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# (Re-)Appropriating Instagram for Social Research: Three Methods for Studying Obesogenic Environments

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## ABSTRACT

The paper discusses three ways of appropriating Instagram for social research through the case of obesity. We draw on the notion obesogenic environments, in which obesity is understood as related to a wide range of cultural, social and physical factors. Together with a group of obesity researchers and cultural analysts we explored a dataset of 82,449 Instagram posts tagged with location from the five most and the five least overweight local authorities in the UK. The geo-located posts were studied through three distinct approaches to the data; each drawing on their own set of interdependent conceptualizations of what constitutes obesogenic environments, Instagram and cultural analysis respectively. The first approach values Instagram as a repository of images that can be coded and counted; while the second asks about the everyday practices of Instagram users. In a third approach we view Instagram itself as an analytical tool that produces a media-specific version of phenomena such as obesity. Following this third appropriation, we conclude that to unlock Instagram's potential for social research it must be considered as more than a collection of user-tagged images, but as an analytical context in its own right.

## CSS Concepts

• **Information systems~Social networks** • **Social and professional topics~Cultural characteristics** • Social and professional topics~Geographic characteristics • **Applied computing~Ethnography** • *Applied computing~Sociology*



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## Keywords

Instagram, social media, obesity, obesogenic environment, cultural analysis, data sprint, geolocated social media data

## 1. INTRODUCTION

An emerging research agenda explores how Instagram data can contribute to understanding obesity [23, 32]. In this paper, we argue this agenda is a useful case for exploring how Instagram can be appropriated in social research. The paper discusses some of the key results and challenges identified during a recent collaboration between obesity researchers and the Techno-Anthropology Lab. The collaborative research examined how to use digital data and digital methods to understand obesity better. The collaboration took the form of a week-long data sprint, where the key question was how to harvest and select Instagram data for qualitative analysis.

The paper's main contribution is to the on-going discussion of how social media can be appropriated and re-appropriated for social research. For more than a decade, cultural analysts have sought ways of exploiting online social data for the study of mundane, everyday settings and practices [5, 9, 14, 26]. With the rise of social media use, the abundance of empirical data has only increased. The increasing availability of detailed and well-structured metadata raises the question of when and how the humanities and social sciences will integrate the plethora of newly available computational methods [18]. We believe Instagram is of particular interest, due to the ongoing visual documentation of everyday life that takes place through the platform.

We argue that obesity research is a useful case for exploring some of these questions. Primarily because recent developments in the field of obesity research have identified that understanding obesity as only related to the two main factors of exercise and diet is problematic. With the concept of 'obesogenic environments' researchers propose to broaden the focus beyond these two factors and ask more generally what environments and practices are correlated with obesity.

Social media data in general, and Instagram data in particular, are highly relevant to research into obesogenic environments. This is because such data are rich in mundane everyday life settings and practices. The potential to use this data also raises new methodological questions that we will explore in this paper. So far, Instagram data has been used to explore obesity in primarily quantitative ways, which is obviously important given the abundance of available data. However, the question we raise in this paper is how to make quantitative and qualitative approaches work together when utilizing Instagram data for obesity research.

The paper thus situates itself within what is currently taking shape as 'quali-quantiative' methods [4, 15, 38], which - in contrast to mixed methods approaches - exploit the 'zoomability' of digital datasets. Zoomability allows for seamless navigation between quantitative overviews and in-depth qualitative analysis without changing registers. Some common problems in this type of 'quali-quantiative' methods revolve around: working through digital interfaces [20]; soliciting data collection from application program interface's (API) [16]; gauging the performative role of algorithms in the field [3]; figuring out what analytical status to attribute to digital traces [17]; and how to square such traces with more traditional styles of qualitative inquiry [27].

We are going to argue that Instagram data can be re-appropriated for social research in (at least) three different ways. We flesh out these three appropriations through an experiment in which we harvested and analyzed Instagram posts from ten geographical locations known to have populations with the five highest Body Mass Index's (BMI), and the five lowest BMIs in the United Kingdom. Our experiment is thus based upon the premise that BMI and geographical location map onto each other. This allows us to explore the different ways of appropriating Instagram for obesity research and various versions of the obesogenic environment and cultural analysis.

In the next section, we briefly present the notion of obesogenic environment. After that, we discuss the existing Instagram literature and outline our own cultural analytical approach before we move on to describing how one might harvest geo-delineated data from Instagram. Following this, we outline three modes of appropriating Instagram for cultural analysis of obesogenic environments, namely: (1) as a camera or repository documenting everyday life; (2) as an everyday practice to be studied as part of the environment; and (3) as an analytic device in its own right. We end by proposing that, while all three approaches have merits, the third approach is preferable because it takes into account the media specificity of Instagram.

## 2. OBESOGENIC ENVIRONMENTS

In this paper we recount an experiment designed to explore the question of how Instagram can be appropriated for cultural analysis in the specific context of obesity research. In late October 2015 we conducted a data sprint with an interdisciplinary group of researchers from the Governing Obesity project at the University of Copenhagen (http://go.ku.dk/). The project is comprised of biomedical scientists, physicians and nutritionists, as well as ethnologists, historians and anthropologists. What unites them is their shared interest what they call 'obesogenic environments'.

The notion of 'obesogenic environment' was first suggested and defined by Swinburn et al. in 1999 as "the sum of influences that the surroundings, opportunities, or conditions of life have on promoting obesity in individuals or populations" [36, p.564]. This re-definition of the object of study within obesity research from the individual, physiological body to the individual, physiological body in a physical, economic, historical, social, cultural and psychological environment has turned obesity research into an interdisciplinary field of study.

This interdisciplinary field of research has not succeeded in stabilizing a shared understanding of obesogenic environments. While some studies work to define the impact of environmental factors on the individual [13], others stress the "interdependence and interconnectivity" of these environmental factors, depicting obesity as "a phenomenon with strong historical and sociocultural dimensions" [22, p.1503]. In short, the notion of obesogenic environments signals an interest in determining which and how everyday settings and practices relate to obesity.

## 3. (RE-)APPROPRIATING INSTAGRAM FOR CULTURAL ANALYSIS

Social research on Instagram is still in its infancy. A search for the keyword 'Facebook' on PubMed yields 1397 results at the time of writing, while 'Instagram' only returns 33 papers. And while searches for 'Facebook' and 'Twitter' yields 1,501 and 2,001 results in the ACM Digital Library, a search of 'Instagram' returns only 63 records. This number has been increasing over the last years, from 1 record in 2012, to 33 in 2015. The numbers reflect how the platform has been expanding its reach dramatically over the last few years, from less than 100 million monthly active users in January 2013 to 400 million in September 2015[a]. But despite this rapidly growing interest, a substantial body of Instagram-related research has yet to appear. This dearth of research is particularly noteworthy given the potential to use Instagram data for investigations of everyday life and everyday environments, including obesity.

A major part of the research that does exist has focused on Instagram as home to the 'selfie' [10, 12, 35]. This is related to a more general research agenda regarding the rise of Instagram as a social media platform and how its functionalities, such as 'liking', commenting and tagging, are used [1, 8, 11].

Other researchers ask how Instagram data can be of use to social research more generally, such as gaining data about traffic conditions, by treating Instagram users as 'citizen sensors' [24, 34]. In this strand of research Instagram posts from restaurants has for example be used to understand how people interact with food. Early results suggest that photos of unhealthy food receive comparatively more likes, with photos from donut shops scoring highest [18]. However, these results are not unequivocal, as can be seen in another recent paper, which argues that 'moderately healthy food' is both most common and most supported by users on Instagram [32].

These efforts raise questions about how Instagram data can be used for social research. Specifically, can Instagram be useful beyond tracking what is 'most liked' in relation to various topics and variables [21]? In relation to cultural analysis and obesity research specifically, there is a question of whether Instagram data can be used to explore obesogenic environments qualitatively.

We suggest that an interest in 'environments' makes a cultural analysis perspective relevant. Cultural analysis is the study of mundane, everyday settings, and practices. These "small matters" are understood to be empirical and analytical entrances to illuminate "larger issues"; in our case, the obesity epidemic [6]. Cultural analysis can be conducted in a number of different ways: prosaic registrations of the things and people that make up everyday life; hermeneutically inspired studies of how people give meaning to their everyday settings and practices; and performative studies of how everyday settings and practices enact realities. We propose that none of these approaches to cultural analysis are authoritative. Instead, our main goal in this paper is to explore how different approaches distribute different roles of research to Instagram, the obesogenic environment, and to the analyst.

We pursued these questions of how cultural analysis and obesity research can support each other through the format of a 'data sprint' [28]. The data sprint is a relatively new format for research collaboration that aims to create shortcuts for moving between digital data and expert questions. A prominent example of the data sprint format is the EU-funded eMaps project, which used input from climate change experts to build digital maps to aid climate change negotiations and policies [37]. The idea is that with the broad range of new analytical possibilities opened by digital data, it is crucial to be able to quickly move back and forth between research questions and data experiments. This can be facilitated by bringing together leading experts on the specific issue in question, in this case obesity, and people with experience in digital research.

In our case, we had participation from 9 obesity researchers, 8 digital methods specialists, and 5 student assistants. The objective of the data sprint was to try to understand if, and how, it would be possible to study obesogenic environments through social media. The data sprint approach is guided by the notion of quali-quantitative methods [4, 15]. The general ambition is not to make a fundamental distinction between qualitative and quantitative 'levels' in the analysis, but constantly ask how quantitative techniques can also inform qualitative study, and vice versa. Such an ambition raises methodological challenges that we explore by asking how Instagram may contribute to the understanding of obesogenic environments.

In this paper we argue, that Instagram, can be used to conduct cultural analysis that is just as valid as traditional cultural analytical methods - such as the qualitative interview or participant observation

These differences in understandings of the notion of the obesogenic environment – or different theoretical and analytical commitments – also came to the fore during the data sprint; resulting in different ways to (re-)appropriate Instagram for obesity research. Therefore, this case is well suited for exploring a range of systematic utilizations of Instagram for cultural analytical research.

# 4. RESEARCH DESIGN

In the following, we elaborate on how one might appropriate Instagram through the notion of obesogenic environment. More specifically we ask: What role does Instagram play in research if view obesogenic environments as:

1. environmental factors impinging on the individual [13]
2. environmental factors that are interdependent and interconnected with historical and sociocultural dimensions [22]

While these two research questions relate to existing ways of conceptualizing the obesogenic environment, the data sprint's work with Instagram also brought to the foreground a new Instagram-specific way of approaching obesogenity. Our third and final research question is: What role does Instagram play in research if we view obesogenic environments as:

3. media-specific concepts that are co-created by Instagram's technological possibilities

These different takes on what defines an environment also change the role for cultural analysis, which we will explore in detail after introducing our data collection process.

## 4.1 Data set

Our data set is comprised of a total of 82,449 geo-tagged Instagram posts from the five most and the five least overweight local authorities in England. Adult overweight data by local authority is available via Public Health England[b]. We used rankings published in 2014 to select local authorities for analysis. Due to differences in both the size of the geographical areas they cover, and in the level of Instagram activity within these areas, the dataset is unevenly distributed across local authorities (see Table 1 and explanation below).

### *4.1.1 Designing the harvest*

The Instagram API allows harvest of geo-tagged images within a radius of up to 5 km from a given map coordinate. We used Free Map Tools[c] to draw radiuses of 1, 3 or 5km around 138 map coordinates. This gave us 10 sets of overlapping circles of varying diameter covering each of the 10 selected local authorities. We used them as harvest points (latitude, longitude, radius) to get images and metadata through the Instagram API with a custom built Python script. Duplicates resulting from overlapping harvest points were subsequently filtered out.

Since we expected weekdays to be qualitatively different, both in terms of what and who is posting to Instagram, we wanted to ensure that at least one full week of data was available for each harvest point (e.g., comparing Friday nights across local authorities).

Since the API requires research to specify a desired number of Instagram posts for each harvest point back in time from an end date (it does not allow a start date), we also needed to ensure some proportionality in the number of images demanded for differently sized harvest points.

After selecting an end date (23rd of October 2015) we therefore set the number of desired Instagram posts for each harvest point relative to its size (e.g., every time we asked the API for 10 images from a harvest point with a 1km radius, we asked for 250 images from a harvest point with a 5km radius). We then proceeded to harvest incrementally in small batches until a full week of Instagram posts had been obtained for all harvest points within a given local authority.

This means that for harvest points with low Instagram activity the dataset covers several weeks (in rare cases several months), whereas it covers only one week for the most active harvest points. This allows us the flexibility to either filter the set to one week across all harvest points (specifically the 17th to 23rd October 2015), or to keep the number of Instagram posts from each harvest point proportional to its size. The latter is important since some of the more sparsely populated rural areas are sporadically represented if the set is filtered to one week only.

**Table 1: Overview of the dataset**

| *Local authority* | *Instagram posts (% of which hashtagged)* | *Distinct users (relative to population size)* | *Overweight* |
|---|---|---|---|
| *Brighton and Hove* | 14346 (60%) | 8098 (5%) | Least |
| *Chelsea and Kensington* | 23578 (65%) | 15581 (10%) | Least |
| *Hackney* | 15796 (63%) | 9450 (4%) | Least |
| *Richmond upon Thames* | 10702 (65%) | 7008 (4%) | Least |
| *Tower Hamlets* | 10277 (66%) | 6931 (3%) | Least |
| *Copeland* | 2764 (61%) | 1264 (4%) | Most |
| *Doncaster* | 5767 (59%) | 2845 (1%) | Most |
| *East Lindsey* | 2531 (63%) | 1234 (1%) | Most |
| *Ryedale* | 3161 (55%) | 1561 (3%) | Most |
| *Sedgemoor* | 3704 (57%) | 2049 (2%) | Most |

### *4.1.2 Overall characteristics and limitations*

There are, to our knowledge, no reliable statistics available on the proportion of images generally tagged with location on Instagram (we have seen loose figures from the past four years spanning from 5% to 25%, none of them specific to the UK, and none of them verifiable). Generally speaking it is to be expected that the majority of images actually posted to Instagram in our selected local authorities are not tagged with location, and thus fall outside our harvest criteria.

Given that the dataset was constructed with the primary aim of supporting experimentation with ways of selecting images for qualitative analysis, the volumes shown in Table 1 were deemed sufficient. We were particularly interested in the percentage of Instagram posts with hashtags, since they provide an obvious way to filter the set thematically. Although there are somewhat fewer Instagram posts with hashtags in the most overweight areas, they are never below 55%.

We were also interested in using caption text for filtering. A simple search on the 10,277 Instagram posts from Tower Hamlets (an average sized local authority in terms of Instagram volume) revealed for example that 3.5% mention 'food', 1.7% mention 'friends', and 1.6% mention 'fitness' in the caption. This led us to believe that themed image sets of size suitable for qualitative analysis could be feasibly delineated.

Further filtering options are offered by the metadata. All images are time stamped (dd/mm/yy hh:mm) when they are posted, not when they are taken, which seems a likely explanation why activity peaks on Sunday night across all 10 local authorities. All images are also associated with a location name (e.g., Uncle Eddie's Motortrack or The Gentlemans Retreat); a user ID and user name; a like count; and an indication of users tagged in the picture.

It is clear from the difference in volume between the most overweight and the least overweight local authorities, that there is generally more Instagram use in less overweight areas. Rather than being an indication of anything obesity related, this could be explained by the fact that the least overweight areas are more densely populated, have higher socio-economic status[d], and possibly also higher bandwidth (although we found no good way of testing the latter).

There is, however, a smaller discrepancy in the *number of Instagram posts per user* if we compare the least overweight areas (~1.5) with the most overweight areas (~2). This can obviously not be explained by the difference in population size. If we look at the number of distinct users *relative to the population of each local authority*, this pattern is repeated (see Table 1). There appear to be more Instagram users per inhabitant in the least obese areas.

This tendency is particularly clear in the Chelsea and Kensington subset. For the purposes of our harvest, two harvest points cover the local authority with an equally high Instagram activity. This means that the subset, though large, is only comprised of one week of data. We should therefore expect the number of distinct users to be relatively low (more weeks increase the chance of more users tagging their Instagram posts with location in the area). Instead the volume of distinct users relative to the size of the population is twice as high (10%) as in the second highest area (Brighton and Hove, where the number of distinct users corresponds to 5% of the population).

It seems reasonable to assume that these discrepancies are due to the fact that tourists and visitors pass through London - especially areas like Chelsea and Kensington - at a much greater rate than, for example, Doncaster or East Lindsey. Indeed, the fact that an image has been tagged with location tells us nothing as to where the user is from. The pattern is also evident if we compare the most overweight local authorities between themselves. In Copeland, which comprises the southwestern corner of the Lake District National Park, and in Ryedale, which comprises the better part of the North York Moors National Park, are both popular destinations and there are more people using Instagram relative to the population, than in other most obese areas.

It must therefore be assumed that the dataset is geographically delimited only in the sense of where the pictures are taken and not where the users are from. There are no failsafe solutions to this problem, at least not through the Instagram API. One option is to try and glean the information from the user bio. Casual experiments with this approach have proven sketchy at best. Another option is to construct a series of tangential datasets based on the same harvest criteria, but from different time periods. It would potentially permit the identification of a subset of recurrent users for each of the local authorities, thus filtering out visitors. Alternatively, one could examine the media history of each user in the current dataset and thus restrict the set to users with recurrent posts in the same area. We consider this further work. For the purposes of the experiment reported in this paper, however, it was not a resource that was available to us.

## 5. THREE APPROPRIATIONS OF INSTAGRAM

As described above, our data collection suggested a set of difficulties for the cultural analyst interested in figuring out how the obesogenic environment can be understood through Instagram posts. In the following, we describe three different appropriations of Instagram that were developed while working with the data. Each provide a different answer to what cultural analysis with Instagram looks like:

1. *Instagram as a camera that produces photographic representations of the obesogenic environment.* To appropriate Instagram for obesity research here means finding ways of categorizing, counting and comparing the obesogenic environment depicted in these photographic representations;
2. *Instagram as one element in the everyday practices that make up the obesogenic environment.* To appropriate Instagram for obesity research here means to find ways of exploring how Instagram is part of the practices that make up the obesogenic environment. It means finding ways of exploring how Instagram is both shaped by and is shaping the practices of which it is part;
3. *Instagram as an analytical device that takes part in exploring and impacting obesity (and all other phenomena) in specific ways.* Users of Instagram consider what is worth posting and are provided technological possibilities to do so. Instagram might thus be seen as a method for exploring and producing obesogenic environments that can be re-appropriated by obesity researchers.

## 5.1 Instagram as camera

The first analytical approach tries to overcome the problem of linking the individual Instagram user to the fives highest and lowest BMI-areas by focusing on one version of what the obesogenic environment is.

### *5.1.1 Environment as extraneous factors*

Here, the notion of obesogenic environment is defined as a series of external factors that impact the individual citizen's BMI. Approaching Instagram through this understanding of the obesogenic environment means that we are not concerned with the individual user and where he or she lives. Instead, we are interested in where a photo is geotagged. Instagram posts depict the physical environment of each high or low-BMI areas, and this depiction provides the researcher with data about the factors that comprise an obesogenic environment in each area.

### *5.1.2 Instagram produces a repository*

This appropriation of Instagram takes advantage of the use of cameras and subsequent storage of photographs in repositories covering different geographic environments. An example of this is the project 'Selfiecity'[e], in which a team of scholars, led by Lev Manovich, use Instagram selfies from five different cities across the world to investigate the style of self-portraits in different cultures [10]. In this project, Instagram as a medium is not in focus, but is rather a way of gaining access to data. The assumption in this kind of study is that through its users' photos, Instagram's camera allows us to *see* everyday practices and environments. In turn, these practices and environments can be recorded, counted and analyzed through content analysis [30].

For the project Selfiecity, researchers were interested in, among other things, "algorithmic estimations of eye, nose and mouth positions, the degrees of different emotional expressions"[e]. Within obesity-oriented studies of Instagram, a computerized approach to sorting Instagram's food photographs automatically calculates calories of food on posted photos [32]. This style of obesity research explores a broad range of factors in the depicted environment that support being obese, in a word an environment's 'obesogenicity' [36]. Such factors are for instance the existence or absence of recreation and sports facilities; cycle paths; availability of buses and bus stops; media (e.g., women's magazines); food marketing (e.g., fast food advertising); and the availability of fresh food [36].

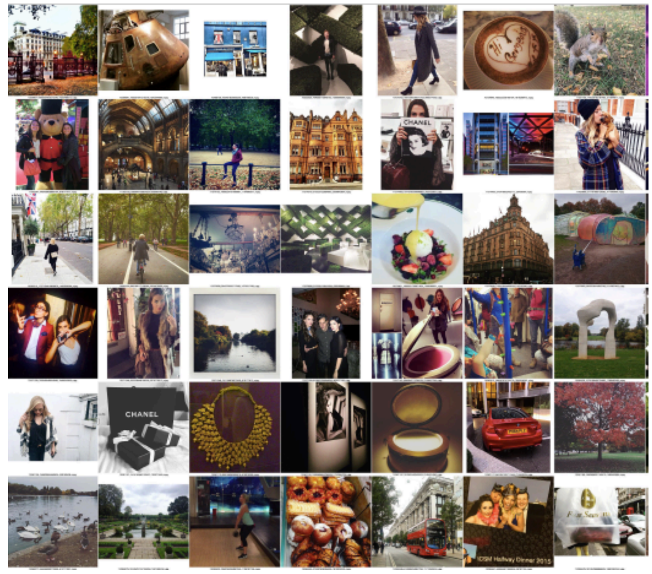

**Figure 1: A sample of 42 Instagram posts from Chelsea & Kensington showing how Instagram can be seen as producing a repository.**

### *5.1.3 Cultural analysis as recording reality*

In the appropriation of Instagram as camera, posts about everyday environments and practices thus lend themselves to a cultural analysis based on recording and counting. To gain an overview of obesogenicity (or, oppositely, the 'leptogenicity') in our study's 10 areas, the researcher can now begin to code what objects and activities are present in their sample's depictions of the local environment. Subsequently, one can count the existence of the above-mentioned obesogenic factors to determine the obesogenicity of each area, and see whether these align with the local population's BMI or offer surprising results to be further studied by obesity researchers.

Using Instagram as a camera through which to study the external factors of obesogenic environments highlights one of the medium's unique qualities. Namely that Instagram offers wide-ranging visual access to everyday life in different geographic regions. However, this approach is also highly sensitive to issues of representation since 'Instagram as camera' suggests that the media accurately represents reality. This stands in stark contrast to the fact that, as we have already established, we are only looking at everyday life as photographed by as little as one percent of the population in a local area. It seems reasonable to suspect that this severely limits our ability to identify all the relevant obesogenic factors present in the areas included here.

Further, the issue of representativity points to what cultural analysts consider a larger problem with the present versions of obesity and Instagram. Using Instagram as camera and considering external factors of obesity represent conceptualizations that black box users/subjects and their social practices as constitutive of everyday life.

## 5.2 Instagram as part of the environment

As an alternative, a logical next step is to view Instagram instead as an integral part of the obesogenic environment.

### *5.2.1 Environment as everyday practices*

The move implies a change in the conceptualization of the obesogenic environment. The obesogenic environment can no longer be reduced to environmental factors surrounding and impinging upon the individual, but as the everyday practices of that individual, such as shopping, cooking, cleaning or, indeed, posting to Instagram ('instagramming').

### *5.2.2 Instagramming as a an everyday practice*

From an anthropological perspective, posting to Instagram as a meaningful everyday practice, is similar to posting to the web. Since the late 1990s ethnographers have sought to ground online activity through the ethnographic study of selfsame in everyday (offline) practice. This grounding shows that the Internet and social media are not monolithic. Rather, they are shaped by and in turn shape the particular social, cultural and material everyday practices in which they are used [24, 25].

### *5.2.3 Cultural analysis as socio-technical perspective*

To appropriate Instagram for obesity research in this context entails studying how everyday practices are shaped by and shape the use of Instagram. What is the relationship between how people use Instagram in their everyday lives and obesity? What cultural differences in the everyday practice of posting to Instagram might we be able to decipher and describe? Our dataset offers some possibilities for exploring this question. Across all 10 local authorities we see that posting activity on Instagram peaks on Sunday nights, as illustrated in the below heat map for Doncaster (Figure 2).

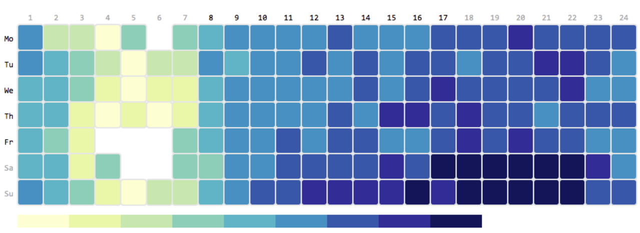


**Figure 2: Heat map of 'instagramming' activity for Doncaster.**

Thus, we can say that across all 10 local authorities, 'instagramming' seems especially meaningful Sunday night. The next step would be a qualitative and comparative analysis of what Instagram users find it meaningful to post at this particular time, which might reveal important differences.

A related approach would be to explore the data to identify interesting users, and follow them and their Instagram use. Based on user IDs, a more user-centric data collection could be pursued. To some degree, the Instagram-specific metadata thus allow for us to 'hang out' [39] with the Instagram users of our dataset and to begin to understand how and why specific posts are produced and posted.

But whereas traditional and 'analogue' ethnographic methods such as interviewing and observing are designed and employed to deliver "thick descriptions" [7] of the 'how' and 'why' of everyday practices it is less clear what the medium-specific metadata can tell us about the meaningfulness of everyday practices. How and why, exactly, is Sunday night a meaningful time to produce and post Instagram posts? How to understand the meaning of user actions? As a medium, Instagram does not offer 'thick' answers to such questions.

Within this appropriation of Instagram for obesity research, to 'stay with the medium', i.e. to conduct the inquiry through Instagram alone, therefore quickly becomes a challenge. Leaving the medium behind is tempting and perhaps the only solution if one is interested in questions like how Instagram users – and non-users for that matter – attribute meaning to the medium and how the medium in turn gives meaning to people's everyday lives (ultimately a hermeneutic ambition that can only be achieved through lived experience).

At the same time, what this second and somewhat user-centric appropriation of Instagram disregards, are the specific analytics deployed by Instagram. Instead of situating Instagram in an already existing everyday sociality, we could instead focus on Instagram as itself offering ways of ordering and making sense of the everyday, including how this might perform new kinds of obesogenic environments. This option is explored in the third and last appropriation of Instagram where medium becomes a method for social inquiry.

## 5.3 Instagram as analyst

This third version begins from the fact that Instagram, like other online media, is already in the business of conducting various kinds of analysis on itself. Material components of a specific analytical practice on Instagram include the user profile; the use of hashtags; the ability to like or follow; the search features; the interface and the photo feed [20, 31]. Taken together with (and to some extent understood as constitutive of) the way users interact on the platform, this practice routinely poses questions to us about 'instagrammability'. In other words: should this image go online?

From the perspective of the user this question of 'instagrammability' emerges in relation to specific hashtags, specific locations, or other users; all of which may be tagged when uploading. The questions can thus be broken down into very platform-specific problems like deciding if this is #foodporn, if it is worthy of being tagged with a famous location, or what friends should go in the picture. It is clearly not just a generic matter of deciding if the image is of sufficient aesthetic quality in some generic sense. Furthermore, when on Instagram, questions about tagging are asked in a media environment that trains us on how others are answering the same questions. We are kept updated on what #foodporn is currently becoming in the hands of the people we follow, for instance.

### *5.3.1 Environment as deployed by Instagram*

If we look at Instagram this way it becomes impossible to separate the medium from the notion of environment. The analytical context for studying obesogenic environments is here Instagram itself. That is: how are users responding to, working with, organizing and interacting around questions of instagrammability.

Hashtags like #picoftheday, #dogsofinstagram, and #foodporn suggest that Instagram users are reflective about tagging as a way to order images. Such tags seem to acquire a certain generic meaning across sites and rally a broad range of users behind them. This is useful for a cultural analysis, because such tags are ascribed a media-specific meaning that can serve as context for comparisons between locations, time-slots, and so on. For example, if we look at #foodporn, and compare how that tag is used across more and less obese areas, we situate our comparisons in relation to an Instagram-specific practice where food is made a topic of interest together with the medium.

### 5.3.2 *Instagram tagging as analytical practice*

If we consider Instagram and its users as co-analysts, we should ask ourselves how they would be of assistance in research. Tagging is a way to order content. The most direct analogy to standard practices in cultural analysis would be to coding: i.e., the process of working through qualitative material (interviews, field notes, images) and enriching it with metadata (themes covered, questions raised, actors involved, events mentioned).

The dataset comprises 85,630 different hashtags that are, in a sense, elements of an open and crowd-sourced coding structure. Instagram thus could be said to run its own on-going content analysis [23]. The obvious first question to ask would be whether or not such an analysis reveals differences between high and low BMI areas? And, if so, what it can tell us about the quality of these differences?

None of the 85,630 hashtags found in the set are unique to the high BMI areas (i.e., none of them are found across all of the overweight local authorities, while simultaneously never being found outside these areas). If we look at the low BMI areas, however, they are characterized by 287 unique hashtags. That suggests a qualitative difference in content between low and high BMI areas.

Given that four out of five of the low BMI areas are located in London (with Brighton being the only exception), some of the uniqueness is expectedly associated with the city (hashtags include #thisislondon, #ilovelondon, #thames, #bigben, and #towerbridge). Other hashtags on the low BMI unique list hint at a more affluent lifestyle, such as #investment, #jewelry and #christianlaboutin. Many hashtags signal specific preferences in relation to diet and personal fitness, such as #yogi, #yogateacher, #avocado, #dairyfree, #sushi, #veganfoodshare, #rawvegan and #korean.

The differences become clearer if we look at the hashtags found across all 10 local authorities and compare their ranking (see Table 2). Following the example of [23] we ranked all hashtags according to the frequency with which they occur in low BMI and high BMI areas respectively. We then substracted the low BMI rank from the high BMI rank to obtain the difference in ranking for each hashtag. The resulting list can be ranked again to give the most popular high-difference hashtags in low BMI areas in positive values, and the most popular high-difference hashtags in high BMI areas in negative values.

**Table 2: Most differently ranked hashtags between low and high BMI areas. Displayed as top 15 most popular high difference hashtags in low and high BMI respectively**

| Low BMI areas | High BMI areas |
|---|---|
| #today | #spider |
| #heaven | #loveher |
| #artist | #brother |
| #yum | #horse |
| #good | #boyfriend |
| #repost | #blueskies |
| #instacool | #lovelyday |
| #goodmorning | #country |
| #liveauthentic | #mtb |
| #mirror | #jump |
| #shopping | #railway |
| #house | #lovehim |
| #old | #ford |
| #the | #cow |
| #interiors | #motorbike |

Table 2 considers the 291 hashtags found in all 10 local authorities. It reveals a difference in the prevalence of these hashtags between low and high BMI areas (it does not compare top hashtags, which would require a control to be of any value, but rather compares the hashtags that are most differently ranked in low and high BMI areas respectively). From this we could make categorized lists focusing, for example, on food, health, family or activity related tags, and we could use those to profile everyday life in our selected high and low BMI areas. The question remaining would be: What does it actually tell us when a certain hashtag is prevalent in an area?

### 5.3.3 *From cultural analysis of content to cultural analysis of contexting*

With the notion of Instagram as analyst, we can move beyond a conceptualization of users as coders of content and consider their actions as an analytical context as well. This entails moving from an exploration of individual hashtags to an exploration of co-occurring tags. In such an exploration, a network of hashtag relations is generated, where the tags can be interpreted as part of different communities.

Figure 3 shows a network of hashtags (represented as nodes) co-occurring (represented as edges) in the high BMI areas. It is filtered to a minimum co-occurrence of three per local authority (i.e., two hashtags have to co-occur at least three times in the same local authority for an edge to be considered). Hashtags that are only found in one of the five local authorities (the majority) are colored according to the local authority in which they are found.

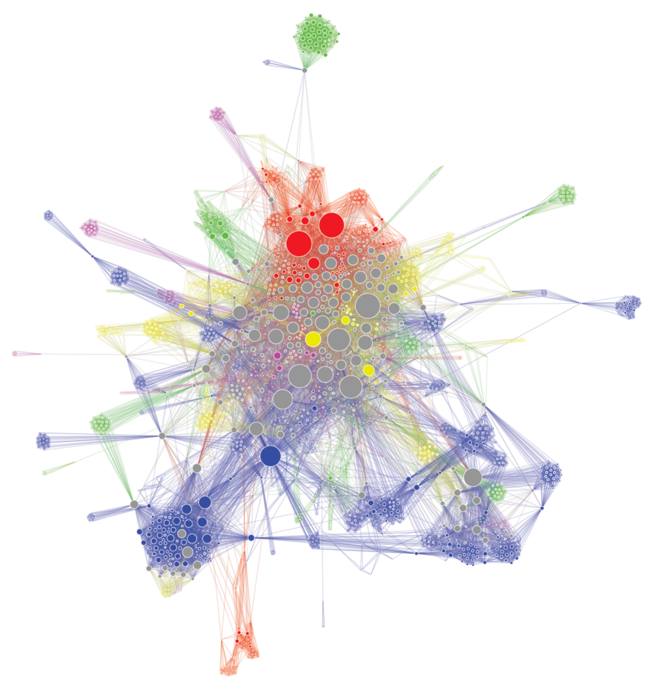

**Figure 3:** Network of co-occurring hashtags in high BMI areas. Nodes colored by local authority (grey nodes representing occurrence in multiple authorities) and sized by degree (representing volume of co-occurrences with other hashtags). The graph has been spatialised with a force vector algorithm (ForceAtlas2) showing communities of hashtags frequently used together as visually clustered.

Figure 3 reveals a series of hashtag communities, i.e., hashtags that tend to co-occur. One initial way to investigate these communities is to think of them as either user-, geo- or media-syncratic. User-syncratic communities are driven by a single user with a strongly patterned tagging behavior (e.g., around a hobby like home cinema). Geo-syncratic communities involve multiple users, but are specific to a location. In Figure 3 they emerge around places like the Lake District, Cheddar Gorge or a barbershop / tattoo parlor in Doncaster. Essentially all the colored nodes belong to either user- or geo-syncratic hashtag communities.

The grey nodes, which are found towards the middle of the graph, represent hashtags that occur in multiple areas. Given that this is data from the five high BMI local authorities, one might expect a large cluster of hashtags co-occurring across multiple areas to constitute an obeso-syncratic community. This is not the case. 51 hashtags are found in at least four of the five high BMI areas. These are, without exception, also found in at least four of the five low BMI areas. They must thus be considered media- rather than obeso-syncratic.

From the perspective of a cultural analysis in general, user-syncratic hashtag communities are of limited interest given that they cannot be said to involve sociality. From the perspective of a cultural analysis of obesogenic environments specifically, the geo-syncratic communities are of limited interest as well given that they do not align with a difference in BMI.

A similar argument could in principle be made against the media-syncratic communities as well – they do not align with BMI differences either – but that argument presupposes that the only thing we are interested in is showing differences (which is indeed the presupposition if we are appropriating Instagram to help us tag content). Yet, the media-syncratic hashtag communities affords a different opportunity, namely to provide a context for comparison. As such, they constitute what George Marcus would call posited logics of association [19].

In sum, what this third approach offers is a way to use Instagram not just as offering an abundance of interesting content, but also offering a context with which to render this meaningful content. Obesogenic environments can be compared in relation to how Instagram practices, such as tagging around #foodporn, differ across localities.

## 6. DISCUSSION

In the first appropriation Instagram is understood as a camera and thus as a repository of images depicting an extraneous environment. It assumes a theoretical version of obesogenic environments as constituted by a set of identifiable, external factors (such as supermarkets or fast food restaurants) that one can simply spot in the pictures. It also assumes a rather naïve version of cultural analysis that ignores the social dimensions of the user as an integral part of what gets to go on Instagram, how, and in what situations.

Contrarily, in the second appropriation, the user became the focal point of analysis. Instagram is here taken to be part of, rather than a vantage point from which to look at, the everyday practices making up obesogenic environments. This leads to questions that inevitably divert the inquiry away from the medium. Understanding why Sunday night is a good time to post on Instagram is ultimately best investigated together with the people who Instagram. To see the medium as part of an offline practice thus implies an offline cultural analysis.

Thirdly we have showed how to appropriate Instagram as an analytical tool. Where the first and second approach entails challenges with incorporating the constitutive role of, in one case Instagram's users and in the other the mediums specificity, the third approach can be understood as situating analysis at the interface between research methods and the methods already operated with the medium. As such, the third approach is inherently skeptical of approaches that critique Instagram from an outside perspective. Instead, the third approach favors to think of Instagram as a methodological ally [2].

In the third approach, pursuing a style of analysis that has become quite familiar to social media research, one option is to consider Instagram as itself facilitating a running content analysis of images as users upload and tag them. As already shown by [23], looking at how the same hashtags rank differently in high and low BMI areas (see Table 2) can be helpful in providing an overall thematic profile of 'instagramming' areas. We found that to be true as well.

However, a network analysis of co-occurring hashtags (see Figure 3) showed no clear high or low BMI thematic communities. Indeed, where there are clear differences in the prevalence of individual hashtags in high and low BMI areas, the patterns with which hashtags are used together, what we may consider a form of sociality around hashtags, do not align with the BMI divide.

Instead we see a range of media-syncratic hashtag patterns, i.e., hashtags that are used in similar ways across low and high BMI areas. Rather than discarding these hashtags as uninteresting for the cultural analysis, we argue that they can provide the analytical context for a qualitative exploration of the images. Knowing that images are tagged with similar hashtag combinations makes for a stronger comparative case. What is #instagood or #workout in high BMI and low BMI areas thus become an interesting question to ask, because a qualitative difference in the images will speak to a difference in what is instagrammable (deserving of the tag #instagood or #workout) between these areas. In this way, this approach provides a potentially promising alternative method for building analytical purchase with Instagram in a cultural analytical context.

Although we have focused on the way the third approach offers a new way of doing cultural analysis with Instagram, the relevance of approach one, two and three, and the degree to which their limitations are problematic, depends on one's research agenda. Within one agenda, the interest may be directed towards the significance of Instagram's specific environment, or it may simply be to collect information as one would from any other archive, habitat or medium. Instagram can be a rich resource for observations about objects, people and practices in a given area, or present itself as an ideal place to identify prospective informants for qualitative interviews, cases in which a full-fledged co-hashtag analysis of the specific meaning attributed to instagram posts may be beside the point. If we broaden our focus from cultural research to health care, Instagram may for instance hold promising potential for the use of ecological momentary interventions (EMI). In EMI, carefully timed messages to participants are used as part of psychosocial and health behavior treatment. In this study, the mundane depiction of everyday life as seen through Instagram, presents itself as an interesting tool for the creation of dynamic and individually tailored ecological momentary interventions.

# 7. CONCLUSION

In this paper we have discussed three appropriations of Instagram for cultural analysis in general, and for cultural analysis of obesogenic environments in particular.

Based on our experience of collaborating with a team of obesity researchers (bio-physical scientists, dieticians, physicians, ethnologists, anthropologists and historians) we have showed how different notions of environment, different ideas about cultural analysis, and different understandings of Instagram as a medium are mutually constitutive and interdependent. This became apparent through a data sprint with the objective of testing Instagram's potential for cultural analysis. The experiment crystalized three possible appropriations of the medium when studying the everyday circumstances of obesity.

We considered a dataset of 82,449 Instagram posts tagged with location from the five most and the five least overweight local authorities in the UK[f]. We have shown how it is possible to pursue a range of approaches to make sense of such photos on Instagram.

To conclude, the approaches can be divided into two ways of doing cultural analysis with the medium: The first way includes "Instagram as camera" (5.1.) and "Instagram as part of the environment" (5.2). What these approaches have in common is that they build on pre-existing methods, specifically a qualitative content analysis approach and a more ethnographic approach.

A second way is captured by the approach to "Instagram as analyst" (5.3), which builds on the methods that are native to Instagram itself, specifically hashtagging, instead of trying to fit Instagram under pre-existing methods. We propose that Instagram, to explore its potential, must be considered as more than a collection of user-tagged images, but as an analytical context in its own right.

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# 9. NOTES

[a] Available at http://www.statista.com/statistics/253577/number-of-monthly-active-instagram-users/

[b] See http://www.noo.org.uk/visualisation

[c] Available at http://www.freemaptools.com/radius-around-point.htm

[d] See https://www.noo.org.uk/LA/obesity_prev

[e] http://selfiecity.net

[f] The study presented in this article has not received ethical approval/IRB exception, as these are not required at Aalborg University nor institutionalized in the Danish system, where the study was conducted. However, we acknowledge our ethical responsibility to the Instagram users whose data we have utilized for this study, and have only included images and other data from profiles where this information was made publicly available. Data has been harvested through the Instagram API in compliance with the terms of use.

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