Computers in Human Behavior 46 (2015) 45–56

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Personality and location-based social networks

Martin J. Chorley, Roger M. Whitaker *, Stuart M. Allen

School of Computer Science & Informatics, Cardiff University, 5 The Parade, Roath, Cardiff CF24 3AA, UK

ARTICLE INFO

Article history:

Keywords:
Social network
Location-based social network
Personality
Foursquare

ABSTRACT

Location-based social networks (LBSNs) are a recent phenomenon for sharing a presence at everyday locations with others and have the potential to give new insights into human behaviour. To date, due to barriers in data collection, there has been little research into how our personality relates to the categories of place that we visit. Using the Foursquare LBSN, we have released a web-based participatory application that examines the personality characteristics and checkin behaviour of volunteer Foursquare users. Over a four-month period, we examine the behaviour and the "Big Five" personality traits of 174 anonymous users who had collectively checked in 487,396 times at 119,746 venues. Significant correlations are found for Conscientiousness, Openness and Neuroticism. In contrast to some previous findings about online social networks, Conscientiousness is positively correlated with LBSN usage. Openness correlates mainly with location-based variables (average distance between venues visited, venue popularity, number of checkins at sociable venues). For Neuroticism, further negative correlations are found (number of venues visited, number of sociable venues visited). No correlations are found for the other personality traits, which is surprising for Extroversion. The study concludes that personality traits help to explain individual differences in LBSN usage and the type of places visited.

1. Introduction

The patterns that emerge through collective human mobility behaviour are now understood for wide ranging and important applications (Song, Qu, Blumm, & Barabási, 2010). As well as identifying inherently similar personal travel patterns and interactions (Gonzalez, Hidalgo, & Barabasi, 2008), mobility has also been studied at the individual level (Williams, Whitaker, & Allen, 2012). However, the conclusions of these studies are primarily structural in nature. While they extract the patterns of where people go and when they go there, along with the groups that result, these studies do not address how individual differences in activity may correspond to personal characteristics. Characterisation of individual mobility behaviour, extending to the types of location visited and characteristics of the user, has until recently, been unachievable. Now, through the use of smartphones (Whitaker, Chorley, & Allen, 2015) we are able to examine data from location-based social networking applications that log a presence at a physical location, that is shared with others in real-time. Given the freedom that humans have in exercising choice over their activity, it is possible that personal character and disposition are important drivers for the places that people choose to visit.

Currently, relatively little is known about the relationship between human mobility and personality. In this area, Wang and Stefanone (2013) examined the personality characteristics that lead individuals to share their location-based checkins with other Facebook users. This study considered how frequently users decided to checkin, based on self-reported data. However, it is possible that personality characteristics also relate to an individual's choice of places to visit. To explore this, we use Foursquare,[1] a location-based social network,[2] to examine the relationship between the types of location visited and the personality profile of the user. Using a new web-based participatory tool developed for this purpose, over a four month period we collected data on the personality characteristics and behaviour of 174 anonymous users of the Foursquare smartphone application, who collectively checked-in at 119,746 street-level locations a total of 487,396 times. This novel approach allows the first examination of human mobility behaviour at street level, in relation to human personality.

* Corresponding author.
E-mail addresses: m.j.chorley@cs.cardiff.ac.uk (M.J. Chorley), r.m.whitaker@cs.cardiff.ac.uk (R.M. Whitaker), s.m.allen@cs.cardiff.ac.uk (S.M. Allen).

[1] http://www.foursquare.com.

[2] Foursquare have recently reorganised their business model and check-ins are now made through a dedicated application called Swarm: http://www.swarmapp.com.

http://dx.doi.org/10.1016/j.chb.2014.12.038
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1.1. Location-based social networks

Examples of location-based social networks (LBSNs) include Facebook, Foursquare and Google+. These services operate through location-aware smartphones, with users explicitly recording their presence at a location via an application. This action is a 'checkin', which is a message shared via a dedicated social network in near-real time. In a LBSN the geographical location of a user is normally represented as a *venue*, being a meaningful place at street level, for example a shop, park, or building. From massive user participation, taxonomies of venues have grown and have become widespread for urban areas throughout the developed world.

For this study we use Foursquare, which has become the most popular dedicated LBSN, reaching 50 million users in 2014.[3] Besides popularity, a major advantage of Foursquare is its focused functionality; unlike Google+ and Facebook, Foursquare only offers location-based services, hence users are not distracted by other communication. Locations in Foursquare can be defined anywhere by anyone, and are categorised under a hierarchical taxonomy with nine high level categories covering (at the time of data analysis) approximately 663 lower level categories. Consequently LBSNs provide a convenient means to investigate the characteristics of individual users and the places where they choose to record a visit.

The dedicated LBSN provided by Foursquare makes an interesting comparison to Facebook and Twitter. Facebook is a highly popular social network service and in 2014, it exceeded 1.35 billion users.[3] The service enables users to curate an online representation of themselves through the information they choose to reveal on their profile, the content and comments they share as personal updates, and the communication their content receives from their 'friends'. The user has a degree of control over the extent to which others can view their profile. Online social interaction is a dominant feature of Facebook, allowing users to connect and communicate online. Commenting on and 'liking' of status updates, uploaded photos, and shared content is commonplace, along with the sending of public and private messages between users. Since 2010 it has been possible to share a physical location with a status update in Facebook. However this is not the main focus of the Facebook service, which is geared towards facilitating online social interaction.

The primary focus of Twitter is communication, sharing and consuming content in the briefest of forms, using micro-blog updates (called tweets) limited to a total of 140 characters in length. Twitter is also highly popular, reaching 300 million users in 2014.[3] Tweets are broadcast to a user's 'followers', and this builds up a network structure. Users can republish content that they receive on their time line (called a retweet), which leads to content propagation (Webberley, Allen, & Whitaker, 2011). Along with knowledge of the follower, the retweet count represents useful meta-data (Chorley, Colombo, Allen, & Whitaker, 2015) that influences the selection of content for consumption. Twitter provides the opportunity to create an online persona through tweets, the numbers of followers and their response to content through replies and retweets. As with Facebook, Twitter provides a means to append tweets with a location, which can add further context. In contrast to Facebook, fewer opportunities are provided for social interaction through this network.

While both Twitter and Facebook provide a means for communicating and sharing content online, the LBSN provided by Foursquare is focused on associating individuals with places through checkins and broadcasting these to friends in the online network. Although opportunities for communication are provided, these are more limited than in either Facebook or Twitter, and are focused around the checkin events; there is no method of communication between users other than comments or 'likes' on checkins. Users may represent themselves by the places they check into, and by the tips or photographs they leave at venues. Unlike Twitter and Facebook, user representations do not stem from what messages they post to the service, or from what content they share, but primarily from which physical places they checkin at.

1.2. Personality

Arguably, personality traits are deep and natural human characteristics (Passini & Norman, 1966). These represent the persistent disposition of an individual, capturing how a person may approach and respond to wide-ranging situations throughout their lives. Traits theorists argue that these predispositions may influence behaviour, and personality traits have been demonstrated as influential for wide-ranging aspects of human activity, including consumer marketing (Odekerken-Schröder, De Wulf, & Schumacher, 2003), student behaviour (Greenberger, Lessard, Chen, & Farruggia, 2008), performance at work (Barrick & Mount, 1991), musical taste (Rentfrow & Gosling, 2003), leadership of change (Judge & Bono, 2000), travel behaviour and residence decisions (Prevedouros, 1992) and smoking (Terracciano & Costa, 2004).

Concerning technology, dimensions of personality have been shown to be correlated with a number of activities including: computer self-efficacy (Saleem, Beaudry, & Croteau, 2011), mobile phone use (Butt & Phillips, 2008; de Montjoye, Quoidbach, Robic, & Pentland, 2013), social network activity for Twitter (Golbeck, Robles, Edmondson, & Turner, 2011; Quercia, Kosinski, Stillwell, & Crowcroft, 2011), online (rather than location-based) Facebook usage (Amichai-Hamburger & Vinitzky, 2010a; Correa, Hinsley, & De Zuniga, 2010; Quercia, Lambiotte, & Stillwell, 2012), media consumption (Cantador, Fernández-Tobías, Bellogín, Kosinski, & Stillwell, 2013) and wider Internet activity (Hamburger & Ben-Artzi, 2000; Landers & Lounsbury, 2006).

Work on the types of scenario in which personal activity is congruent to personality traits (Sherman, Nave, & Funder, 2012) highlights scenarios with features including: freedom from structure, lack of behavioural expectations, autonomy, self-expression, opportunity to engage competencies and support for relations to others. This characterises the freedom in the decision making for many day-to-day activities, such as in consumer related and social scenarios. Although there has been some ongoing debate (Block, 2001), there has been a general convergence on the use of a five-factor model (Goldberg, 1990) that assesses personality in terms of *Openness, Conscientiousness, Agreeableness, Extraversion* and *Neuroticism*.

Openness encompasses traits such as originality, curiosity, spontaneity and imagination. High levels of Openness may indicate an artistic nature, with a desire to increase the breadth and depth of ideas, views and experiences encountered. Low Openness may tend to indicate a more conservative or conventional attitude. *Conscientiousness* relates to characteristics such as organisation, resourcefulness, diligence and perseverance. A high score in Conscientiousness can indicate a focused and organised approach to everyday activity. *Extraversion* is associated with sociability, assertiveness, being outgoing and seeking interactions with others. High scorers tend to be very sociable with large groups of people, while low scorers are more likely to be more reserved and introverted. *Agreeableness* relates to cooperative, courteous and empathetic behaviours that are trusting and avoid conflict. *Neuroticism* relates to impulsiveness and emotional instability, also covering negative emotional expression. Neuroticism scores are high in those prone to experiencing stress, worry and sensitivity to threats.

Consistent with other work, to quantify personality we use the dimensions of the five factor model (Gosling, Rentfrow, & Swann,

[3] Source: statista.com.

2003) assessed through a questionnaire. The shorter instrument presented by Gosling et al. (2003) assists in data collection when participants are unsupervised, such as for Internet-based scenarios.

2. Key variables, personality traits and hypotheses

Compared to other online social networks, LBSNs have added a spatial dimension, allowing an individual's mobility to be observed by their network neighbours. Rather than technology mediating discussion about places (Goodings, Locke, & Brown, 2007), the user is immersed in the physical environment and checkins act to signal a presence and persona online (Sutko & e Silva, 2011). This signalling process goes beyond a grid reference statement of location (Humphreys, 2012), revealing some of the place-identities that an individual is exposed to (Proshansky, Fabian, & Kaminoff, 1983) and chooses to expose to others (Wang & Stefanone, 2013; Whitaker et al., 2015). Although there have been developments towards a social psychology of place (Stedman, 2002), the role of LBSNs in this field is at a very early stage (Schwartz & Halegoua, 2014).

In Section 2.1 we introduce the LBSN variables observed in this study. In Sections 2.2–2.6 we consider user personality and online social networks. We also consider why the LBSN variables have potential relationships with an individual's personality.

2.1. LBSN variables

We investigate whether the traits embedded through personality correlate with an individual's choice of venues, as revealed through participation in the LBSN. Reflecting the hybrid nature of LBSN, the variables we consider are *location-based* and *social*. For a given LBSN user, the variables we study are:

- number of checkins;
- number of distinct venues visited;
- diversity of checkins;
- diversity of venues visited;
- number of checkins at sociable venues;
- number of sociable venues visited;
- average popularity of venues visited.

Location-based variables (number of distinct venues visited, diversity of checkins, diversity of venues visited, number of sociable venues visited, average popularity of venues visited) reflect the characteristics of a place, venue categorisation or spatial distance. The social variables (number of checkins, number of checkins at sociable venues, number of sociable venues visited, number of distinct venues visited) reflect online sharing of knowledge with others through checkins, or being in a location that is affiliated with socialising. Number of distinct venues visited and number of sociable venues visited are both location-based and social variables.

These variables capture user interaction with LBSNs and potential individual differences. The *number of checkins* reflects the overall intensity of usage, which can be influenced by a user's diligence and the importance an individual user places on maintaining a social presence through the LBSN. The *number of distinct venues visited* also reflects this, but additionally provides insight into the variety of places visited between Foursquare categories. In measuring *checkin diversity* we assess the checkins a user makes across each of the Foursquare categories of place. We characterise this using the Shannon diversity index (Section 4.3) which we apply to identify the *diversity of checkins* and *diversity of venues visited*. The breadth of types of place visited is a function of the choices people make. These are based on functional needs and an individual's disposition, which are likely to vary considerably between individuals. We also assess checkin diversity on a spatial basis, assessing the average distance between venues at which checkins are made. This measure also has relevance to assessment of venue popularity. To consider the *number of checkins at sociable venues* and *number of sociable venues visited*, we classified Foursquare venues on their sociability by crowdsourcing opinion on Foursquare categories of place (Section 4.4). These sociability variables are measured by the extent to which an individual prioritises checking into places one would expect to visit with friends to socialise or engage in activities together. Therefore these variables are influenced by individual differences in how people engage with others.

Finally, to assess *average popularity of venues visited*, we consider '*tips*', '*likes*', *checkins at venues* and *the average distanced between venues*. A '*tip*' in a LBSN represents a comment on a venue, made for others to see. A '*like*' is a binary flag that is a quick way of expressing positive sentiment about a location, without posting a tip. We can consider the *average popularity of venues visited* from the perspective of a given user j in five ways:

- *average check-in popularity:* a weighted average of the total number of checkins made by all Foursquare users at the venues that have been visited by user j;
- *average number of venue visitors:* a weighted average of the total number of all Foursquare users checking in at the venues that have been visited by user j;
- *average 'tip' popularity:* a weighted average of the total number of 'tips' left by all Foursquare users at the venues that have been visited by user j;
- *average 'like' popularity:* a weighted average of the total number of 'likes' left by all Foursquare users at the venues that have been visited by user j.
- *average distance travelled:* the average distance between all pairs of venues that have been visited by user j;

To calculate these averages, let c_i be the total number of checkins made by all Foursquare users at venue i, and let V_j be the total set of venues j visits. Let p_{ij} be the proportion of checkins user j makes at venue i. Then the average check-in popularity for user j is defined as $\sum_{i \in V_j} p_{ij} c_i$. Average number of venue visitors, average 'tip' popularity and average 'like' popularity are defined similarly. We also assess popularity in terms of the distance a user travels to visit a venue, calculating the average distance between venues across all venue pairs visited by a user.

As many of the experimental variables are closely related, we identify the extent of correlations between them, as presented in Table 1. *Diversity of checkins* holds the greatest number of significant correlations with others. For *number of checkins* and *number of venues*, weak negative correlations are held with the popularity-based variables. For *number of checkins* these are mostly insignificant correlations. Beyond the popularity variables, the *number of checkins* and *number of distinct venues visited* hold moderate to strong significant correlations with the other LBSN variables. The popularity-based variables, with the exception of distance travelled, are strongly correlated with each other at a significant level. The popularity-based variables hold mostly weak correlations with all other variables.

2.2. Openness and social networking behaviours

Online social networks have inherent properties of Openness. For example, Correa et al. (2010) show correlation with the use of social networks for interaction on the web. Concerning Facebook content, Moore and McElroy (2012) considered posts and regret as predictors, but these did not perform well. In a further study of personality traits associated with Facebook use, Ross et al.

Table 1
Means, standard deviations and correlation matrix of personality factors and variables.

	Mean	Std	(0) O	(1) C	(2) E	(3) A	(4) N	(5) Number of checkins	(6) Number of venues	(7) Shannon diversity (Checkins)	(8) Shannon diversity (Venues)	(9) Sociable checkins	(10) Sociable venues	(11) Average popularity (Checkins)	(12) Average popularity (Venue Visitors)	(13) Average popularity (Tips)	(14) Average popularity (Likes)	(15) Average distance
(0)	3.8678	0.6091	1.0000**															
(1)	3.4342	0.6478	0.2914**	1.0000**														
(2)	3.1451	0.8333	0.5025**	0.4716**	1.0000**													
(3)	3.5639	0.6395	0.4216**	0.4110**	0.4107**	1.0000**												
(4)	2.9116	0.7263	0.2198**	0.1991**	0.1522*	0.1007	1.0000**											
(5)	2801.1264	2517.9179	0.2435**	0.4180**	0.2904**	0.2474**	0.2138**	1.0000**										
(6)	719.1724	538.9400	0.2486**	0.4504**	0.2786**	0.2473**	0.1807*	0.8887**	1.0000**									
(7)	3.5842	0.6879	0.3436**	0.3858**	0.2656**	0.3231**	0.2399**	0.4776**	0.7207**	1.0000**								
(8)	4.2437	0.7188	0.2966**	0.4066**	0.2913**	0.3025**	0.2252**	0.7515**	0.8379**	0.8091**	1.0000**							
(9)	758.7529	603.9693	0.3184**	0.4187**	0.2915**	0.2261**	0.2363**	0.8548**	0.8791**	0.6394**	0.7736**	1.0000**						
(10)	295.9483	216.2230	0.2831**	0.4634**	0.2898**	0.2545**	0.2023**	0.7588**	0.9241**	0.7758**	0.8173**	0.9192**	1.0000**					
(11)	45.3298	173.5841	0.3564**	0.2221**	0.3129**	0.2690**	0.3941**	−0.1738*	−0.0931	0.1736*	0.0277	−0.0593	0.0424	1.0000**				
(12)	15.0241	69.1007	0.3624**	0.2244**	0.3164**	0.2831**	0.3750**	−0.1763*	−0.0710	0.2166**	0.0471	−0.0409	0.0729	0.9903**	1.0000**			
(13)	0.1607	0.6344	0.3737**	0.2081**	0.2904**	0.3107**	0.3841**	−0.1944**	−0.0937	0.2252**	0.0311	−0.0393	0.0654	0.9496**	0.9653**	1.0000**		
(14)	0.1062	0.4863	0.4070**	0.1962**	0.2852**	0.3194**	0.3902**	−0.1635*	−0.0510	0.2655**	0.0734	−0.0067	0.0979	0.9048**	0.9272**	0.9516**	1.0000**	
(15)	1215654.6427	1592904.9399	−0.1589*	−0.1720*	−0.1252	−0.2163**	−0.1324	−0.1789*	−0.1450*	−0.1109	−0.1157	−0.1453*	−0.1156	−0.0339	−0.0268	−0.0239	−0.0651	1.0000**

* Significant at $p < 0.05$.
** Significant at $p < 0.01$.

(2009a) found that Openness did not necessarily translate to high levels of computer mediated communication knowledge. However in contrast, Amichai-Hamburger and Vinitzky (2010b) correlated this with a wider use of Facebook features. Further research with a student focus (Skues, Williams, & Wise, 2012) also found that individuals with high Openness interact through Facebook to discuss wide-ranging interests. McKinney, Kelly, and Duran (2012) considered narcissism among college students using Facebook and Twitter, with higher levels of narcissism being associated with larger numbers of Facebook friends and with the number of self-centric Tweets.

As Openness captures curiosity and breadth of experience, this trait may be captured in the variables concerning check-in diversity. High Openness individuals could be expected to visit a relatively wide range of venues, consistent with a broader range of checkin categories, and these venues may be more geographically diverse. The number of distinct venues visited may not represent Openness well, because this does not necessarily capture the breadth of venue type. For example, it is possible to check into a large number of distinct venues providing a similar experience or function. Conversely checking into a relatively small number of venues in diverse categories could be explained by significant user curiosity. In addition, high Openness individuals may be positively disposed to using LBSN, and expressing their diverse presence without reservation.

2.3. Conscientiousness and social networking behaviours

There has been relatively little consideration of Conscientiousness in terms of social network use. Ross et al. (2009a) found that there was little evidence to support social networks acting as an unwelcome distraction for individuals scoring highly on Conscientiousness. Contrary to this, Ryan and Xenos (2011) identified that Conscientiousness was correlated with less time using online social networks. Amichai-Hamburger and Vinitzky (2010b) identified that Conscientiousness is positively correlated with a higher number of friends and uploading less content. Hughes, Rowe, Batey, and Lee (2012) examined Conscientiousness and usage of Twitter and Facebook. For social use, a significant negative correlation was found between Twitter usage and Conscientiousness. In terms of the type of content and how social media is used, Moore and McElroy (2012) found that people with high levels of Conscientiousness made a significantly lower number of Facebook wall postings, both about themselves or others, and expressed more regret than their less conscientious counterparts. No relationship was found concerning this trait and frequency of usage, numbers of friends or numbers of photos.

In terms of LBSN usage, Conscientiousness has potential correlation with the variables related to volume of activity, since these are influenced by the characteristics of diligence and persistence. The act of performing a checkin requires a degree of discipline to regularly access a mobile platform in situation, which is similar to regular online social network usage through smartphones. We consider that a LBSN checkin has a weak alignment with procrastination, as studied by Butt and Phillips (2008), since although the LBSN has a social dimension, it is not primarily a dialogue-based communication system. However use of LBSNs could be seen as exhibitionist. It could also be a distraction from the immediate physical environment and higher priority tasks, resulting in less engagement from highly conscientious individuals. This leads us to consider whether the number of checkins is negatively correlated with Conscientiousness, as found for social Twitter usage by Hughes et al. (2012). The extent to which this is true may indicate how participants view LBSN participation in terms of its cognitive burden.

2.4. Extraversion and social networking behaviours

Extraversion is a dominant trait related to online social network usage that seems to cause two effects. Introverts may well gain advantage from interaction through online social networks because they can interface with others without direct interaction, thus removing the need for the same level of interpersonal skill, referred to as "social compensation" (Zywica & Danowski, 2008). Such users strive to gain popularity through Facebook and this has been evidenced in a range of settings such as those identified by Moore and McElroy (2012). Equally, users with high levels of extroversion and offline popularity have been identified as having high levels of Facebook activity and friendship (Wehrli, 2008), which one may naturally expect. In terms of exposing checkins through a social network, Wang and Stefanone (2013) found that Extraversion did not necessarily directly impact on location-based checkin intensity for Facebook, but it did contribute to exhibitionism and the 'presentation of self' (Zhao, Grasmuck, & Martin, 2008).

Given that Extraversion is linked with sociability and seeking interactions with others, the number of check-ins at sociable venues is an important variable to consider. As with online social networks, it is possible that social compensation could occur for introverts, through selective checkins at venues that are more likely to convey an image of outgoing activity. However, from the physical nature of LBSNs, it is anticipated that the genuine characteristics of extraverts could take precedence, who naturally may seek to checkin and regularly display their presence at sociable venues.

2.5. Agreeableness and social networking behaviours

There is noticeably less research on the role of Agreeableness, where some authors have found no relationship with online social network usage (e.g., Amichai-Hamburger & Vinitzky (2010b)), in contrast to others who identify this with more general recreational Internet activity (Swickert, Hittner, Harris, & Herring, 2002). Ross et al. (2009a) postulated that high levels of Agreeableness could result in forming and sustaining larger social networks, but their results did not offer evidence to support this. Beyond social structures, Agreeableness has more relevance to the content that people choose to display online. Moore and McElroy (2012) showed that agreeable people expressed greater levels of regret about inappropriate content that they may have posted on Facebook. People with higher levels of Agreeableness made a greater number of postings about themselves as compared to less agreeable individuals.

In terms of LBSNs, Agreeableness may be reflected in variables characterising location as a function of how tolerant an individual is in visiting unpopular venues. This assumes that the popularity measures of 'tips' and 'likes' capture the potential for venues to meet user's expectations. In contrast, individuals with low levels of Agreeableness may be less likely to tolerate and repeat visits to these venues, assuming that such individuals have a higher propensity to challenge and respond to a situation through behaviour change.

2.6. Neuroticism and social networking behaviours

Individuals with high Neuroticism scores use the Internet to mitigate loneliness and facilitate a sense of inclusion (Butt & Phillips, 2008). Evidence has also been found that high Neuroticism leads to high likelihood of communication through the Internet (Wolfradt & Doll, 2001) when the individual is also socially disposed. For social networking and Neuroticism, positive correlation has been found with time spent on Facebook (Ryan & Xenos, 2011), with a slightly weaker correlation present for time spent socialising (as opposed to information seeking). Moore and McElroy (2012) showed that emotional stability was not significantly related to actual number of friends or photos in Facebook. Unexpectedly emotional instability was positively related to frequency of Facebook use to maintain relationships. However there is evidence from Hughes et al. (2012) that the type of social network is highly influential, where highly neurotic Twitter users were not correlated with its use to alleviate loneliness. Also of interest is that high Neuroticism has been linked to greater accuracy in the display of information on social networking profiles (Amichai-Hamburger, Wainapel, & Fox, 2002) which is possibly a mechanism by which social anxiety is suppressed.

There are mixed findings on Neuroticism from online social networking studies. Compared to online social networks, LBSNs expose day-to-day physical activities. In particular, LBSNs allow others to observe ones own behaviour in a physical context, and this may make highly neurotic users susceptible to anxiety and negative emotions. Consequently there is a basis to investigate whether high levels of Neuroticism correlate with lower overall LBSN activity, such as numbers of checkins. This is contrary to the recent findings associated with Facebook and reflects the different form of social networking in Foursquare, which has more limited scope for dialogue.

2.7. Hypotheses

Based on the existing literature and observations on the characteristics of LBSNs (Sections 2.2–2.6), we formulate the following hypotheses:

H1 Openness is positively correlated with checkin diversity;
H2 Conscientiousness is negatively correlated with number of checkins;
H3 Extraversion is positively correlated with number of checkins at sociable venues;
H4 Agreeableness is negatively correlated with number of checkins at relatively popular venues;
H5 Neuroticism is negatively correlated with number of checkins.

3. Methodology

Our approach involves using data collected from a web-based participatory tool to examine the personality characteristics and checkin behaviour of volunteer Foursquare users. Foursquare is generally regarded as the main LBSN with checkins as its core function, and it provides a rich API that allows application developers access to selected checkin information (subject to terms and conditions). While the popularity and ubiquity of Foursquare were the main drivers behind our selection of this LBSN, the speed and simplicity of the API were also critical for investigating checkin behaviour. However, although LBSNs are now becoming increasingly well-used, they are still relatively niche applications within the general population. This prohibits recruiting a sufficiently large pool of local users, *a priori*, for participation. As such, the experiment was conducted "in-the-wild", using viral social networking to gain willing participants from across the globe. This approach has disadvantages (see Section 3.1) but it opens up a new form of data collection and exploration (Whitaker et al., 2015).

Open to all Foursquare users, the software developed is called the 'Foursquare Personality Experiment'. Each participant conducts the experiment through a webpage.[4] The participant is required to login using their Foursquare account (use of the OAuth protocol ensures that the individual login credentials remain secure

[4] http://www.cs.cf.ac.uk/recognition/foursqexp.

and are not revealed to the experiment). Once authorised, the participant is invited to take a 44 item Big-Five Inventory (John, Naumann, & Soto, 2008; John, Donahue, & Kentle, 1991) personality test online. As this was an experiment in uncontrolled conditions, participation was incentivised by offering a data visualisation tool. On completion of the test, the user is shown the list of places they have previously checked into through Foursquare, and for each place they are able to compare their personality to the aggregated profile created from all participants known to checkin at that location (Fig. 1).

Data is retrieved from Foursquare using the `venuehistory` API function, which provides a list of the venues visited by a specified user, along with the number of times the person has registered a checkin at each venue. Note that for privacy reasons, the API does not make available the time of each visit, demographic information or personal details of the user. To ensure strict compliance with terms of usage, we have not sought to augment the data provided from users' Foursquare accounts with a request for personal details such as gender, location or name.

The venue information that can be retrieved from Foursquare is comprehensive. Each venue has a primary category (taken from a fixed hierarchical ontology provided by Foursquare) and may also have a number of secondary categories. A number of popularity measures can also be retrieved, as described in Section 4.2.3. The amount of information available about a venue combined with the large number of venues that may be associated with a personality profile lead to high dimensionality in the experiment data. A preliminary analysis of a reduced dataset was previously published in (Chorley, Colombo, Allen, & Whitaker, 2013).

3.1. Limitations

The experiment was undertaken without a sample being preselected and without enforcement of controlled conditions. While this has been necessitated by the nature of the technology and the experiment, it means that as compared to lab-based experimentation, control for external factors is compromised. From necessity, we have not requested any personal details when collecting user data and consequently we are not able to precisely characterise the sample in the same way that we would in a controlled environment. Additionally, LBSNs are still primarily adopted by technologically motivated subgroups in society and they may not be representative of the population as a whole. These considerations mean that we are not able to robustly generalise any conclusions from the study to the whole population. Nevertheless, we believe that the results from this study represent a profound step change, because they demonstrate an important proof of concept and they have potential applicability within the LBSN population.

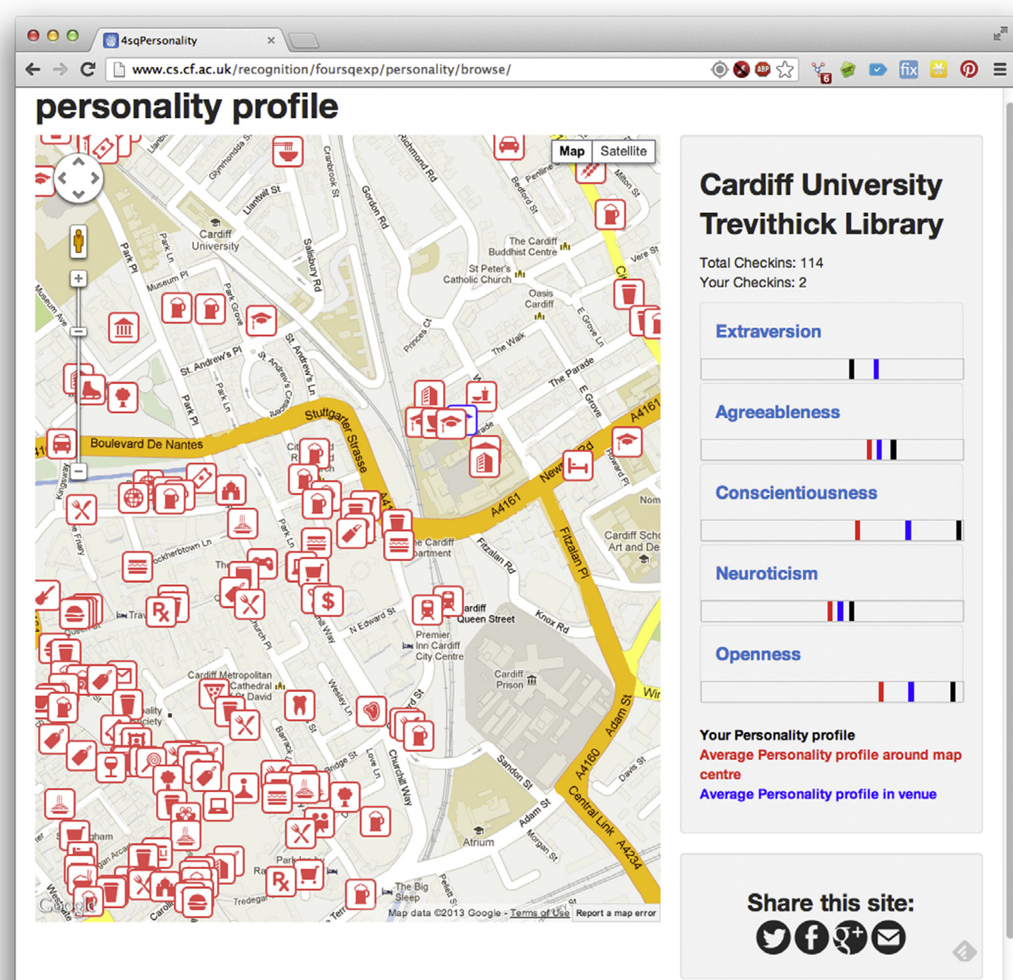

Fig. 1. Foursquare experiment interface, showing the user's personality profile as compared to the aggregated profiles of other visitors at a chosen venue.

4. Results

The experiment was accessed by 218 Foursquare users in the four month period up to January 2014 and 183 users completed the personality test. Of these, 9 users had no Foursquare checkins recorded, so were removed from the data, leaving 174 users. Over their entire history of Foursquare use, the average number of venues visited by a user was 719.172, while the average number of checkins per user was 2801.13. In contrast to many other studies on personality, due to the large range of venue categories, we have a high number of experimental variables (900 in total, as each category can be considered in terms of number of venues visited as well as number of checkins, plus top-level categories, and other variables such as popularity and sociability). To investigate the hypotheses in Section 2.7, we analyse the resultant data in terms of correlations (Section 4.1), number of checkins (Section 4.2.1), number of venues visited (Section 4.2.2), venue popularity (Section 4.2.3), checkin diversity (Section 4.3) and sociability of venues (Section 4.4). In Section 4.5 we summarise the results in light of the hypotheses.

4.1. Correlation analysis

To observe correlation, general types of places have been assessed using the nine high level place categories provided by Foursquare. This is carried out for both the number of checkins (Table 2) and the number of venues visited (Table 3). The data shows that in both cases the correlations are highly structured for the venues at which checkin occurs, with strong relations between the Foursquare categories. Concerning the characteristics of users, the data shows some similarity to Hughes et al. (2012), with the reported correlation coefficients having the same polarity with the exception of one combination (Openness and Neuroticism). However, in some cases (e.g., for Extraversion and Neuroticism) there are significant differences between the reported correlations, and overall there are wide variations in terms of the reported confidence levels between our findings and (Hughes et al., 2012). We also note that the mean and standard deviations of personality scores are similar to those in (Golbeck, Robles, & Turner, 2011; Srivastava, John, Gosling, & Potter, 2003). As such, despite the experimental limitations described in Section 3.1, there is little evidence to suggest that our sample displays personality characteristics that are significantly out of line with related studies. When considering correlations between personality traits and checkin categories, we observe the most significant correlations for Conscientiousness, followed by Neuroticism and then Openness. This is the case for both the number of checkins (Table 2) and the number of venues (Table 3).

4.2. Range of checkin data

The ordered distribution and box plots for the personality data over all subjects is presented in Fig. 2. In searching for group differences we compare upper and lower scoring sub-populations for each of the personality traits. As in (Amichai-Hamburger & Vinitzky, 2010b; Ross et al., 2009b), this approach is useful when considering possible effects within smaller samples. For each personality variable, the personality scores are split into terciles (see Table 4), with the lowest tercile and highest tercile then analysed against each other for significant difference. This is considered for the number of checkins (Section 4.2.1), the number of venues (Section 4.2.2) and venue popularity (Section 4.2.3).

Table 2
Means, standard deviations and correlation matrix of personality factors and number of checkins in each top level foursquare category.

	Mean	Std	(0) O	(1) C	(2) E	(3) A	(4) N	(5) Professional & other places	(6) Shops & services	(7) Residences	(8) Food	(9) Nightlife spots	(10) Travel & transport	(11) Arts & entertainment	(12) Colleges & universities	(13) Outdoors & recreation
(0)	3.8678	0.6091	1.0000**													
(1)	3.4342	0.6478	−0.0130	1.0000**												
(2)	3.1451	0.8333	0.2886**	0.2445**	1.0000**											
(3)	3.5639	0.6395	0.1728*	0.1581*	0.1572*	1.0000**										
(4)	2.9116	0.7263	−0.1160	−0.1450	−0.2125**	−0.2863**	1.0000**									
(5)	499.8678	549.4186	−0.0885	0.1300	−0.0190	−0.0351	−0.1068	1.0000**								
(6)	746.0575	810.0224	−0.1519*	0.1853*	−0.0486	−0.0461	−0.0410	0.7277**	1.0000**							
(7)	242.9023	425.9608	−0.0694	0.0558	−0.0084	−0.0038	−0.0425	0.6462**	0.6029**	1.0000**						
(8)	863.4310	754.1326	−0.0370	0.1351	−0.0742	−0.1341	−0.1087	0.6491**	0.7328**	0.5157**	1.0000**					
(9)	242.4023	358.9004	0.0542	0.1806*	0.0995	−0.0475	−0.0677	0.3499**	0.4248**	0.2769**	0.6120**	1.0000**				
(10)	566.2586	812.8141	−0.1071	0.1144	−0.0340	−0.0743	−0.1868*	0.6498**	0.6832**	0.5141**	0.5920**	0.4435**	1.0000**			
(11)	213.9943	201.0608	0.0420	0.1834*	−0.0064	−0.0082	−0.1634*	0.6241**	0.6681**	0.4617**	0.7587**	0.6263**	0.5820**	1.0000**		
(12)	351.8103	1065.0588	0.0135	0.1101	−0.0339	−0.0079	0.0901	0.3422**	0.4841**	0.3788**	0.3965**	0.1765*	0.4179**	0.4488**	1.0000**	
(13)	400.6264	597.3190	−0.0703	0.1621*	−0.0271	−0.0458	−0.1520*	0.6887**	0.7579**	0.6168**	0.6439**	0.4429**	0.7452**	0.7138**	0.4629**	1.0000**

* Significant at $p < 0.05$.
** Significant at $p < 0.01$.

Table 3
Means, standard deviations and correlation matrix of personality factors and number of venues visited in each top level foursquare category.

	Mean	Std	(0) O	(1) C	(2) E	(3) A	(4) N	(5) Professional & other places	(6) Shops & services	(7) Residences	(8) Food	(9) Nightlife spots	(10) Travel & transport	(11) Arts & entertainment	(12) Colleges & universities	(13) Outdoors & recreation
(0)	3.8678	0.6091	1.0000**													
(1)	3.4342	0.6478	−0.0130	1.0000**												
(2)	3.1451	0.8333	0.2886**	0.2445**	1.0000**											
(3)	3.5639	0.6395	0.1728*	0.1581*	0.1572*	1.0000**										
(4)	2.9116	0.7263	−0.1160	−0.1450	−0.2125**	−0.2863**	1.0000**									
(5)	69.1149	63.4943	−0.0617	0.1507*	−0.0231	−0.0728	−0.1487	1.0000**								
(6)	160.9310	141.8581	−0.1596*	0.2119**	−0.0732	−0.0328	−0.0902	0.8053**	1.0000**							
(7)	11.5690	13.3672	−0.0367	0.0623	0.0341	−0.0219	−0.1144	0.7303**	0.6638**	1.0000**						
(8)	218.9770	165.5475	−0.0342	0.2175**	−0.0319	−0.0702	−0.1228	0.7213**	0.7208**	0.5664**	1.0000**					
(9)	72.9540	73.0989	0.0283	0.2234**	0.1011	−0.0359	−0.1251	0.4592**	0.4424**	0.4062**	0.7694**	1.0000**				
(10)	107.6954	112.5614	−0.0622	0.1424	−0.0465	−0.0610	−0.2079**	0.7855**	0.7390**	0.5616**	0.6898**	0.5514**	1.0000**			
(11)	71.5057	62.8842	−0.0195	0.1844*	−0.0168	−0.0278	−0.1600*	0.7926**	0.7258**	0.5859**	0.8474**	0.6994**	0.7204**	1.0000**		
(12)	21.9310	34.8464	0.0270	0.1753*	0.0067	0.0104	−0.0464	0.6406**	0.5976**	0.5636**	0.5591**	0.3177**	0.5447**	0.5798**	1.0000**	
(13)	90.5805	91.6876	−0.0416	0.1410	−0.0480	−0.0452	−0.2043**	0.8579**	0.8091**	0.6675**	0.7171**	0.5240**	0.8287**	0.7950**	0.5864**	1.0000**

* Significant at $p < 0.05$.
** Significant at $p < 0.01$.

4.2.1. Number of checkins

Statistically significant differences between the top and bottom terciles are evident for the total number of checkins when considering Conscientiousness ($t = -2.315895, p = 0.022628$) and Agreeableness ($t = 1.984877, p = 0.049786$), but not for the other personality variables. For Conscientiousness the lower tercile has a ‘total number of checkins’ (mean = 2198.2069, std = 2158.39867) lower than the top tercile (mean = 3375.78947, std = 3146.72288). This refutes the negative correlation of **H2**, where the distraction from checkins due to the physical environment was expected to result in individuals with high Conscientiousness having a lower usage of LBSN. It appears that, having already decided to use a LBSN, the organised and disciplined nature of highly conscientious individuals results in more checkins being recorded. Consistent with this there is a weak but significant correlation between the total number of checkins and Conscientiousness ($r = 0.168275, p < 0.05$).

Although none of the hypotheses in Section 2.7 addressed Agreeableness and number of checkins, it is interesting to note that the lower tercile group has a higher average number of checkins (mean = 3078.7069, std = 2692.16647) than the top tercile (mean = 2200.54386, std = 1959.82832).

4.2.2. Number of venues

Considering the total number of venues visited, significant differences are shown for Conscientiousness ($t = -2.498753, p = 0.013936$) and Neuroticism ($t = 2.0127, p = 0.046822$). For Conscientiousness, the lower tercile has a ‘total number of venues visited’ (mean = 579.672414, std = 500.773277) lower than the top tercile (mean = 833.140351, std = 574.320726). This contradicts **H2** and indicates that those with a higher Conscientiousness score are displaying a higher level of activity. From these results it appears that as individuals with high Conscientiousness tend to be more focused and organised, they may have a higher number of venues visited simply because of their more disciplined nature in recording checkins. This is consistent with a checkin being a low overhead activity that does not cause a significant distraction to conscientious individuals. A weak but significant positive Spearman correlation between Conscientiousness and the number of venues visited ($r = 0.214793, p < 0.01$) supports this.

With Neuroticism, the total number of venues visited for the lower tercile (mean = 842, std = 667.273273) is higher than for the top tercile (mean = 626.54386, std = 451.958936). A weak but significant negative correlation between Neuroticism and total number of venues visited ($r = -0.171348, p < 0.05$) is also evident. This finding is related to **H5** but involves number of venues visited rather than number of checkins made.

4.2.3. Venue popularity

As defined in Section 2.1, a user’s average venue popularity can be considered in five ways: average check-in popularity, average number of venue visitors, average ‘tip’ popularity, average ‘like’ popularity and average distance travelled. Analysis of each of these revealed no statistically significant differences between the top and bottom terciles for any of the five personality factors, with the exception of Openness. Here a small but significant Spearman correlation is found ($r = 0.15213, p < 0.05$) concerning the number of likes received by a venue. Additionally, for average distance travelled, a weak but significant positive Spearman correlation is found with Openness ($r = 0.161638, p = 0.033104$). This indicates that the average distance between venues is higher for those users with a higher Openness score. This is consistent with highly open individuals travelling further to seek out new experiences.

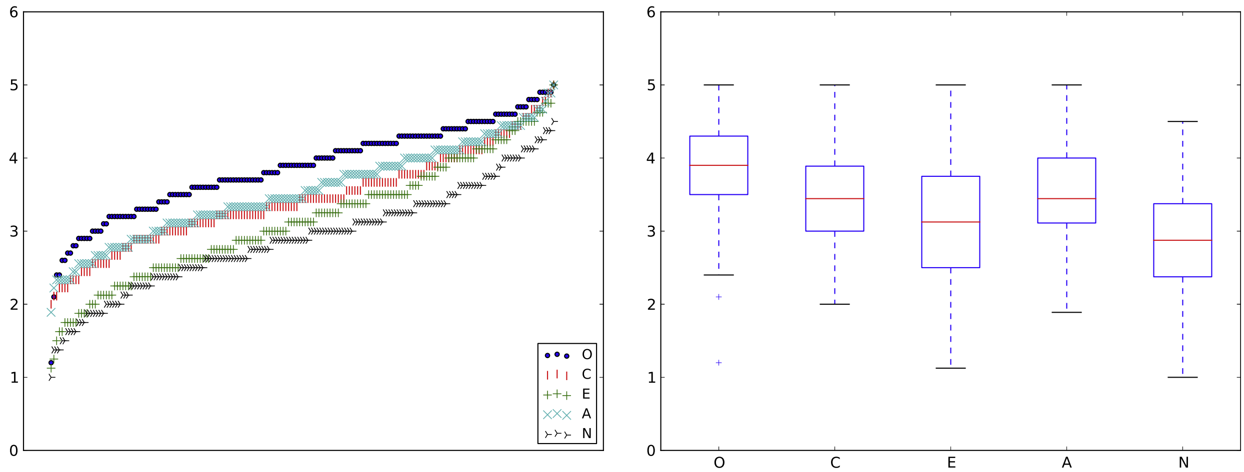

Fig. 2. Ordered distribution and box plots for each personality trait.

4.3. Checkin diversity

By considering the number of venues visited within each category, or number of checkins within each category, it is possible to calculate the diversity of an individual's activity using ecological diversity measures such as the Shannon diversity index (Lande, 1996). In our case, each category of venue (663 categories when analysis was conducted) is considered as a separate species, and the number of checkins (or venues visited) within each category considered as the number of observations of that species.

By examining the top and bottom tercile scores for each personality factor, we find a significant difference between the mean diversity for Conscientiousness concerning the number of venues visited ($t = -2.142748, p = 0.034524$). No other significant differences are found for the other four personality factors. For both checkins and venues, the top tercile mean Shannon diversity score is lower than for the bottom tercile, suggesting that users with a higher Conscientiousness exhibit a higher diversity in their checkin pattern. This is supported by a weak but significant Spearman correlation between Conscientiousness and the diversity of venues checked into ($r = 0.1522, p = 0.044975$). Surprisingly there is no evidence to support **H1** concerning a positive correlation between Openness and diversity of checkins.

Table 4
Lower & upper tercile cutoffs for each personality factor.

Factor	Lower tercile cutoff	Upper tercile cutoff
Openness	3.6	4.2
Conscientiousness	3.22	3.67
Extraversion	2.75	3.5
Agreeableness	3.22	3.89
Neuroticism	2.625	3.25

4.4. Sociable venues

Sociable venues can be considered as those that individuals would be expected to visit to talk and engage in activities, with friends or other people. The high-level Foursquare checkin taxonomy does not provide sufficient demarcation between categories on the basis of sociability. To distinguish which sub-categories can be thought of as 'sociable', crowd-sourcing of opinion was performed using a micro-task service.[5] Participants were shown a list of categories from Foursquare, and asked whether they believed that the category represented 'sociable' venues or not.[6] Each of the categories was shown to at least 5 participants and only those categories rated 'sociable' with a confidence level[7] of at least 80% were considered. In total, 72% of all Foursquare categories were deemed to be sociable, leading to 46,843 total sociable venues in the dataset, divided between the top-level categories as shown in Table 5. The crowdsourced data on sociable categories is available online at https://mobisoc.cs.cf.ac.uk/data/sociable_venues/.

Table 5
Number of 'sociable' venues in each top-level category.

Category	Number of sociable venues
Travel & transport	0
Food	29163
Shops & services	18
Arts & entertainment	3095
Nightlife spots	7721
Outdoors & recreation	5610
Colleges & universities	1236
Residences	0
Professional & other places	0

Examining the number of checkins at sociable venues reveals significant differences between the top and bottom personality terciles for Conscientiousness ($t = -2.140403, p = 0.034597$), with the mean number of checkins for the lower tercile ($\text{mean} = 599.188406, \text{std} = 601.666436$) being significantly lower than that for the top tercile ($\text{mean} = 913.338235, \text{std} = 1042.412651$). This indicates that users with a higher level of Conscientiousness have checked into a higher number of sociable venues, with this supported by a weak but significant Spearman correlation between Conscientiousness and the number of checkins at sociable venues ($r = 0.146891, p = 0.033807$). This is again consistent with the organised nature of Conscientious users, and may also reflect the fact that the utility of a LBSN is related to checking into sociable venues, to some degree.

Considering the number of venues at which checkins are made, we find a significant difference between the top and bottom terciles for Conscientiousness ($t = -3.224935, p = 0.001595$, lower tercile mean = 211.478261, lower tercile std = 174.71149, upper tercile mean = 319.529412, lower tercile std = 212.456049), with a modest positive correlation ($r = 0.232593, p = 0.000702$). However we also find a weak negative correlation between Neuroticism

[5] http://www.crowdflower.com.
[6] Each participant was paid $0.07 per 10 categories assessed.
[7] A measure in Crowdflower, derived from aggregation of weighted trust scores for the commissioned workers.

and the number of venues visited ($r = -0.155625, p = 0.024444$). This indicates that people with a higher Neuroticism score record fewer sociable venues, consistent with the difficulties that Neuroticism brings to sustaining comfortable social relations.

Examining the number of checkins at sociable venues as a proportion of the total number of checkins we find a significant difference between the upper and lower groups concerning their Openness ($t = -2.492301, p = 0.013925$). The lower tercile ($\text{mean} = 0.28647, \text{std} = 0.136702$) has a lower mean proportion of checkins in sociable venues than the top tercile ($\text{mean} = 0.349095, \text{std} = 0.154563$), showing that those with higher Openness make a greater proportion of their checkins at sociable venues. This is supported by a weak but significant Spearman correlation ($r = 0.150946, p = 0.029136$). **H3** anticipated that Extraversion could be expressed through a greater number of checkins at sociable venues, however the data does not support such a correlation.

4.5. Summary of hypotheses

H1 concerning Openness is not supported by a correlation with checkin diversity (Section 4.3). However, a correlation has been found between Openness and the average distance between venues visited (Section 4.2.3). Interestingly Openness has a weak but significant correlation with both venue popularity (in terms of the number of likes recorded at a venue in Section 4.2.3) and the proportion of checkins at sociable venues (Section 4.4). These correlations relate to both spatial and social dimensions of LBSNs.

H2 concerning Conscientiousness is refuted (Section 4.2.1), as a weak but significant positive correlation with the number of checkins has been found. This is in contrast with findings for Twitter (Hughes et al., 2012) which established negative correlations with Conscientiousness. A moderate and significant positive correlation also exists between Conscientiousness and the number of venues visited (Section 4.2.2), also evidenced by a positive correlation with checkin diversity (Section 4.3). These results are consistent with the trait of Conscientiousness not impeding checkins for LBSNs. Interestingly Conscientiousness is also positively correlated with both the number of checkins at sociable venues and the number of sociable venues visited (Section 4.4).

H3 concerns a positive correlation between Extraversion and venue sociability, which is not supported by the data. Additionally no other correlations were found concerning Extraversion within the study. This is unexpected, with the results providing no evidence for phenomenon observed in online social networks, such as social compensation (Zywica & Danowski, 2008).

H4 concerning Agreeableness and a negative correlation with venue popularity is not supported. No hypothesis was made concerning Agreeableness and number of checkins, but a statistically significant difference is present for Agreeableness between the upper and lower tercile scores for number of checkins (Section 4.2.1), which is potentially worthy of further investigation.

H5 concerning Neuroticism was not directly supported, as no correlation with number of checkins have been found. However a negative correlation has been identified between number of venues visited and Neuroticism (Section 4.2.2). A further weak negative correlation has been found concerning Neuroticism and the number of sociable venues visited (Section 4.4). This contrasts with more general Internet usage (Butt & Phillips, 2008) where high neuroticism corresponds to the use of Internet to mitigate loneliness and exclusion.

5. Discussion

Location-based social networks are a relatively new phenomenon that integrate physical human activity with an online social network, providing a new opportunity to discover more about human behaviour and its relation to personality characteristics. Using the popular Foursquare LBSN, we have developed a web-based participatory tool that has allowed an "in-the-wild" study of an individual's personality traits to be compared with the street level places that they visit. To the best of our knowledge this is the first time such a study has been attempted. Because the participants of the study are not controlled, and recording checkins is a highly variable activity, the conclusions from our study need to be set in this context.

Reflecting the hybrid nature of LBSN, the variables considered in this work can be categorised as *location-based* or *social*, or both. The location-based variables (number of distinct venues visited, diversity of checkins, diversity of venues visited, number of sociable venues visited, average popularity of venues visited) reflect the characteristics of a place, venue categorisation or spatial distance. The social variables (number of checkins, number of checkins at sociable venues, number of sociable venues visited, number of distinct venues visited) reflect online sharing of knowledge with others through checkins, or being in a location that is affiliated with socialising. Number of distinct venues visited and number of sociable venues visited are both location-based and social variables. Correlations have been investigated between LBSN variables and the "big-five" personality traits, with interesting findings concerning Openness, Conscientiousness and Neuroticism, but with variation on the original hypotheses. For each of these traits, the findings involve both location-based and social variables.

The results show that Conscientiousness is positively correlated with the number of venues visited, checkin diversity and number of checkins at sociable venues. In comparison to other online social networks, these results contrast with those found by Hughes et al. (2012) for social Twitter usage, where a negative correlation was found with Conscientiousness. For Facebook, Ryan and Xenos (2011) found a significant negative correlation between Conscientiousness and time using the service. Ross et al. (2009a) investigated similar expectations, but for their study it was not a significant factor in any of their analysis.

Consequently, as compared to other online social networks and assuming predominantly social usage of LBSN, Conscientiousness correlates with significantly different user behaviour. It seems that the unique function of LBSNs, where individuals may frequently choose to record and share their presence through a checkin, has the potential to engage those who are diligent, rather than deter them. The efficient nature of communication in a LBSN, for the most part being a trigger to automate a notification, could be significantly below a threshold for distraction from more important tasks. This level of efficiency in communication could be an important aspect for the Conscientious user. Related to this, we note that Hughes et al. (2012) found Conscientiousness correlating positively (rather than negatively) with Twitter usage when the service is used for informational (rather than social) purposes, where alternative services (e.g., web search) offer potentially less convenience.

Openness to experience for LBSN relates to a physical dimension that is not present in online social networks, and this has been evidenced by Openness correlating with predominantly location-based variables (average distance between venues visited, venue popularity, number of checkins at sociable venues). Hypothesis **H1** was not supported, with no evidence of Openness correlating with checkin diversity, as represented by diversity of categories. While this is unexpected, correlation with diversity in physical location is evident through the variable concerning average distanced between venues. The correlations related to venue popularity and sociability are unexpected and worthy of further investigation. As Openness has been correlated with wider use of online social network features (Amichai-Hamburger & Vinitzky, 2010a), LBSN features such as tips and 'likes' may have a greater influence on the high Openness users who use the service to support decision-making. Equally it is possible that popular and sociable locations may offer greater opportunity for exposure to new experiences, and that high Openness individuals may seek to register such experiences through LBSN, given their significant disposition towards this. Consistent with this we note that in previous work on Facebook Skues et al. (2012) identified high Openness individuals as using online social networks to discuss wide-ranging experiences.

For Neuroticism, negative correlations relating to the spatial and social variables have been found (number of venues visited, number of sociable venues visited). Although Hypothesis **H5** was not supported, the correlations identified from analysis differ from findings for online social networks, where increased online participation (Wolfradt & Doll, 2001) and use of the Internet to mitigate loneliness (Butt & Phillips, 2008) were identified. Interestingly, for LBSN, the negative correlation for number of venues visited is consistent with highly neurotic individuals potentially reducing their opportunity to be observed by others at wide-ranging venues, which may be related to heightened social sensitivity and negative emotions. Similarly, the negative correlation with number of sociable venues visited is consistent with high Neuroticism individuals avoiding locations where emotional instability might be heightened.

No correlations were found for Extraversion and Agreeableness. There appear to be fewer findings in the literature on Agreeableness for online social networks, which is perhaps an indicator that this trait is less dominant or harder to identify. A statistically significant difference was found for Agreeableness between the upper and lower tercile scores for number of checkins (Section 4.2.1). Although not established by this result, it leads us to question whether highly agreeable people are more careful in publicising their behaviour. Consistent with this we note that highly agreeable individuals have been found to minimise regret concerning online postings (Moore & McElroy, 2012).

The lack of results for Extraversion is surprising as there are many studies that have found relationships between Extroversion and online activity. For example, users of Facebook with high Extroversion and offline popularity have been identified as having high levels of Facebook activity (Wehrli, 2008). When studying Facebook location-based check-ins, Wang and Stefanone (2013) found that Extraversion did not necessarily relate directly to location-based checkins, but it did contribute to exhibitionism and showing off. There is also the possible effect of social compensation (Zywica & Danowski, 2008), where introverted users strive to gain popularity through online interactions, and this has been evidenced in a range of online settings (e.g., Moore & McElroy, 2012). It is possible that the effects of Extraversion in LBSN activity do exist but may not be evidenced through correlation analysis. This warrants further investigation.

From this investigation we conclude that personality traits help to explain individual differences in LBSN usage and the type of places that individuals choose to record through LBSNs. To the best of our knowledge, these are the first such insights from observed LBSN data, and they pave the way for further investigation in this field.

6. Further work

From this study there is considerable opportunity for further research concerning individual differences and LBSNs. These particularly relate to Extraversion and Agreeableness, where correlations are not evident, as well as further consideration of Openness. Related to Conscientiousness, the relative cognitive burden of a LBSN, and the implications for its usage, is an interesting area for consideration. Furthermore, the role of narrow personality traits in LBSNs are unknown and may give further insight into the use of this technology. More generally, understanding the relationship between preference for different social media (LBSNs and online social networks) and individual differences is valuable, particularly given the significant usage of LBSNs.

Acknowledgement

This work was supported by the RECOGNITION project, Grant No. 257756, funded under the European Commission FP7 Future Emerging Technologies programme, and by a United Kingdom EPSRC Doctoral Award Fellowship, Grant EP/L504749/1.

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