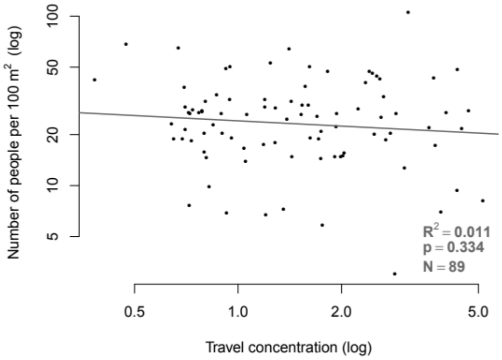
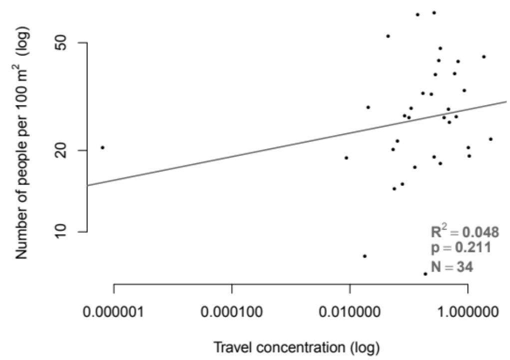


Figure 4: Mean travel concentration against movement density (a) and interaction density (b) for each floor in the sample. All scales except for Visual Mean Depth are logarithmic (base 10).

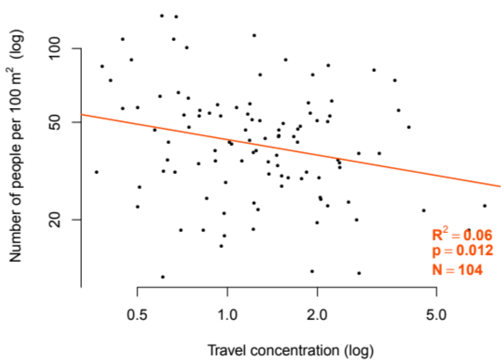
To further identify how travel concentration relates to movement, the sample of floors was split two ways. First, floors were split into two categories depending on whether they show high or low seat density (number of seats / total floor area) using the mean seat density (11 seats per 100 m^2). The second categorisation was done on each of the density splits, denoting whether the travel concentration came from within the floor or from outside. For example, all the paths of staff members that have a seat in a specific floor are collated to a separate in-floor travel concentration metric, while paths of staff members that came from a different floor were collated to an out-of-floor travel concentration metric. The aim with the second split was to separate trails towards attractors that are typically found on each floor (toilets, tea points) from the trails that lead to attractors that are sparse or unique to the building (canteens, entrances).



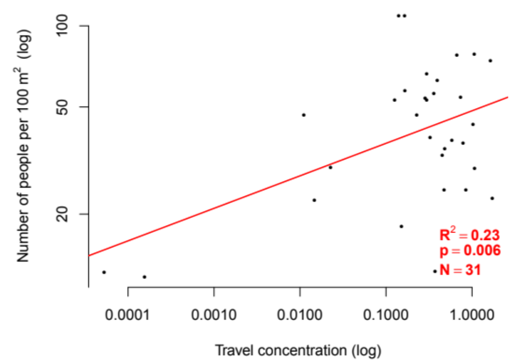
(a) Low seat density/within-floor



(b) Low seat density/out-of-floor



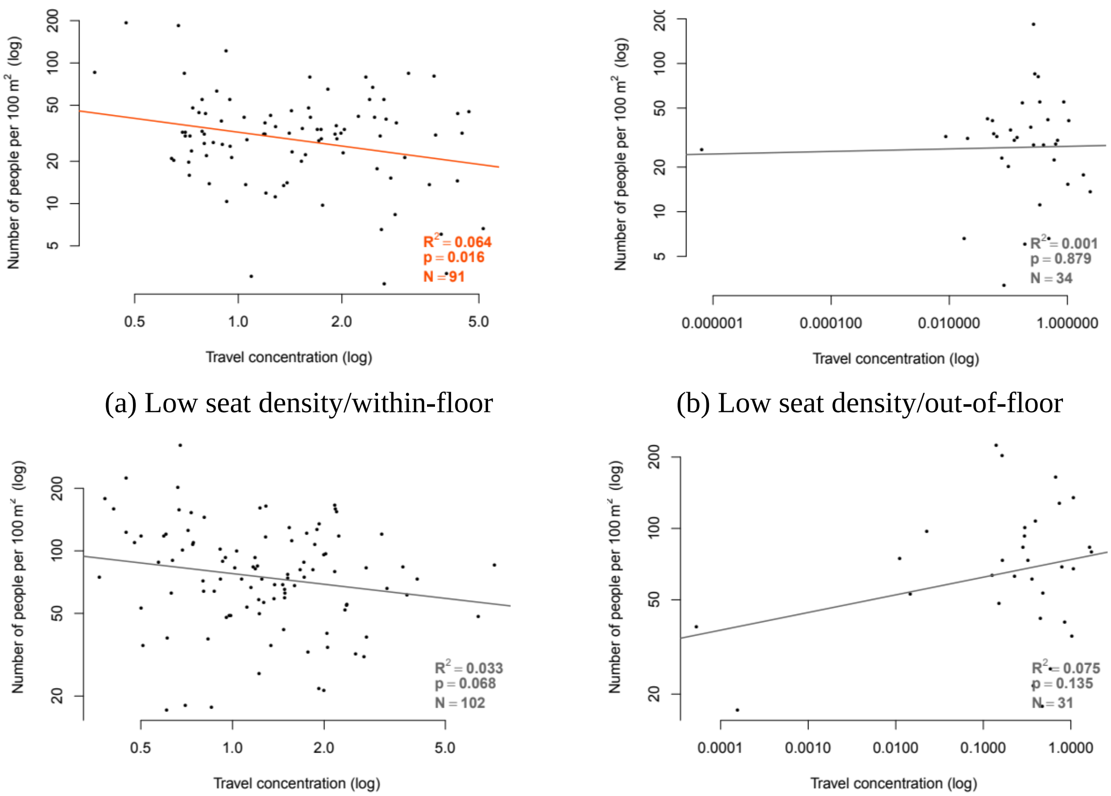
(c) High seat density/within-floor



(d) High seat density/out-of-floor

Figure 5: Mean travel concentration against movement density for each floor in the sample. Low seat density within-floor concentration (a) and out-of-floor concentration (b) and high seat density within floor (c) and out-of-floor (d). All scales are logarithmic (base 10).

The results from these splits are shown in figure 5. Generally, low seat-density floors (a, b) were harder to predict with insignificant results overall (p-value = 0.334 and 0.211 respectively), while high-density floors both have significant results either at the 0.05 significance level (c: p-value = 0.012) or the 0.01 level (d: p-value = 0.006 respectively). When it comes to high-density within-floor or out-of-floor travel concentration it appears that the latter more strongly predicts movement despite the smaller sample (N = 104 against 31 respectively). More specifically, high-density in-floor concentration (figure 5c) appears to be negative, i.e. floors with more common paths tended to attract fewer people moving. This is potentially due to confounding factors because the effect is not particularly strong ($R^2 = 0.06$). On the other hand, in high-density floors out-of-floor travel concentration (figure 5d) significantly predicts movement with a stronger effect ($R^2 = 0.23$). This is expected in floors that contain canteens and entrances because movement will follow specific common paths. For example, the paths of many staff members from other floors will include taking the stairs or elevator to the ground floor and going straight to the entrance thus creating a large concentration of paths from those stairs or elevators to that entrance. Given the strength of this effect it can be assumed that the earlier whole-sample results (figure 4) for movement are driven primarily from out-of-floor concentration.



(a) Low seat density/within-floor (b) Low seat density/out-of-floor

(c) High seat density/within-floor (d) High seat density/out-of-floor

Figure 6: Mean travel concentration against interaction density for each floor in the sample. Low seat density within-floor concentration (a) and out-of-floor concentration (b) and high seat density within floor (c) and out-of-floor (d). All scales are logarithmic (base 10).

The same splits were created for travel concentration against interaction, the results of which are presented in figure 6. In this case only the low-density in-floor concentration (figure 6a) was found to be a significant predictor of the activity density, though with a rather small effect (R^2 = 0.064). It is thus certain that other cofounding factors not taken into account are important for interaction. These results also agree with the general whole-sample results that interaction is a harder office-space activity to predict than movement purely using travel concentration.

Finally, table 1, shows all possible combinations of the four metrics (Travel Concentration total, in-floor and out-floor and Visual Mean Depth), for the full sample, only for high seat-density floors and only for low-density floors for movement and interaction. The results of the regression analyses show that by itself, the new metric does not perform better than Visual Mean Depth unless in highly specialised cases (movement and high seat-density out-of-floor concentration with R^2 = 0.23, also shown in figure 5d). However, in combination, the total Travel Concentration and Visual Mean Depth perform better at the level of the whole sample for both movement (R^2 = 0.22) and interaction (R^2 = 0.13) and best at the aforementioned highly specialised set of cases (R^2 = 0.32).

Behaviour	Movement						Interaction					
Sample	Full		High density		Low density		Full		High density		Low density	
	R^2	p	R^2	p	R^2	p	R^2	p	R^2	p	R^2	p
Travel concentration (log)	**0.10**	**0.00**	0.00	0.64	**0.10**	**0.00**	**0.06**	**0.00**	0.01	0.34	0.01	0.41
Travel concentration [In-floor] (log)	**0.04**	**0.00**	0.06	0.01	0.01	0.33	**0.07**	**0.00**	0.03	0.07	0.06	0.02
Travel concentration [Out-floor] (log)	0.04	0.11	**0.23**	**0.01**	0.05	0.21	0.03	0.18	0.08	0.13	0.00	0.88
Visual Mean Depth	**0.18**	**0.00**	**0.09**	**0.00**	**0.17**	**0.00**	**0.10**	**0.00**	0.04	0.04	0.05	0.04
Travel concentration (log) + Visual Mean Depth	**0.22**	**0.00**	0.07	0.01	**0.17**	**0.00**	**0.13**	**0.00**	0.06	0.02	0.05	0.04
Travel concentration [In-floor] (log) + Visual Mean Depth	**0.17**	**0.00**	**0.09**	**0.00**	**0.15**	**0.00**	**0.11**	**0.00**	0.05	0.04	0.07	0.02
Travel concentration [Out-floor] (log) + Visual Mean Depth	0.10	0.01	**0.32**	**0.00**	0.00	0.37	0.03	0.14	0.05	0.20	-0.05	0.81

Table 1: Multiple scenarios, showing the various combinations of using one of the Travel Concentration metrics or Visual Mean Depth, or a combination of those across the whole sample, for only high seat-density floors and for low seat-density floors, for movement and interaction. Models with high significance (p-value < 0.01) shown in red, while non-significant models (p-value > 0.05) shown in gray.

6 DISCUSSION AND CONCLUSION

This paper introduced a new spatial metric for the study of targeted movement in office spaces called Travel Concentration. It was shown that while similar endeavours were attempted, they were never tested on a large sample of workspaces and were applied to spatial models with low levels of detail. For this paper the metric was instead tested against a large sample of office spaces and in the grid-like representation typically used in the context of Visibility Graph Analysis. It was then shown that the metric is able to predict movement and interaction, albeit not particularly strongly throughout.

The few significant results from the splits according to seat density point at specific contexts the metric would work in, while in other cases provided future potential strategies for exploration. More specifically it was found that when there is a clear common travelling trajectory for most of the staff members (from their seat to the building entrance or a canteen) then the travel concentration provides a good approximation for movement. Weaker but still significant effects were found in cases of high-density floors and in-floor concentration and movement. The combinations with Visual Mean Depth proved successful in some cases indicating that the metric could be a useful addition to a larger set of metrics in regressions with multiple variables. In a similar vein, the relationship between the metric and interaction was only found significant at the low seat-density floor group also pointing to the need for more elements of spatial configuration to be taken into account.

Such additional elements of spatial configuration will be examined in future steps in this research allowing thus for more robust predictions of activity to emerge. To attain a more complete set of factors, building-wide metrics from the field of space syntax will be included such as metric depth, but also more metrics that measure local properties of space such as the distances to barriers and other potentials, many of which we have described in a recent publication (Koutsolampros et al., 2019). Beyond new metrics however, future research will aim to build robust spatial models that properly capture the nuances of spatial configuration, but also allow for understanding how that spatial configuration relates to human behaviour and how their combination can be employed to feed evidence back into the design process.

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