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Is the popularity of social networking services beneficial for public health? Focusing on active travel and BMI

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ABSTRACT

Social networking services (SNSs) can affect people's behaviour in a variety of ways; and through this their health outcomes. People generate and are exposed to content which circulates easily among a large, geographically dispersed population. They can also engage in supportive or competitive activities with their connections and the wider community. This online activity may lead to changes in behaviour and positive health outcomes e.g., exercising more or eating more healthily. Engaging with a SNS may also lead to negative outcomes such as depression, addiction, and less participation in offline social communities. As the number of SNS users has been increasing dramatically, it is important to understand if this will be beneficial or detrimental for public health. In this study, we examine how the frequency of SNS use is associated with active travel (i.e., walking and cycling) and body mass index (BMI) in the Glasgow and Clyde Valley Planning area, Scotland. We employ both a self-reported measure of active travel from a travel diary (N = 1684) and an objective measure of average walking hours from Global Positioning System (GPS) data (N = 282) collected in 2015. These are analysed with statistical models (i.e., binomial logistic regression, multinomial logistic regression and linear regression models). We find that there is no significant association between the frequency of SNS use and our subjective measure of active travel, while people who intensively use SNS are more likely to be obese than non-users. However, analyses with an objective measure of average walking hours (GPS) show that people who intensively use SNS spend less time walking and tend to be obese, calling for further analyses.

1. Introduction

The Internet, one type of Information and Communication Technology (ICT), has led to significant changes to the way people live and travel. For example, an increasing number of people work away from traditional offices, which may reduce the need for commuting, at least in the short term. People may shop online instead of travelling to a physical shop. On the other hand, people may travel more because of time savings achieved through Internet use. Several studies have found significant effects of ICT on physical trips; although results are mixed (Choo et al., 2005; Hong and Thakuriah, 2016; Mokhtarian et al., 2006; Mokhtarian and Tal, 2013; Tonn and Hemrick, 2004; Wang and Law, 2007; Zhu, 2012).

People use the Internet for a variety of different purposes. One popular activity is using social media/social networking services (SNSs)[1] to form or maintain relationships with others. Around 76% of U.K. Internet users have an SNS account, with the services being more popular with younger people (Ofcom, 2017). Other countries have similar trends. For example, in the U.S., the Pew Research Center notes a dramatic increase in the share of the population using social media. In 2015, around 65% of

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[1] Social media is generally used as an umbrella term to refer to online platforms which allow users to share content. SNSs are considered social media but have certain characteristics which set them apart from other social media. According to Boyd and Ellison (2007), SNS can be defined as "web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system. The nature and nomenclature of these connections may vary from site to site."

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Americans used SNSs compared to just 5% in 2005 (Perrin, 2015; Pew Research Center, 2018). Greenwood et al. (2016) found that around 80% of U.S. Internet users use Facebook with the younger generation using it more often than older generations. Outside of the Anglosphere, Statista (2018) shows that the SNS penetration in Asia Pacific is high and has been increasing year on year.

SNSs have some interesting characteristics that could lead to changes in people's travel behaviour and level of physical activity. For example, they are an inexpensive and easy way to reach a large, geographically dispersed population, they provide social support, the ability to engage in competitive behaviour, and can be linked to activity tracking apps. Some of these characteristics could increase the level of active travel (i.e., walking and cycling) and improve health outcomes. For example, the social support provided by SNSs may provide people with encouragement to reach their activity and health goals. Conversely, engaging with SNSs may lead to addiction or depression, as discussed in Section 2. Because the popularity of SNSs is expected to continue to grow in the future, it is critical for planners and public health professionals to understand how the use of SNSs is related to the level of physical activity and health outcomes. Unfortunately, empirical studies about their relationship are scarce, partly due to a lack of appropriate data.

In this paper, we set out to answer the question of whether the frequency of SNS use is associated with the level of active travel (here, active travel indicates either walking and cycling trips) and a person's body mass index (BMI). BMI is known to be affected by a person's level of physical activity and high BMI has been linked to numerous negative health outcomes (Andersen et al., 1998; Shelley et al., 2005; Weinstein et al., 2004).

We used data from a household survey conducted in Glasgow, Scotland. The survey covers a range of topics and includes information on self-reported frequency of SNS use, weight and height. In addition, participants completed a travel diary with some also carrying a Global Positioning System (GPS) tracking device. We employed statistical models (i.e., binomial logistic regression, multinomial logistic regression and linear regression models) to answer our research questions.

Rather than relying on self-reported measures of active travel in the form of a one-day travel diary, we also calculated average walking hours per person per day objectively using GPS trajectories. This is because survey respondents often ignore short active travel trips when reporting their travel information, potentially leading to erroneous conclusions about the relationships of interest. Utilising both subjective and objective measures of walking allows us to reach more robust results.

2. Literature review

In this section, we review relevant literature dealing with SNSs specifically, and social media more broadly. Given that the two share many characteristics, our approach ensures we capture all relevant studies, although we focus on SNSs in our analysis.

Due to the popularity and unique characteristics of social media/SNSs (e.g., being a cheap and easy way to reach and interact with a large, geographically dispersed population), a growing body of research has examined how interventions using social media platforms could change the way people behave. For example, studies have investigated the benefits of social media for modifying or promoting desirable health behaviour. Some found that many people use social media to search for health and well-being information, and that in this way it can be an effective tool to meet peoples' health needs and potentially change their behaviour (Korda and Itani, 2013; Lenhart et al., 2010).

Laranjo et al. (2015) conducted a meta-analysis to evaluate the effectiveness of various SNS interventions on different health outcomes and behaviours (e.g., weight loss and physical activity). They concluded that SNSs have the potential to encourage healthier behaviour. In addition, SNSs provide a form of social support and competition by allowing users to share their experiences and get feedback (Stragier et al., 2017). Receiving positive feedback for sharing information about healthy behaviour, such as being more active, or comparing the level of healthy behaviour with others may reinforce such behaviour, thereby increasing the level of physical activity (Berkman et al., 2000; Zhang et al., 2016). Connected to this, many studies have already examined the potential effects of SNSs and other social media on diet (Williams et al., 2014). In summary, the unique characteristics of SNSs render it a way to deliver effective behavioural interventions.

However, it is hard to conclude whether the use of SNSs in the absence of a deliberate intervention will have effects on health behaviour or outcomes. There are some reasons to suppose that such effects may exist. For example, Burke and Heiland (2007), in their study of the social dynamics of obesity, draw on the social interaction literature within economics as well as theories from social psychology and sociology positing that people like to conform (e.g., Bernheim (1994)'s theory of conformity). Receiving positive feedback for healthy behaviour may encourage more of such behaviour.

Using the theory of the firm, Becker (1965) highlights the time constraints people face in allocating time between their non-work activities. Time spent on the Internet or social media could reduce the time available for other activities (Nie et al., 2002), for example socialising or physical activities. Tandon et al. (2014) showed that bedroom media devices such as televisions and computers could lead to sedentary behaviour among young people. Marshall et al. (2004) also found a significant negative relationship between television viewing and physical activity in young people, although its magnitude was small.

Other sorts of negative effects are also possible. Pantic (2014) reviewed empirical studies showing both positive and negative impacts of SNS use on mental health. People who use online communication services with friends and family could receive social support, resulting in beneficial mental-health impacts. On the other hand, the use of SNSs could result in negative perceptions of life or depression. For example, Chou and Edge (2012) found that undergraduate students who spent more time on Facebook perceive that other people are happier and have better lives. Pantic et al. (2012) found a significant positive association between time spent on SNSs and depression among high school students. It is known that people with depression tend to be less physically active (Paluska and Schwenk, 2000). If the negative effects of SNS use on mental health dominate the positive effects, people who use SNSs more frequently could have sedentary lifestyles, resulting in various health problems. Moreover, Kuss and Griffiths (2011) argued that people might not participate in offline social communities due to SNS use.

In the fields of transport or urban planning, active travel is often considered a desirable travel behaviour for improving our environment and personal health (de Nazelle et al., 2011; Frank et al., 2006; Lubans et al., 2011; Sallis et al., 2004; Smart, 2018). In addition, it is a type of physical activity which benefits public health. Several health experts recommend at least 30 min of daily physical activities, and some research showed the benefits of daily walking (e.g., walking to public transport stations) for achieving this goal (Besser and Dannenberg, 2005).

Nowadays, several SNSs allow third-party apps (e.g., physical activity tracker apps) to connect to them to share content. Use of these apps may result in behaviour change, as it is considered that setting goals and making them public is an effective way of helping people stick to their goals, especially if they receive positive feedback and encouragement from their friends. For example, the Strava app can share cycling and running activities directly to platforms such as Facebook and Twitter. Li et al. (2018) identified that positive confirmation is one of the primary driving forces which keep people using such apps over time. By sharing their travel/activity information with their friends through SNSs, people could be motivated to achieve their goals and obtain more positive confirmation. Therefore, it is reasonable to assume that the use of SNSs might influence the level of active travel and health outcomes. What is unclear is whether their influences would be good or bad due to the positive and negative potentials outlined above. Unfortunately, to the best of our knowledge, no empirical studies have examined how the frequency of SNS use is associated with the level of active travel and related health indicators.

This study contributes to relevant literature by examining the net associations between SNS use, active travel and BMI in the Glasgow and Clyde Valley Planning area, U.K. Another important contribution of this study is to utilise GPS data to compare the results with those from self-reported travel information (i.e., from a travel diary). It has been well documented that the trip information recorded in travel diaries and from GPS data differ significantly due to memory decay or ignorance of short trips (Shen and Stopher, 2014; Stopher et al., 2007). In particular, total hours of active travel could be significantly different. Comparing model results from both objective and subjective measures of active travel will allow us to examine their relationship more rigorously. Therefore, we calculated an objective measure of average walking hours from GPS trajectories and utilised it for further analyses.

3. Data and method

We utilised the integrated Multimedia City Data (iMCD) survey (including a one-day travel diary) conducted by the Urban Big Data Centre (UBDC) in Glasgow. It aims to collect information about education, ICT use, attitudes, belief and diverse social and travel activities from a representative sample of residents in the Glasgow and Clyde Valley Planning area. The survey was conducted from April to November 2015 through face-to-face interviews. A total of 2095 participants from 1511 households completed the survey. The representativeness of the survey was assured by the survey company (Ipsos MORI, 2015). In addition, 320 respondents agreed to carry a GPS device for one week (more about the iMCD project can be found in Thakuriah et al. (2016)).

We made use of three parts of this data set for the analysis. First, the main iMCD survey was utilised to measure important determinants of active travel and BMI including attitudes towards active travel, the frequency of SNS use, and socio-demographic factors.[2] A body of previous literature shows the importance of attitudes in explaining travel behaviour (Anable, 2005), especially in land use-travel behaviour analyses (Cao, 2010; Handy et al., 2006; Hong and Chen, 2014) although some found different results (Naess, 2014). That is, people who prefer walking tend to walk more than those who don't, regardless of their residential locations. The survey includes several attitudinal questions about different transport modes. For example, it asks if walking for a regular or daily journey is something the interviewee likes. The answer is measured by a five-point Likert scale, anchored by strongly disagree and strongly agree. Since our analysis focuses on active travel, we included two attitudinal variables about walking and cycling. These were included in the analytical models as continuous variables.

The survey also asks how often the interviewee looks at SNS sites or apps such as Facebook, Twitter and Instagram. The answer is measured by a seven-point Likert scale (i.e., never, less than once a month, at least once a month, at least once a week, a few times a week, at least once a day and several times a day). This is the main variable of interest for our study and is treated as a categorical variable in our analyses. Due to the uneven distribution of responses for each category and a lack of responses for certain categories, we created three new categories: 1: Non-user ('never'); 2 Moderate user (from 'less than once a month' to 'at least once a day') and; 3 Intensive user ('several times a day').

The survey asks for the weight and height of the interviewee, and the survey company calculated BMI (i.e., $weight(kg)/height(m)^2$). In addition, they recategorised it as a categorical variable: underweight, healthy weight, overweight and obese. We utilised this categorical variable as one of our dependent variables. Since there are only a few respondents who are underweight (i.e., only about 3%), we combined them with the healthy weight group. It is worth noting that self-reported BMI could be underestimated compared to the measured BMI, requiring care when interpreting results (Gosse, 2014).

Some people may have limited mobility due to chronic health problems. To account for this, we utilised two survey questions. The first question asks if the interviewee has any physical or mental health conditions or illnesses lasting or expected to last for 12 months or more. If the interviewee says yes, the following question ("how often are you able to travel to places such as work, shopping, health care, etc. on your own") was asked and answered by a six-point Likert scale (1: always–6: never). We defined "healthy" if the interviewee says "no" for the first question or "Always" for the second question. In addition, several socio-demographic factors (including age, gender, household size, working status, whether they hold a valid driving licence and whether they have access to the

[2] Key survey questions are shown in Appendix A.

Table 1
Descriptive statistics for all iMCD respondents and the subset with GPS data.

	iMCD				GPS			
	Mean	Median	1st Qu	3rd QU	Mean	Median	1st Qu	3rd QU
Socio-demographics								
Age	49.99	50.00	35.00	65.00	48.33	48.00	36.00	61.00
Gender (male = 1)	48.46%				45.74%			
Household size	2.50	2.00	2.00	3.00	2.62	2.00	2.00	3.00
Work (work = 1)	47.39%				49.65%			
Driving licence (own = 1)	69.18%				73.40%			
Internet connection (home = 1)	83.02%				90.43%			
Health (healthy = 1)	89.07%				92.55%			
Attitudes								
Walking (walking is something I like)								
Strongly disagree	11.11%				5.67%			
Disagree	8.55%				6.03%			
Neutral	10.27%				8.87%			
Agree	37.41%				37.94%			
Strongly agree	32.66%				41.49%			
Cycling (Riding a bicycle is something I like)								
Strongly disagree	50.30%				45.39%			
Disagree	19.00%				19.15%			
Neutral	10.81%				14.18%			
Agree	12.53%				10.99%			
Strongly agree	7.36%				10.28%			
Frequency of Social Networking Services use								
Non-user	44.00%				36.17%			
Moderate user (maximum at least once a day)	27.55%				29.08%			
Intensive user (several times a day)	28.45%				34.75%			
Travel & BMI								
Frequency of active travel (from a one-day travel dairy)								
No trip	72.39%				64.18%			
1–2 trips	19.71%				26.60%			
3+ trips	7.90%				9.22%			
BMI								
Underweight & healthy weight	45.13%				41.49%			
Overweight	35.75%				38.30%			
Obese	19.12%				20.21%			
Walking minutes from travel diary	12.64	0	0	10	13.87	0	0	20
≥ 30 min walking (travel diary)	15.68%				18.44%			
Avg. Walking hours per day (GPS trajectories)					0.43	0.34	0.18	0.60
≥ 30 min walking (GPS trajectories)					33.33%			
Sample size	1684				282			

Internet from home) from the main iMCD survey were included in the analyses.

The self-reported frequency of active travel (i.e., walking and cycling) was extracted from a one-day travel diary. The travel diary records all trips the interviewee had on the day before the interview date. It should be noted that although the travel diary collects travel information for one day, the survey was designed to collect representative travel patterns in the Glasgow and Clyde Valley Planning area. Therefore, the interview dates were allocated as evenly as possible across the week. We extracted the number of active trips based on the information about the mode of travel (i.e., walking and cycling). For our analyses, we recategorised the frequency variable into three categories: 0, 1–2 times and 3+ times. This is because many people did not make any active travel trips (see Table 1).

Determining levels of outdoor physical activity using GPS movement data has proved to be achievable; resulting in promising, high-quality results (Rundle et al., 2016). Moreover, several active travel studies confirmed the differences in objective and subjective measures of active travel as discussed above. Thus, we calculated an objective measure of average walking hours per person per day from GPS data to examine whether it produces results consistent with subjective measures. The iMCD survey includes GPS trajectories for a sample of 320 respondents who carried a GPS device for, on average, one week. This generated 6,970,690 raw GPS points where each location record contained a participant ID, latitude, longitude, elevation, dilution of precision, date and time. UBDC had formal approval from the ethics committee at the University of Glasgow before they collected GPS data. The collected GPS movement data were first cleaned and filtered to minimise the number of erroneous records (those with low precision caused by the satellites' geometry). To identify transport modes for each trip, we first segmented trajectories into homogeneous sub-trajectories using a statistical measure (i.e., a Spatio-Temporal Kernel Window (STKW) developed by Siła-Nowicka et al., 2016).[3] The adopted method

[3] The pseudocode for the algorithm is available as a Supplementary material for Siła-Nowicka et al. (2016).

shows high accuracy levels for trajectory segmentation. The STKW was calculated based on a spatio-temporal density of GPS locations and the algorithm proves to be very sensitive to even small changes in moving behaviour, therefore allowing for more accurate travel mode classification. Secondly, we applied a two-step feedforward neural network with a general backpropagation algorithm to classify the homogeneous segments; first to distinguish movement from non-movement segments and then to classify movement segments into specific travel modes (i.e., driving, walking, flying or on a ferry). The accuracy of the method was more than 96% for detecting driving and walking modes, which equals or exceeds the level of accuracy achieved in previous studies for travel mode detection (Siła-Nowicka et al., 2016; Xiao et al., 2015). We also checked the accuracy with our iMCD *activity* diary (a prompt recall instrument where the participants identified all their trips, modes of transport as well as time and duration of each trip for the first day of the GPS-based travel survey. This is not the same as the one-day *travel* diary mentioned earlier.) which serves as a ground truth for testing the model, and achieved a similar level of accuracy. With the trajectories classified by mode of travel, we summed the time and distance travelled per mode per participant.

Average walking hours per person per day were calculated from the processed GPS data and considered as a dependent variable for our analysis. We consider only walking trips for two reasons. Firstly, the cycling mode share is low in Glasgow and hence only small numbers of cyclists are captured in the survey (i.e., 1.1%). Secondly, many cyclists often share roads with buses and follow them, making it hard to distinguish these two modes (i.e., cycling and buses) correctly based on the information of speed, stops and routes. Moreover, we employed average walking hours per person per day for our analyses instead of the frequency of walking trips because: 1) walking hours is a more appropriate measure of physical activity than the frequency of walking trips; and 2) the frequency of GPS-based walking trips might be disrupted and give us an incorrect number of walking trips. For example, if a person goes for a walk with dogs, stops for a while on a bench and walks again, it will be identified as two walking trips rather than one. In addition to the average walking hours per person per day, we measured if the participant walked at least 30 min per day on average (i.e., the recommended level of physical activity). Two measures were calculated based on a one-day travel diary (subjective measure: self-reported travel duration) and GPS trajectories (objective measure), respectively. The same survey and processed GPS data are available to other researchers upon application (http://ubdc.ac.uk/).

For the in-depth analyses, multinomial logistic regression, linear regression and binomial logistic regression models were employed. One of the dependent variables (i.e., number of active trips) is ordinal so an ordered logistic regression model could be employed. However, an additional analysis showed that our data do not meet the assumption of proportional odds. Therefore, we decided to use multinomial logistic regressions for our analyses. Specifically, multinomial logistic regressions were utilised to examine the relationship between the frequency of SNS use and the self-reported frequency of active travel as well as BMI. The association between the frequency of SNS use and objectively measured average walking hours per person per day was examined through a linear regression model.[4] Finally, the relationship between the frequency of SNS use and walking at least 30 min per day was investigated with binomial logistic regressions. After removing all missing values, we have a total 1684 and 282 observations from main survey and GPS data, respectively. All independent variables and dependent variables are presented in Table 1 with descriptive statistics. For the analyses, R was used (R Core Team, 2018).

4. Results

The descriptive statistics for the iMCD survey and GPS observations are shown in Table 1. Here, we put the iMCD survey data first, with the GPS equivalent in brackets. The average age of our respondents is about 50 (48) years old. Nearly half of our respondents identify as male (46%), and there are 2.50 (2.62) household members on average. About 47% (50%) of the respondents are workers and 69% (73%) of them have a valid driving licence. About 83% (90%) of the respondents have access to the Internet from home and 89% (93%) of them have good health. In general, our respondents like walking for their regular or daily journeys on average; however, this is not the case for cycling. Respondents who supplied GPS data have a higher rate of SNS use. About 44% (36%) of the respondents never look at SNS sites or apps such as Facebook, Twitter or Instagram while about 28% (35%) of them look at SNS sites or apps several times a day. In general, respondents who supplied GPS data tend to make slightly more active trips than those from the main iMCD survey. To be clear, we compared the frequency of active travel measured by a one-day travel diary (subjective measure) for both samples. Nearly two-thirds of our respondents did not make any active travel trips on the day before the interview was conducted. About 20% (27%) of people made one or two active trips on that day and only about 8% (9%) of them made more than three active trips per day. Nearly half of our respondents are in the healthy weight group, 36% (38%) of them are overweight and about 19% (20%) are obese. On average, people walked about 13 (14) min per day and 16% (18%) of them walked at least 30 min per day.

The results from the multinomial logistic regression models for self-reported active travel and BMI are shown in Tables 2 and 3. Several socio-demographic factors show significant associations with the frequency of active travel, and they are consistent with previous studies. Older people tend to make fewer active travel trips. Workers tend to make fewer active travel trips than non-workers, and people who possess a driving licence are less likely to walk or cycle than those who do not hold a driving licence. Healthy people are more likely to make 1–2 active trips compared to 0 active trip.

Attitudes towards walking and cycling have very significant and positive associations with the frequency of active travel, and this is consistent with previous studies. Specifically, people who like walking or cycling tend to make more active trips than those who do not, and most estimates are statistically significant at the 5% level.

[4] We took a square root transformation for average walking hour per person per day due to its skewed distribution and inclusion of zero value.

Table 2
Results for the association between the frequency of SNS use and self-reported active travel.

	1–2 times				3+ times			
	β	SE	P-Value	Exp(β)	β	SE	P-Value	Exp(β)
Intercept	**-2.576**	**0.498**	**0.000**	**0.076**	**-5.000**	**0.872**	**0.000**	**0.007**
Socio-demographics								
Age	**-0.013**	**0.005**	**0.006**	**0.987**	**-0.019**	**0.007**	**0.008**	**0.981**
Gender (male = 1)	0.204	0.134	0.129	1.227	-0.349	0.203	0.085	0.705
Household size	-0.074	0.055	0.176	0.929	-0.075	0.077	0.329	0.927
Work (work = 1)	**-0.648**	**0.147**	**0.000**	**0.523**	**-0.656**	**0.207**	**0.002**	**0.519**
Driving licence (own = 1)	**-0.567**	**0.153**	**0.000**	**0.567**	**-0.806**	**0.215**	**0.000**	**0.447**
Internet connection (home = 1)	0.181	0.203	0.372	1.199	0.571	0.353	0.106	1.770
Health (healthy = 1)	**0.937**	**0.286**	**0.001**	**2.552**	0.931	0.492	0.058	2.537
Attitudes								
For me, walking/cycling is something I like (1: Strongly disagree–5: strongly agree)								
Walking	**0.393**	**0.063**	**0.000**	**1.482**	**0.772**	**0.123**	**0.000**	**2.164**
Cycling	**0.120**	**0.050**	**0.016**	**1.127**	0.115	0.071	0.107	1.122
Social networking services (Ref: Non-user)								
Frequency of SNS use								
Moderate user	0.032	0.174	0.853	1.033	0.318	0.269	0.238	1.374
Intensive user	-0.392	0.203	0.054	0.676	0.078	0.298	0.793	1.082
Sample size	1684							

Table 3
Results for the association between the frequency of SNS use and BMI.

	Overweight (BMI)				Obese (BMI)			
	β	SE	P-Value	Exp(β)	β	SE	P-Value	Exp(β)
Intercept	**-1.373**	**0.400**	**0.001**	**0.253**	**-1.460**	**0.481**	**0.002**	**0.232**
Socio-demographics								
Age	**0.018**	**0.004**	**0.000**	**1.018**	**0.021**	**0.005**	**0.000**	**1.021**
Gender (male = 1)	**0.430**	**0.116**	**0.000**	**1.537**	0.206	0.142	0.146	1.229
Household size	0.058	0.046	0.214	1.059	-0.028	0.058	0.627	0.972
Work (work = 1)	**0.272**	**0.130**	**0.036**	**1.312**	0.209	0.159	0.190	1.232
Driving licence (own = 1)	0.016	0.136	0.909	1.016	-0.104	0.162	0.520	0.901
Internet connection (home = 1)	**0.362**	**0.175**	**0.039**	**1.436**	**0.420**	**0.214**	**0.050**	**1.522**
Health (healthy =1)	-0.135	0.201	0.502	0.874	-0.042	0.236	0.860	0.959
Attitudes								
For me, walking/cycling is something I like (1: Strongly disagree–5: strongly agree)								
Walking	-0.025	0.048	0.606	0.976	**-0.171**	**0.055**	**0.002**	**0.843**
Cycling	**-0.142**	**0.045**	**0.002**	**0.867**	**-0.183**	**0.058**	**0.002**	**0.832**
Social networking services (Ref: Non-user)								
Frequency of SNS use								
Moderate user	-0.060	0.152	0.691	0.941	0.257	0.188	0.171	1.293
Intensive user	-0.091	0.172	0.598	0.913	**0.426**	**0.210**	**0.042**	**1.531**
Sample size	1684							

The frequency of SNS use (i.e., *Moderate user* and *Intensive user*) shows no significant association with the self-reported frequency of active travel. As we discussed in the literature review, there could be both positive and negative effects of SNS use on the level of active travel, potentially cancelling each other out. Moreover, it is possible that response errors in the survey (e.g., self-reported active trips) could contribute to this conclusion.

By comparing results from Tables 2 and 3, we can see the potential relationship between the level of self-reported active travel and BMI. For example, the results show that older people tend to make fewer active travel trips and are more likely to be overweight or obese. In addition, people who have affirmative attitudes towards active travel tend to make more active trips and are less likely to be overweight or obese. Finally, intensive SNS users are more likely to be obese ($\beta_{Intensive\ user\_Obese} = 0.426$) than non-users. However, our results do not show a clear relationship between the level of active travel and BMI with the frequency of SNS use. In sum, our results imply that the popularity of SNS may be associated with negative health-related indicators but there is no evidence that any of this effect operates through differences in the level of active travel.

As indicated, the level of active travel measured by a travel diary and GPS trajectories can vary, potentially giving different results. To check the sensitivity of our model results, we utilised GPS data and examined the relationship between the frequency of SNS use and objectively measured average walking hours. Here, we calculated average walking hours per person per day and employed a linear regression model. In addition, we re-ran the same models (i.e., multinomial logistic regression models for self-reported walking travel and BMI) with the respondents who carried a GPS device. The self-reported walking trip frequency and BMI

Table 4
Results for the association between the frequency of SNS use and average walking hours per person per day from the GPS sample.

	iMCD survey								GPS sample	
	Walking frequency				BMI (Reference: Underweight + Normal)				Average walking hour per day	
	1–2 times		3+ times		Overweight		Obese			
	β	P-value	β	P-value	β	P-value	β	P-value	β	P-value
Intercept	**-2.866**	**0.025****	-18.360	0.993	-1.214	0.282	**-2.735**	**0.055***	**0.669**	**0.000****
Socio-demographics										
Age	-0.006	0.615	-0.016	0.393	0.019	0.104	**0.041**	**0.005****	**-0.003**	**0.008****
Gender (male = 1)	0.392	0.200	-0.233	0.630	**0.608**	**0.038****	0.090	0.807	0.005	0.878
Household size	0.122	0.327	0.082	0.660	0.074	0.546	0.162	0.275	-0.018	0.153
Work (work = 1)	-0.428	0.183	-0.235	0.623	0.024	0.938	-0.151	0.694	-0.037	0.250
Driving licence (own = 1)	**-0.729**	**0.050***	-0.876	0.104	0.474	0.198	0.303	0.493	**-0.119**	**0.002****
Internet connection (home = 1)	0.454	0.404	16.606	0.994	0.053	0.921	0.160	0.803	**0.095**	**0.079***
Health (healthy = 1)	0.755	0.296	0.992	0.378	0.327	0.591	0.266	0.706	0.059	0.332
Attitudes										
For me, walking/cycling is something I like (1: Strongly disagree–5: strongly agree)										
Walking	**0.311**	**0.057***	0.157	0.520	-0.149	0.303	-0.216	0.209	**0.034**	**0.020****
Cycling	0.121	0.284	-0.002	0.993	-0.126	0.255	-0.213	0.153	-0.008	0.511
Social networking services (Ref: Non-user)										
Frequency of SNS use										
Moderate user	-0.518	0.188	-1.110	0.103	-0.459	0.211	-0.287	0.548	0.027	0.476
Intensive user	-0.301	0.480	-0.268	0.662	0.250	0.541	**1.064**	**0.033****	**-0.075**	**0.070***
Adjusted R^2									0.097	
Sample size							282			

** Significant at the 0.05 level.
* Significant at the 0.1 level.

for the GPS sample were calculated from a one-day travel diary and main survey, respectively. The results are shown in Table 4. After removing all missing values, a total of 282 participants are included in the analyses. Due to the small sample size, we use a 10% level of significance when interpreting results. Compared to the previous results, fewer variables turn out to have significant associations with self-reported walking trips and BMI. This makes sense when we consider different sample sizes. However, the overall trends are very similar. People who have a valid driving licence tend to make fewer walking trips than those who do not though those who have affirmative attitudes toward walking are more likely to do so. The associations between the frequency of SNS use and walking trips as well as BMI are consistent with the previous results. *Intensive users* are more likely to be obese ($\beta_{Intensive\ user\_Obese} = 1.064$) while there is no significant association between the frequency of SNS use and the level of walking trips. However, the analysis with objectively measured average walking hours per person per day produced a different result. People who use SNSs several times a day spend fewer hours walking than non-users, indicating the negative association ($\beta_{Intensive\ user\_walking\ hours} = -0.075$) between them. This shows the potential link between the frequency of SNS use, the level of walking trips and BMI, requiring further analyses.

Additional analyses were conducted to examine the relationship between the frequency of SNS use and walking for at least 30 min per day, and the results are shown in Table 5. Results are consistent with the previous ones. Models with subjective measures of walking hours (calculated from a one-day travel diary) produce no significant association between the frequency of SNS use and walking for at least 30 min per day while a model with the objective measure of average walking hours per person per day show a very significant negative association ($\beta_{Intensive\ user\_\geq 30\ min\ of\ walking} = -0.911$). That is, intensive SNS users are less likely to walk at least 30 min per day than people who never use SNSs.

It is worth noting that this study does not estimate causal impacts of SNS use on walking and BMI, and longitudinal data as well as more sophisticated analytical models are required in the future. In addition, our data does not allow us to examine different activities on SNSs. With more detailed data about people's use of SNSs, we could begin to test hypotheses such as whether receiving positive feedback on posts about healthy behaviours encourages more of such behaviour.

5. Conclusion

Social media, especially SNSs, has a great potential to be an effective platform for delivering interventions aimed at improving public health. Its strengths, including being an easy way to reach a large population, to share information and to interact with others, has received much attention from researchers. Many have found significant health benefits of SNSs in increasing levels of physical activities and thereby promoting healthier lifestyles. However, there are also negative effects on health, particularly mental health, which require more in-depth analysis. Although some data limitations exist, this study is the first empirical work to utilise both subjective and objective measures of walking trips and to examine the relationship between SNS use, active travel, and health. It highlights an interesting pattern in the data and a need for further investigation.

Our results show that intensive users of SNSs are more likely to be obese than non-SNSs users. As previous literature revealed, using SNSs could result in mental health issues as well as more sedentary lifestyles. This implies that even though there are positive

Table 5
Results for the association between the frequency of SNS use and ≥ 30 min of walking.

	iMCD survey			GPS sample					
	Subjective measure			Subjective measure			Objective measure		
	β	SE	P-value	β	SE	P-value	β	SE	P-value
Intercept	**-4.524**	**0.633**	**0.000**	**-3.771**	**1.548**	**0.015**	0.178	1.174	0.880
Socio-demographics									
Age	-0.009	0.005	0.097	-0.011	0.013	0.409	**-0.034**	**0.011**	**0.003**
Gender (male = 1)	-0.088	0.146	0.545	0.084	0.335	0.801	-0.071	0.287	0.803
Household size	-0.013	0.058	0.824	-0.023	0.139	0.866	**-0.234**	**0.121**	**0.053**
Work (work = 1)	**-0.666**	**0.155**	**0.000**	-0.340	0.342	0.320	-0.390	0.299	0.192
Driving licence (own = 1)	**-0.476**	**0.162**	**0.003**	-0.631	0.394	0.109	**-1.002**	**0.352**	**0.004**
Internet connection (home = 1)	**0.576**	**0.244**	**0.018**	**1.486**	**0.808**	**0.066**	**1.116**	**0.572**	**0.051**
Health (healthy = 1)	**1.175**	**0.388**	**0.002**	0.706	0.831	0.395	**1.167**	**0.672**	**0.083**
Attitudes									
For me, walking/cycling is something I like (1: Strongly disagree–5: strongly agree)									
Walking	**0.598**	**0.081**	**0.000**	**0.346**	**0.191**	**0.070**	0.169	0.144	0.240
Cycling	-0.037	0.054	0.493	0.068	0.121	0.578	-0.129	0.109	0.237
Social networking services (Ref: Non-user)									
Frequency of SNS use									
Moderate user	0.247	0.190	0.194	-0.295	0.420	0.482	0.201	0.352	0.567
Intensive user	-0.141	0.220	0.521	-0.434	0.462	0.347	**-0.911**	**0.410**	**0.026**
Sample size		1684				282			

health-related functions of SNSs, SNS use and other factors including potential exogenous determinants could be strongly and positively correlated with BMI. Therefore, it is important to find out how to mitigate the negative associations between SNS use and health.

Secondly, our analysis shows that utilising subjective and objective measures of active travel will lead to different conclusions. As indicated earlier, it is well known that people ignore short active trips easily, resulting in differences between the self-reported and actual levels of active travel. Our GPS analyses show that intensive users of SNSs tend to spend less time walking and are more likely to be obese. Therefore, there could be potential links between these three factors, calling for further analyses in the future.

Our results imply that it is important for transport planners to take the potential harmful effects of SNS use on the level of active travel into consideration. This is particularly true if the level or intensity of SNS use changes over time. For example, it may be harder than expected to reach the already ambitious targets which have been set for active travel mode share in Scotland and other countries. This may have a knock-on effect for addressing the obesity problem.

Aside from the existing strategies for increasing active travel, our results suggest that one additional approach may be to target intensive users of SNSs with effective interventions designed to increase physical activity. Their high frequency of using these services should mean that they are easier to access than people who use the services infrequently.

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Conflict of interest

None.

Appendix A. iMCD survey questions

Attitudes

HOW MUCH DO YOU AGREE OR DISAGREE WITH THE FOLLOWING STATEMENTS ABOUT CYCLING?
FOR ME, TO RIDE A BICYCLE FOR REGULAR OR DAILY JOURNEYS IS:
Something i like
HOW MUCH DO YOU AGREE OR DISAGREE WITH THE FOLLOWING STATEMENTS ABOUT WALKING?
FOR ME, WALKING FOR REGULAR OR DAILY JOURNEYS IS:
Something i like

Strongly agree [1]
Agree [2]
Neutral [3]
Disagree [4]
Strongly disagree [5]
Don't know [6]

We changed the order of answer (i.e., 1. Strongly disagree–5: Strongly agree) for our analyses.

SNS use

INCLUDING ALL THE WAYS YOU ACCESS THE INTERNET, {INCLUDING USING APPS ON YOUR PHONE}, USING THE PHRASES ON THIS CARD HOW OFTEN DO YOU DO THE FOLLOWING THINGS ONLINE?

Looking at social networking sites or apps (such as Facebook, Twitter, Instagram)

Response options

Several times a day [1]
At least once a day [2]
A few times a week [3]
At least once a week [4]
At least once a month [5]
Less than once a month [6]
Never [7]

We changed the order of answer (i.e., 1. Never–7: Several times a day) for our analyses.

BMI

COULD I ASK YOU YOUR HEIGHT?

AND WOULD YOU MIND IF I ASKED YOU WHAT YOUR WEIGHT IS?

Health

DO YOU HAVE ANY PHYSICAL OR MENTAL HEALTH CONDITIONS OR ILLNESSES LASTING OR EXPECTED TO LAST FOR 12 MONTHS OR MORE?

Yes [1]
No [2]
Don't know [8]
Refused [9]

HOW OFTEN ARE YOU ABLE TO TRAVEL TO PLACES SUCH AS WORK, SHOPPING, HEALTH CARE, ETC. ON YOUR OWN?

Always [1]
Most of the time [2]
About half of the time [3]
Sometimes [4]
Never [5]

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