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Using digital social market applications to incentivise active travel: Empirical analysis of a smart city initiative

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ABSTRACT

Information and communication technologies (ICTs), such as mobile communication networks, and behaviour-based approaches for citizen engagement play a key role in making future cities sustainable and tackling persistent problems in high-density urban areas. In the context of Sharing Cities, an EU-funded programme aiming to deliver smart city solutions in areas such as citizen participation and infrastructure improvements of buildings and mobility, a prominent intervention has been the deployment and monitoring of a Digital Social Market (DSM) tool in Milan (Italy). The DSM allows cities to engage with residents and encourage sustainable behaviours by offering non-monetary rewards. This paper aims to evaluate the effectiveness of the DSM approach to promote active travel (cycling and walking) by analysing the data collected through the app as well as through participant surveys. Our model results show that a broader engagement with the DSM app (number of claps to posts, number of posts made, non-monetary rewards earned by participating in non-travel events) is positively correlated with the monitored level of active travel. Lifestyles, attitudes, and social influence also explain the variability in cycling and walking. This highlights the importance of investigating these factors when replicating such initiatives on a large scale.

Introduction

As cities account for more than 50% of the global population, 75% of the global energy use and 70% of the global CO2 emissions (International Energy Agency (IEA), 2021), behaviour-based approaches for climate mitigation have the largest potential in cities. While urban infrastructures determine the capacity to deliver urban services, the way people interact with urban systems determines their effective environmental impacts. Therefore, to deliver sizable impacts, behaviour-based approaches to promote sustainable urban living are central to reducing climate change impacts.

Information and communication technologies (ICTs) (e.g. mobile communication networks and the internet), and the integration of this technology within cities, play a key role in supporting sustainable lifestyles in the future (Bibri & Krogstie, 2017; Silva et al., 2018; Yovanof & Hazapis, 2009). Indeed, this technology enables smart cities to be supported as prototypes to manage the issues created by urbanisation (Wu et al., 2018) and enables their sustainable development to tackle the problems (e.g. climate change and inequalities) that have become a popular focus in urban western cities (Angelidou & Psaltoglou, 2017; Yigitcanlar, 2016). The success of a smart city is, therefore, dependent on the citizens' behaviour, and a better exploration of human behaviours and their social interactions during the development of smart cities is fundamental (Naphade et al., 2011). In the everyday life of citizens, several behaviours can be influenced by the rapid dissemination of information through online interactions via web-based applications in real-time (Centola, 2010). Looking at some case studies analysed in different disciplines, we can, for example, observe that the use of web-based applications to report the electricity consumption of a peer network can significantly lead to a reduction in consumption (Peschiera et al., 2010), word-of-mouth interactions through Facebook can have an impact on consumers' decision of purchasing certain types of cars

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(Hutter et al., 2013), virtual communities with a web review system affect the tourism and hospitality industry (Mauri & Minazzi, 2013) and web-based interactions can influence purchasing behaviours of online shoppers (Isa et al., 2016).

Citizen participation and city infrastructure improvements have been at the centre of Sharing Cities, a large European Union Horizon 2020 programme (January 2016 to December 2021) that has aimed to deliver scalable and replicable smart city solutions in three European cities Lisbon (Portugal), London (UK) and Milan (Italy) (Euro Cities & Greater London Authority, 2015; Sharing Cities, 2015). With the cooperation across government bodies, academia and industry, the 34 partners of Sharing Cities have worked to design, integrate and deploy sustainable solutions for low-carbon transport, energy consumption and building retrofit while engaging the citizens as part of the solutions (Zavitas et al., 2019). One of the most prominent citizen engagement initiatives that Sharing Cities has conceptualised and implemented is the large-scale deployment and monitoring of "Digital Social Market" (DSM) tools in Lisbon, London and Milan. In each city, the general DSM framework was deployed using different apps, different contexts and focusing on different sustainable behaviours (Sharing Cities, 2020a). In general, a DSM tool is an online platform developed on a smartphone application through which cities can engage with residents and encourage sustainable behaviours by offering rewards (Rolim & Baptista, 2021; Sharing Cities, 2020b; White and Marchet, 2021). These rewards are not monetary but are instead in the form of tokens that can typically be redeemed through activities supporting sustainable local community living in the form of discounts in shops supporting local commerce or micro-donations to local social institutions (e.g. schools and charities). When the awarded tokens are publicly displayed in online communities, they can also be used for peer-to-peer recognition of sustainable living achievements (White & Marchet, 2021). Indeed, it has widely been investigated that individuals would be attracted to perform an activity when incentives are involved (Ayres, 2010) and these incentives have been used to motivate behavioural changes related, for example, to health (Corepal et al., 2018), water-saving (Novak et al., 2018) and sustainable travel behaviours (Zhu et al., 2020). Under the Sharing Cities project, the DSM apps were deployed in the three cities to test effectiveness in promoting several pro-environmental behaviours (PEBs), such as active travel, participation in community activities, promoting and raising awareness of sustainable living and reducing energy use. Particularly, the increase of walking and cycling share is an important measure to develop urban sustainability towards low carbon and efficient cities (Bullock, Brereton, & Bailey, 2017; Fenton, 2017).

Given the importance of the behavioural aspects for the success of smart city initiatives related to sustainable living (Naphade et al., 2011), what is the effectiveness of such DSM approaches in promoting sustainable mobility behaviours such as active travel, in particular cycling and walking, and how can this effectiveness be evaluated?

This paper contributes to exploring the above research question by analysing data collected through the activity of online social media applications as well as through participant survey responses. Specifically, we address two research objectives within the context of promoting active travel using DSM initiatives. First, we aim to develop an understanding of the relationship between the amount of active travel and the metrics quantifying engagement in a DSM environment, such as the number of posts, comments and participation in physical events promoted digitally through the environment. By using empirical evidence to quantify this relationship, we enable a mechanism for evaluating the effectiveness of the DSM initiative. Secondly, we want to quantify the extent to which lifestyles, attitudes and influence from family and friends are relevant in explaining the variability in DSM user engagement with regards to sustainable lifestyle choices (including active travel).

The research objectives are addressed using the case study of a DSM implementation in Milan, called SharingMi (Sharing Cities, 2020a). Relying on an existing application platform (i.e. the greenApes app, https://www.greenapes.com/en/), SharingMi introduced a personal reward system in exchange for continued citizen-focused behavioural changes around the themes of mobility, energy and consumption reduction and community participation.

This paper thus continues and extends the scientific discussion on subjects that have been prominent in recent years such as the development of smart cities and resilient environments, the promotion of sustainable living and the analysis of social aspects related to sustainable behaviours, focusing, in particular, on encouraging environmentally friendly and healthy travel behaviour (i.e. active travel).

The rest of this paper is organised as follows. Section 2 briefly summarises the current literature on social influence, decisions influenced by online interactions and incentives to encourage the behavioural shift. Section 3 presents the background and conceptual framework. Section 4 shows the methodology adopted in this research. Section 5 illustrates and discuss the results. Finally, Section 6 concludes the paper. A list of abbreviations used in this paper is provided in a table of nomenclature (Table A. 1) in the Appendix.

Literature review

Social influence and digital technologies

As widely studied in social science literature, the decisions made by individuals are often based on the actions of others (Turner, 1991). Social influence might intentionally or unintentionally affect changes in individuals' attitudes, perspectives and actions (Gass & Seiter, 2015) with individuals yielding to social force (Pratkanis, 2007).

According to social psychology theory, individuals tend to conform to seek social acceptance in a group setting (Cialdini & Goldstein, 2004). This involves a change in an individual's attitudes and beliefs, longing to fit in with the social group, where individuals conform to enjoy certain incentives or evade certain forms of penalties (Cialdini & Goldstein, 2004). One might practise sustainable behaviours, which include pro-ecological, frugal, altruistic and equitable actions aimed at the conservation of ecosystems and human resources (Tapia-Fonllem et al., 2013), in order to be part of and feel accepted in a sustainable community to match with their peers' beliefs. This normative influence, which characterises some conformity processes, is an important determinant that could impact decision-making (Nolan et al., 2008). When they are exposed to an unfamiliar social setting, individuals are likely to associate themselves with others for verification (Cialdini, 2007). They would also tend to consult other members of their social group when facing uncertainties (i.e., informative influence). This behaviour is more apparent when individuals do not have sufficient knowledge on the subject matter and they are more inclined to make verdicts which are based on their peers' decisions (French, Raven and Cartwright, 1959). This is, for example, observed in certain parts of the world where electric vehicles are new to the market and the individual's purchasing decision could be dependent on others' reviews and recommendations (Cherchi, 2017).

People influence each other by exchanging information through different modes of interactions, such as face to face interactions and ICTs (Sharmeen, Arentze and Timmermans, 2013). Since an emotional connection is a vital attribute for people (Sarason, 1974), the advent of online social network platforms, such as Facebook and Twitter, where people socialise digitally, have become extremely popular and radically changed the interactions between individuals. These online networking websites act as a medium to enhance communications (Livingstone & Brake, 2010) and to share knowledge and opinions within online social circles (Alassiri et al., 2014). With the rapid dissemination of information via web-based applications on a real-time basis, decisions can be influenced by the opinions shared on the internet. Indeed, previous studies largely show that web-based interactions can impact behaviours in a wide range of different contexts, including purchasing preferences of online shoppers (Chen, Wang, & Xie, 2011; Isa, Salleh, & Aziz, 2016),

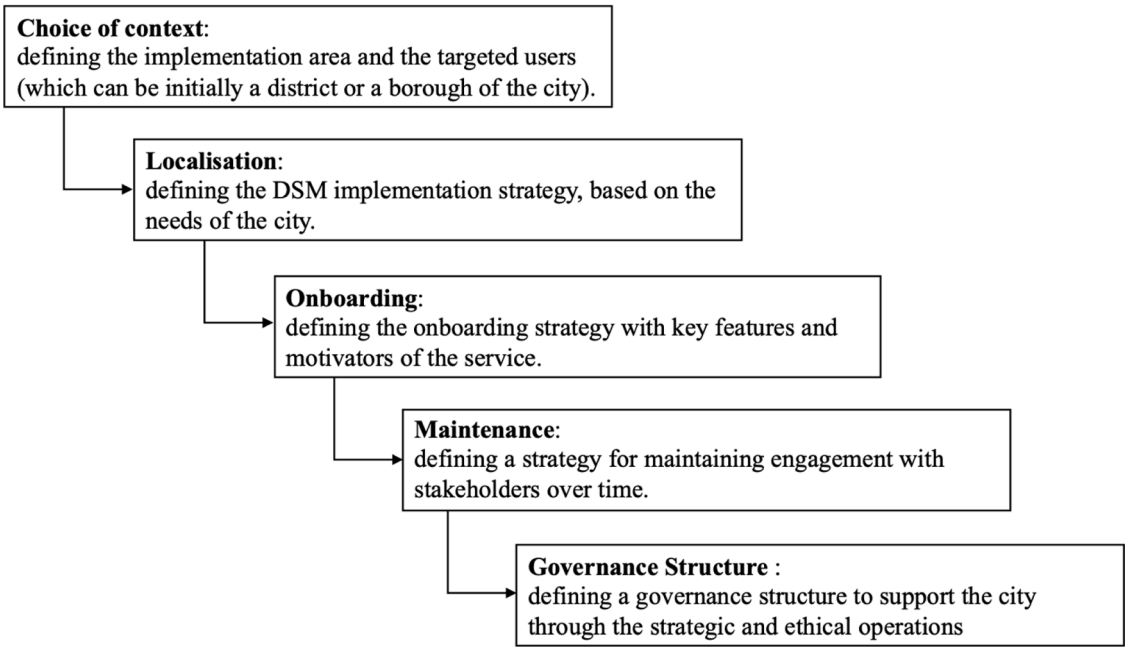

Fig. 1. SharingMi DSM architecture.

decisions made in the hospitality industry based on web reviews (Mauri & Minazzi, 2013) and health behaviours spread in a web-based community (Centola, 2010). These web-based applications can, therefore, be employed in urban areas to boost several types of sustainable behaviours.

"Digital social influence" for sustainable living

City policies are currently focusing on innovative strategies to tackle the growing concerns of climate change through the development of smart city programmes (Yigitcanlar, 2016). This is crucial because, in order to be considered smart, cities need to be sustainable first (Ibrahim et al., 2018; Yigitcanlar et al., 2019). One of the main challenges in urban areas is indeed represented by traffic and its negative externalities, congestion and pollution. With urbanisation sprawling across cities, transport is essential as it provides links for people to reach their destinations. Although there have been several technological improvements to cope with traffic pollution (i.e., the development of low-emission and electric vehicles), the transportation sector is still one of the primary sources of greenhouse gas emissions. The urban transport sector generates 4 gigatonnes of CO2-eq, which is more than 40% of the global emissions from the transport sector (International Energy Agency (IEA), 2021). However, "hard" interventions alone, such as increased cost of cars through taxation and improving public transport system infrastructures, are not entirely effective in encouraging people to adopt sustainable behaviours (Stopher, 2004). City authorities, recognising this, actively consider implementing "soft" interventions, such as through the help of smart applications (Vinci & Di Dio, 2014), to reduce car usage by encouraging a shift towards sustainable transport modes (Cellina et al., 2020; Di Dio et al., 2018; Gärling & Fujii, 2009; Sottile et al., 2020).

Social influence might play a fundamental role in determining the success of these "soft" interventions related to travel behaviour. Besides the individual's attributes and characteristics, their social network might also influence the individual's choice of using public transport (Goetzke, 2008). Similarly, social influence can lead to the adoption of more sustainable travel behaviour, such as cycling (Manca, Sivakumar, & Polak, 2019; Sherwin, Chatterjee, & Jain, 2014) and walking (Kamargianni & Polydoropoulou, 2013). Nonetheless, it has been shown that comparative happiness arising from social and interpersonal comparison is an important factor determining commute satisfaction (Abou-Zeid & Ben-Akiva, 2011). To amplify the effect of social influence to drive certain behaviours, "soft" interventions can be supported by the employment of an online social network platform where people can interact and exchange information, which is one of the main objectives of Sharing Cities project (Sharing Cities, 2020a).

Moreover, information exchange in social interactions might be combined with incentive strategies such that people would be well-informed of their actions and get rewarded for their good actions (Stern, 1999). When an external influence is required to motivate behavioural changes in individuals it is possible to employ the use of incentives (Lehman & Geller, 2004). A consumer's behaviour and decisions are the result of trade-offs between variables associated with benefits and costs, and the provision of incentives might change the perception of these benefits and costs. Individuals are generally attracted to perform an activity when incentives are involved (Ayres, 2010) while reluctant behaviour would be observed when there are no perceived benefits (Kreps, 1997). On the other hand, imposing penalties would have an even greater impact on behavioural shift as the effect of penalties would enable individuals to skew towards compliance behaviours (Amini, Ahmad and Ambali, 2014). Yet, prospect theory in behavioural economics illustrated that view on gains are considered more favourable than the view on losses (Kahneman & Tversky, 2013). Some studies showed that incentives can be a factor in the behavioural shift. They can be used to motivate behavioural change in health for young people (Corepal et al., 2018) and also encourage people to accept weight loss programmes (Promberger, Dolan and Marteau, 2012). Sustainable behaviours could also be encouraged using incentives and their positive effects can be observed on water-saving behaviour (Novak et al., 2018), electric vehicles purchase (Hardman et al., 2017) and sustainable behaviours in travel, such as departure time planned during off-peak-hours (Zhu et al., 2020). Nonetheless, the provision of monetary and non-monetary incentives can have different impacts on environmental attitudes and behaviours. Indeed, behavioural shifts through monetary incentives can be temporary (i.e., it fades with the end of the incentive), while non-monetary measures, which imply knowledge and moral persuasion, can have a greater impact on long-term behaviours towards sustainability (Rajapaksa et al., 2019).

The use of incentives might be very useful in creating awareness about sustainable programmes (Timlett & Williams, 2008). However, such programmes are characterised not only by the use of incentives but also by a certain level of communication and engagement that can even play a more important role in the behavioural shift of the individual. Therefore, it can be difficult to isolate the effect of incentives from the effect of communication and engagement (Timlett & Williams, 2008).

While existing studies recognise that social influence and incentives are able to spur decision making on sustainable living, there is still limited research on the effectiveness of social influence through online interactions in promoting sustainable living. The research presented in this paper contributes to filling this gap by examining online social interactions and their effectiveness in promoting active travel amongst the participants of the SharingMi initiative in Milan, which is part of the EU-funded Sharing Cities project. The aim of this initiative was to promote sustainable behaviours through the local implementation of a DSM (built upon an existing app; greenApes). This application was used to enable the exchange of information amongst SharingMi participants about their own sustainable living practices, to promote sustainable activities such as active travel, and to provide non-monetary incentives for participation in such activities.

In summary, this paper contributes to the literature by presenting novel evidence about the relationship between personal active travel, and the influence that can be generated by DSM apps through online interactions, posts and "claps"[1] about sustainable lifestyle practices and non-monetary rewards.

The SharingMi initiative as an empirical context

The DSM is a smartphone application that provides a platform to facilitate the exchange of information and interaction among individuals, and the accounting of actions (in the real world and online) that are rewarded. This is central to sustaining citizen engagement and building the foundation for behavioural changes (Cellina et al., 2020; White & Marchet, 2021).

In the context of Sharing Cities, from an operational point of view, as illustrated by White and Marchet, the DSM architecture used to develop and implement SharingMi can be summarised as shown in Fig. 1:

Built upon an existing app "greenApes" (https://www.greenapes.com/en/), a digital platform rewarding subscribers for sustainable actions and ideas, SharingMi was launched on the 21st of February 2019 in the pilot area of Porta Romana Vettabbia, but was quickly opened up to the whole Milano community. By signing up to the DSM and participating in a range of sustainability-related activities, participants could earn tokens: a) by changing the way they get around the city (i.e. cycling, walking or using public transport instead of using a car), b) by reducing the energy they use at home or switching to renewable energy, c) by joining city challenges and events, or d) by sharing green ideas and stories with the SharingMi online community. They earned non-monetary rewards (called "BankoNuts"), which could be redeemed to access goods and services at shops and other outlets, as a reward for leading a more sustainable or greener lifestyle.

Different steps of data collection have been undertaken to fulfil different objectives for the monitoring process.

App users' questionnaire

To perform a disaggregated analysis relating app usage to participant attitudes, a web-based questionnaire was developed and administered from February to April 2020. An identifier linking questionnaire data to individual app users was used for those respondents who gave consent to access their app activity for research purposes, and 83 greenApes users responded to the survey. The attitudinal questionnaire contained psychometric statements that are commonly used to investigate attitudes and norms in several fields of research such as transportation, behavioural economics, psychology and sociology. We drew on the previous literature to develop this list of psychometric statements. In particular, the statements related to attitudes on sustainable living and app usage are drawn based upon existing theoretical frameworks. The first is the Theory of Planned Behaviour (TPB) (Ajzen, 1991) which states that acted behaviours are centralised around the intention of the individual to perform the activity. This intention is in turn influenced by factors such as attitudes towards the behaviour (how the individual perceives the outcome of the activity), subjective norms (how people around the individual influence his/her intention to perform the activity) and perceived control behaviours (how the individual views the difficulty level of the activity, influenced by experiences). The second theory is the Reflexive Layers of Influence (RLI) (Axsen & Kurani, 2014), which attempts to explain how social interactions affect the adoption of new technology. This theory identifies three layers that characterise the influence on adoption: awareness, assessment and self-concept. We apply these theories to the adoption of sustainable living actions. In the case of the adoption of sustainable lifestyles, the TPB explores for example how attitudes towards sustainable living influence the adoption of sustainable actions (e.g. using sustainable travel modes like cycling or walking). In the same context, the layers of influence (from RLI) are the individual's awareness about sustainable living, the assessment of the information related to sustainable living and, finally, the self-concept, that is the understanding one has of how sustainable living fits his/her own life.

The two above theories applied to the adoption of sustainable living allow us to analyse the interactions between the DSM app users and how these translate into sustainable living behaviours. Finally, the only socioeconomic information available is on age, gender and city of residence. 67% of the respondents are female and 64% are from Milan. Unfortunately, age is not available for 61% of respondents and could not be employed during the estimations.

App usage data

The usage of the greenApes app over 17 months (from February 2019 until the end of June 2020) was obtained from the app administrators. This included posts, comments, claps, demographics, interests, challenges, and non-monetary rewards for leading a more sustainable or greener lifestyle. Regarding the active travel information (e.g. walking and biking distance in meters), the greenApes app was able to track participants' walking and cycling distance by linking up with tracker applications, such as AppleHealth and GoogleFit. In total, 7255 observations for 83 greenApes users who responded to the questionnaire were collected from the app. For our analyses, these observations were aggregated weekly for each respondent. This led to weekly counts of active km travelled as well as weekly counts of other app activities (e.g. posts and claps) for each individual over an observation period, that starts when the individual performs his/her first activity or challenge through the app and ends on the 30th June 2020. Overall, the final panel dataset used for the estimations includes 3986 weekly observations.

Conceptual Framework

The relationship between the data collected through the app and the questionnaire can be organised into the conceptual framework represented visually in Fig. 2. This shows four sets of factors that could potentially affect active travel among the SharingMi participants, as measured in km travelled per week, which could also interact with each other. While the identification of a causal nexus between these factors and active travel would require experimental design strategies that were not considered at the time of the design of the SharingMi initiative, this study analyses the observed data to explore the relationship in Fig. 2,

[1] A button in the app that users can click to show appreciation for other users' posts. Posts and claps are visible to all users.

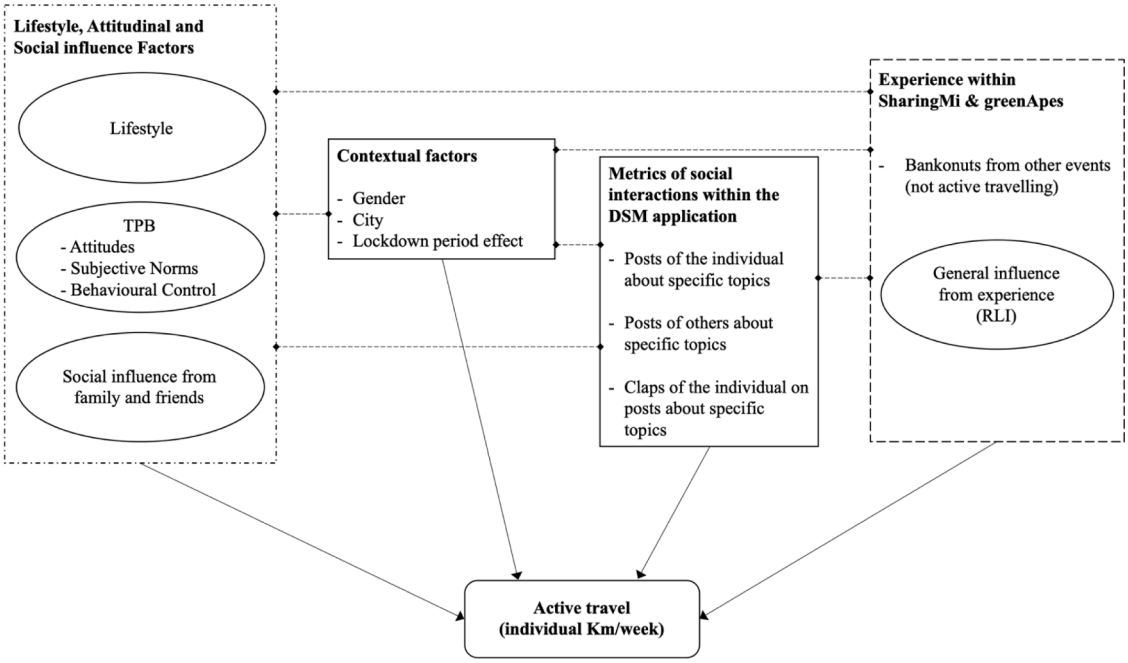

Fig. 2. Conceptual framework.

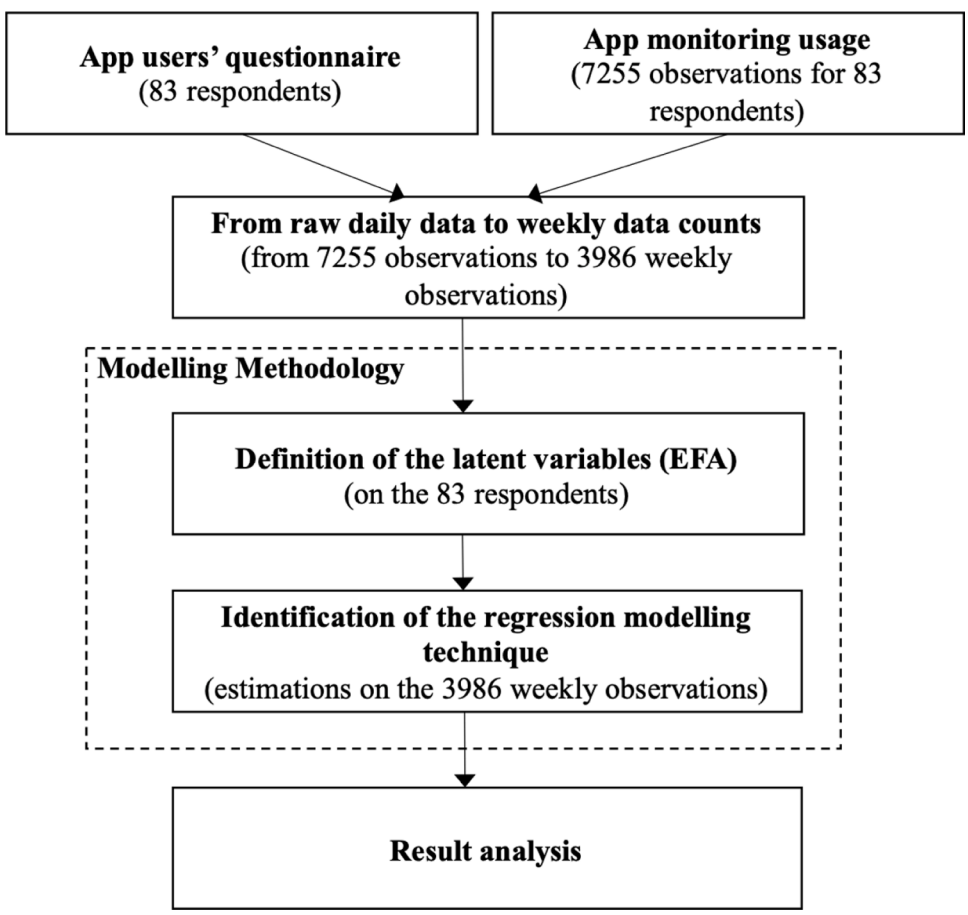

Fig. 3. Analysis steps - from data collection to results.

and potentially support the generation of hypotheses for further experimental studies to establish causality.

Contextual factors include socioeconomic variables (age and city of residence) and a variable to consider the fixed effect of the pandemic lockdown period in Italy (9 March 2020 - 18 May 2020). Lifestyle, attitudinal and social influence factors are a set of latent variables that

Table 1
Test of sampling adequacy and reliability.

Test	Threshold	Value			
		Lifestyle	TPB	Social influence from family and friends	RLI
Test of multicollinearity	det > 0.00001	0.0376	0.0290	0.0714	0.0024
KMO sampling adequacy	KMO > 0.5	0.75	0.70	0.74	0.86
Bartlett's test	p < 0.001	1.00^-23	2.71^-23	9.44^-33	1.40^-94
Reliability test (McDonald's ω)	ω > 0.7	0.83	0.78	0.87	0.96

were obtained from the analysis of respondent statements regarding lifestyle, TPB constructs (attitudes, subjective norms and behavioural controls) and social influence from family and friends. As measures of the influence generated by the social interactions through the DSM app, three variables were identified: number of posts per week written by the individual about specific topics (e.g. cycling, biking or subjects other than mobility), number of posts per week written by other individuals about specific topics, and number of claps per week made by the individual on posts about specific topics. Finally, to account for the influence of the experience within the SharingMi & greenApes application, one variable measured the number of BankoNuts earned from events not related to active travel while the other variables were obtained from the latent construct related to the overall influence from the experience (i.e., the RLI).

Methodology

This research explores the correlation between the number of counted km per week of active travel by each individual (over several weeks) and a number of directly measurable attributes (e.g. number of posts) and latent variables identified from four theoretical constructs. As shown in Fig. 3, the model methodology presents two sequential phases 1) define the latent variables resulting from the analysis of the psychometric statements in the web-based survey and 2) identify the best regression model to analyse the response variable (i.e. the counted km per week).

Defining the latent variables

First, exploratory factor analysis (EFA) was performed to understand the level of correlation among the statements and identify the underlined latent variables characterising the respondents. These statements were divided into 4 theoretical constructs based on their main theme and the related theory from which they are adapted (lifestyle, TPB, social influence from family and friends, RLI). The analysis of sampling adequacy and reliability was performed on each of the constructs. As shown in Table 1, none of the constructs had particular problems of sampling adequacy or reliability. The test of multicollinearity showed there was no problem with multicollinearity (Prato, Bekhor and Pronello, 2005). The KMO index always greater than or equal to 0.70 indicated a good level of sampling adequacy (Kaiser, 1974). The null hypothesis of the identity matrix can always be rejected according to the very small p-values of Bartlett's test (Bartlett, 1951). Finally, McDonald's omega was employed to test sample reliability. Differently from Cronbach's alpha, which is used for unidimensional tests of reliability, McDonald's omega is more appropriate in multidimensional tests (Revelle & Zinbarg, 2009; Sijtsma, 2009). All the four constructs showed high or great reliability with each omega greater than or equal to 0.78.

EFA was implemented on each theoretical construct using principal axis factoring and varimax rotation. The similarity of the output generated by EFA, i.e. the factor loading values, are used to identify the latent factors (Comrey & Lee, 1992; Tabachnick, Fidell, & Ullman, 2007). We consider a factor loading greater than |0.42| as the threshold to find a balance between keeping important items and avoiding overlapping of items for different factors. The latent factors extracted for each theoretical construct are presented below in Tables 2 to 5.

First, the lifestyle practices and lifestyle openness (or liminality) were evaluated according to the respondent's frequency of engagement in each activity (Axsen, TyreeHageman and Lentz, 2012). The results of EFA identified three main factors in this specific sample of greenApes users. Active people who love nature and the outdoors, also like playing sports, recreation or exercise, socialising with others and have different

Table 2
EFA, Lifestyle (adapted from RLI).

Activities	Active & Social	Altruistic -Spiritual	Consumeristic
Discussing or researching automobiles.	0.03	-0.12	0.5
Home remodelling or "fix-it" projects.	0.17	0.25	0.5
Nature and the outdoors.	0.53	0.25	0.35
Playing sports, recreation or exercise.	0.53	0.22	0.33
Religious or spiritual practices.	0.07	0.71	0.05
Shopping.	-0.13	0.05	0.44
Socializing with others.	0.62	0.25	0.02
Taking care of or spending time with family.	0.13	0.64	0.01
Volunteering or giving to charity.	0.1	0.63	0.05
I often try new activities.	0.53	-0.06	0.07
I have many different groups of friends.	0.79	0.07	-0.27
I often make new friends.	0.75	0.14	-0.09

Note. in bold the factor loading greater than |0.42| characterising the latent factors.

Table 3
EFA, TPB.

Statements	Pro-environment	Pro-sharing	Active modes-aware
More cycling and walking contribute to reducing pollution	0.63	-0.03	-0.28
More public transport contributes to cleaner air	0.46	0.14	-0.33
I like taking part in reducing climate change	0.31	0.44	-0.09
Cities' regulations must protect the environment	0.81	0.16	0.08
I like helping the environment	0.71	0.28	0.17
Sharing goods and services benefit me financially	0.18	0.69	-0.06
I can see myself engaging in sharing clothes often in the future	0.4	0.43	0.21
I can see myself sharing my car for a trip in the future	0.06	0.62	0.1
I find the app easy to use	0	-0.29	0.14
I quite enjoy using the greenApes app	0.18	0.12	0.38
In my city, there are many cyclists and pedestrian	0.04	-0.36	0.61
In my city, many people like cycling and walking during their spare time	-0.25	0.02	0.71
In my city, drivers do not respect cyclists	0.13	0.2	-0.21

Note. in bold, the factor loading greater than |0.42| characterising the latent factors.

Table 4
EFA, Social influence from family and friends.

Statements	Discussing sharing and reusing	Discussing sustainable travel modes and the danger of cycling
You discuss with family and friends about cycling and walking	0.42	0.58
You discuss with family and friends about using public transport	0.28	0.82
You discuss with family and friends about reusing old clothes	0.85	0.2
You discuss with family and friends about sharing old clothes	0.94	0.15
You discuss with family and friends about shopping in local markets	0.43	0.35
Family and friends think cycling in the traffic is dangerous	0.02	0.45
Family and friends think drivers do not respect cyclists	0.26	0.3

Note. in bold, the factor loading greater than |0.42| characterising the latent factors.

Table 5
EFA, Influence from experience (adapted from RLI).

Statements	Awareness of sustainable living	Assessment of sustainable living	Self-concept
Awareness of sustainable living.	0.76	0.38	0.37
Other people's perceptions of sustainable living.	0.77	0.33	0.34
Sustainable living benefits for me.	0.24	0.67	0.53
Sustainable living benefits for society.	0.36	0.81	0.18
Environmental impacts of sustainable living.	0.27	0.79	0.27
How sustainable living fit with my lifestyle.	0.31	0.23	0.85
My overall understanding of sustainable living.	0.33	0.31	0.78

Note. in bold, the factor loading greater than |0.42| characterising the latent factors.

groups of friends. This first factor is a combination of lifestyle practices and lifestyle openness items. A second lifestyle tendency defines more of a spiritual person as it is characterised by the correlation between religious activities with caring and volunteering activities. The third factor represents the consumeristic individual, who likes to research or discuss cars, like home remodelling and shopping (Table 2).

Table 3 shows the analysis of latent psychometric tendencies that characterise the components of the Theory of planned behaviour for which attitudes, norms and perceived behavioural control are behind the intention of a choice or behaviour (Ajzen, 1991;Hamari et al., 2016). As previously mentioned, in this specific case, the statements were adapted to reflect the intention to live sustainably (which is, in fact, the main purpose of the app) and were evaluated on a 5-Likert scale according to the level of agreement with each statement. Three latent variables that characterise the respondents are identified. The "pro--environment" profile cycles and walks to reduce pollution, uses public transport to reduce pollution, and wants to help the environment. The "pro-sharing" profile includes people that think sharing goods and services is financially beneficial and can see themselves often sharing their car. The "active modes-aware" profile is related to subjective norms on

Table 6
Latent variables.

Constructs	Latent Variables
Lifestyle	Active and Social
	Altruistic-Spiritual
	Consumeristic
Attitudes, Subjective Norms and Behavioural Control	Pro-environment
	Pro-sharing
	Active modes-aware
Social influence from family and friends	Discussing sharing and reusing
	Discussing sustainable travel modes and the danger of cycling
Influence from experience	Awareness of sustainable living
	Assessment of sustainable living
	Self-concept

active travelling modes of transport (i.e. walking and cycling) that characterise the city where the respondents live.

The third theoretical construct regarding the possible social influence from external sources gives an indication about the level of agreement on statements that involve family (e.g. parents and siblings) and close friends (Table 4). The first identified factor refers to discussions with family and friends about sharing and reusing old clothes and shopping in local markets, while the second factor correlates discussions about environmentally friendly modes of transport and the perceived danger of cycling.

Finally, to investigate how SharingMi and the greenApes app experience changed the participant's understanding of sustainable living, a series of statements were evaluated by stating the level of change (from no change to significant change). The factors reflect the three layers characterising the RLI theory: awareness of sustainable living, assessment of personal, societal and environmental benefits of sustainable living and effect of self-concept and lifestyle of sustainable living.

After the investigation of high factor loadings, the following latent variables were identified (Table 6):

These latent variables were included in the model as factor scores, which are composite variables providing information on factors identified during the EFA (DiStefano, Zhu and Mindrila, 2009).

Identifying the regression technique

As previously mentioned, the response variable considered in this work is the counted number of km per week of active travel by each person over the observation period (starting from their first activity in the app). We are technically dealing with count outcomes since observations are measured as non-negative integer values {0, 1, 2, …} (Cameron & Trivedi, 2013). The employment of a linear regression model, which assumes normally distributed residual errors, can produce inconsistent and biased results (Long, 1997) for two reasons. First, the data is positively skewed, and many observations have 0 value (Fig. 4), which prevents a possible logarithmic transformation of the skewed distribution into a normal distribution. Second, a linear regression model can produce wrong, negative predicted values (Gardner et al., 1995). Therefore, the employment of Poisson and negative binomial regression models are recommended (Gardner, Mulvey, & Shaw, 1995; Long, 1997). The Poisson regression model is characterised by the following probability distribution (Eq. 1):

$$Pr(y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!} = for\, y = 0, 1, 2 \tag{1}$$

Where y is the observed response variable and μ is the expected value of a Poisson distribution.

The negative binomial regression model is used when the Poisson regression model presents problems of overdispersion that arise when the dispersion in the outcome is underfitted by the model (Long &

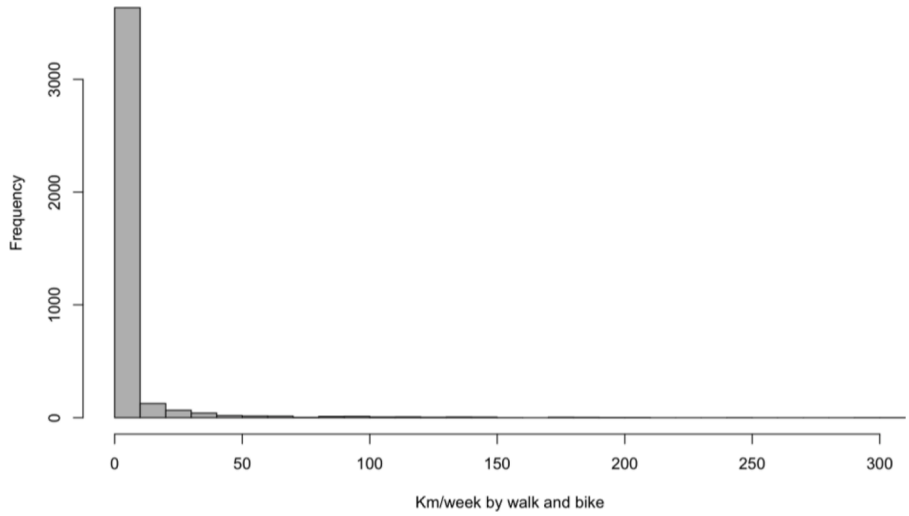

Fig. 4. Frequency distribution of the response variable.

Freese, 2006). Indeed, this type of model includes a parameter α to take into account the unobserved heterogeneity within the observations and to help address the overdispersion problem (Cameron & Trivedi, 2013; Long, 1997) The probability distribution for the negative binomial becomes (Eq. 2):

$$Pr(y\mu,\alpha) = \frac{\Gamma(y+\alpha^{-1})}{y!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y} \quad (2)$$

Where μ is the expected value of a Poisson distribution, α is the dispersion parameter and $\Gamma(\ )$ is the gamma function as the error added in the negative binomial regression model is assumed gamma distributed (Cameron & Trivedi, 2013; Long, 1997). When $\alpha = 0$, the negative binomial distribution matches the Poisson distribution.

For this study, Poisson regression was initially tested. However, due to considerable overdispersion, a negative binomial regression was employed. Moreover, a random effect was considered in order to investigate the variation across observations of the same individual. The models have been estimated using maximum likelihood estimation with the R package "lme4" which enabled us to fit a generalized linear mixed-effects model with both fixed and random effects (Bates et al., 2012).

Our results, though not representative for a population of urban travellers, are meant to provide insights regarding the effectiveness of DSM apps in promoting sustainable travel behaviour.

Model results and discussion

The estimation of the negative binomial regression model showed several interesting and significant results (Table 7). All the variables of the conceptual framework presented in Fig. 2 were tested during the model estimation. The final model shows the best possible combination of the explanatory variables (Note that some variables have been scaled, as indicated in Table 7, to help the model converge during the estimations). To better visualise the results, Fig. 5 provides a diagram with the directions of the estimates.

Activity in the app

There is a positive relationship between the active travel km per week and the activity of the users on the app. Indeed, according to the estimates, the greater the number of written posts and claps made by the individuals to the posts of others, the greater is the expected number of active km travelled by walk and bike.

Specifically, the three parameters related to the activity in the app are all positive and significant at more than 97% confidence level. First, as expected, there is higher sensitivity for the number of claps on posts about mobility compared to posts about other subjects related to sustainable living. Second, the number of posts about walking submitted to the app by the individual also seems to positively affect the number of km a week. No significant estimates were found related to the number of posts about cycling or other subjects not concerning mobility. Several estimations were also performed to test the effect of the number of posts written by others by subject (i.e., walking, cycling, mobility in general and other subjects) but also in this case the parameters were found to be not significant.

Therefore, the active travel participation of the individual seems to be affected by the posts of others that are considered to be important and "deserve a clap" more than the number of posts of others in general. It also seems to be connected to the individuals' willingness to socially interact on the app, share their experience through posts, specifically about walking activities, and influence the rest of the community (Wang & Fesenmaier, 2004).

Lifestyle

For what concerns the lifestyle segment, the "Active and Social" lifestyle is positively correlated with the number of active km travelled. Although it is only significant at a 90% confidence level, it is worth noting that factors related to lifestyle openness (also called liminality) tend to be associated with interest in environmentally sustainable behaviours: e.g. the willingness to buy an electric vehicle (Axsen, Orlebar, & Skippon, 2013; Manca, Sivakumar, Daina, Axsen, & Polak, 2020) . A positive correlation was also observed with the "consumeristic" lifestyle, while people devoted to "Altruistic-Spiritual" activities are negatively correlated with the active travel km. Arguably, Altruistic-Spiritual profiles may prefer to avoid potentially slower active modes to leave more time for activities meaningful to them, while consumeristic SharingMi/greenApes profiles may engage in more active travel to "buy locally". It is important to also note that this analysis does not benefit from the availability of a wide range of sociodemographic descriptors and therefore the factor analytic constructs could be proxying for sociodemographics.

TPB

Amongst the TPB variables, participants with "pro-sharing" attitudes are less likely to participate in active travel-related events. This negative correlation (significant at a 94% confidence level) is not necessarily surprising, as the identified "pro-sharing" attitude specifically relates to

Table 7
Model results.

Fixed effects:				
Segments	Parameters	Estimate	t-test	
	Intercept	-4.216	-5.21	***
Activity in the app	Claps to posts on active travelling per week * 10^{-2}	3.725	2.22	*
	Claps to posts on other subjects (not active travelling) per week * 10^{-2}	2.279	3.77	***
	Posts made by the individual on walking per week * 10^{-1}	1.063	2.44	*
Lifestyle	Latent variable – Active and Social	0.855	1.69	ˆ
	Latent variable – Altruistic-Spiritual	-1.808	-3.38	***
	Latent variable - Consumeristic	1.218	2.13	*
TPB. Attitudes	Latent variable – Pro-sharing	-0.971	-1.88	ˆ
TPB. Behavioural control	Dummy variable - Quite enjoying using the GreenApes app	2.533	2.82	**
Influence from family and friends	Latent variable - Discussing sustainable travel modes and the danger of cycling	-1.653	-3.06	**
Influence from experience	Bankonuts earned from other events (not active travelling) per week * 10^{-3}	2.132	2.08	*
Contextual factors	Dummy variable - Living in Milan during lockdown period	-0.580	-2.69	**
Random effects:	Std.dev.	95% conf.int.		
Intercept varying across Individuals (83 groups)	3.29	2.60 - 4.28		
	Value			
Number of observations	3986			
Df residuals	3972			
Log-Likelihood	-4421			
AIC	8870.6			
BIC	8958.6			
Testing for Under/ Overdispersion and Zero-inflation:	Ratio Obs/Sim	p-value		
Nonparametric dispersion test	1.013	0.68		
(Null hypothesis H_0. mean deviance residual fitted = simulated-refitted)	(H_0 cannot be rejected, which means there is no evidence of overdispersion or underdispersion)			
Zero-inflation test	0.974	0.4		
(Null hypothesis H_0. observed zeros = expected zeros with simulation)	(H_0 cannot be rejected, which means there is no evidence of zero inflation)			

Significance of parameters: 0 *** 0.001 ** 0.01 * 0.05 –0 *** 0.00 ˆ 0.1

sharing goods and services, rather than experiences. Furthermore, amongst the items with the highest loading for this factor, there is a statement that specifically refers to "sharing their car for a trip in the future", which could be picking up on the individuals who own a car.

Further, an indicator variable "quite enjoying using the greenApes app" (taking the value 1 if the person agreed or strongly agreed, 0 otherwise) suggests that users who enjoy the app are also more likely to engage in active travel. However, this is likely to be capturing self-selection behaviour as it could equally include individuals who enjoy using the app as they enjoy participating in the active travel events as well as individuals who participate in active travel because they find the app enjoyable to use. What is certain is that the two are strongly and positively correlated.

Influence from family and friends

For this segment, the variable concerning participants who "discuss sustainable travel modes and the danger of cycling" with family and friends was significant at more than 99% confidence level, and was predictably negatively correlated with active travel (which includes cycling). This suggests that influence from other sources, not necessarily coming from online interactions, need to be taken into account to better understand the success of such interventions.

Influence from experience

The latent variables related to the RLI theory, "Awareness", "Assessment" and "Self-concept", did not turn out to be statistically significant. Instead, earning BankoNuts from other events that are not about active travel (e.g. food, waste management and fashion) is positively and significantly correlated to participation in active travel events. This shows that being involved in multiple activities which also provide incentives is strongly correlated with overall levels of participation and the success of the online community (Wang & Fesenmaier, 2004).

Contextual factors

Since the period of observation included the COVID-19 impact (i.e. the lockdown in Italy lasted 3 months from March to May), a dummy variable was included to consider the fixed effect of the lockdown in Milan (i.e. the city directly involved in the SharingMi programme) compared to other cities during the lockdown and, in general, the rest of the other monitoring periods without lockdown. Given the negative and significant parameter, the greenApes user in Milan seemed to walk and cycle less during the lockdown. This can also be related to the very strict lockdown imposed in Milan and its region, which was the area affected by the first outbreak in the Western part of the world.

Finally, the random effect, capturing the effect of intercepts varying across individuals, is statistically significant at more than 95% confidence level. In terms of goodness-of-fit, it is important to test the presence of overdispersion and underdispersion, which are manifested when the residual variance is respectively larger or smaller than expected given the fitted model. A non-parametric dispersion test on the re-fitted residuals (Hartig, 2019), to investigate the null hypothesis H_0 that the mean deviance residual fitted equals the simulated-refitted, was performed. According to the test, the null hypothesis cannot be rejected so there is no evidence of overdispersion or underdispersion. Moreover, a zero-inflation test has also been performed to investigate the null hypothesis H0 that the observed zeros equal the expected zeros with simulation. Again, the null hypothesis H0 cannot be rejected, which means there is no evidence of zero inflation. Both tests can be found in Table 7.

Conclusions

Smart city initiatives include a wide range of innovative measures to achieve sustainable living and tackle the challenges faced in the upcoming decades. And yet, the current approaches taken towards smart cities development has mainly been top-down. To achieve the long-term sustainability goals, behavioural change among citizens is necessary and one of the potential tools to facilitate this change is the introduction of DSM apps into the market. The DSM is a bottom-up social approach to share information about users' sustainable actions and facilitate interaction within the online platform.

This study aims to evaluate the effectiveness of DSM approaches to promote active travel through the SharingMi DSM implementation in Milan. SharingMi introduced a personal reward system in exchange for

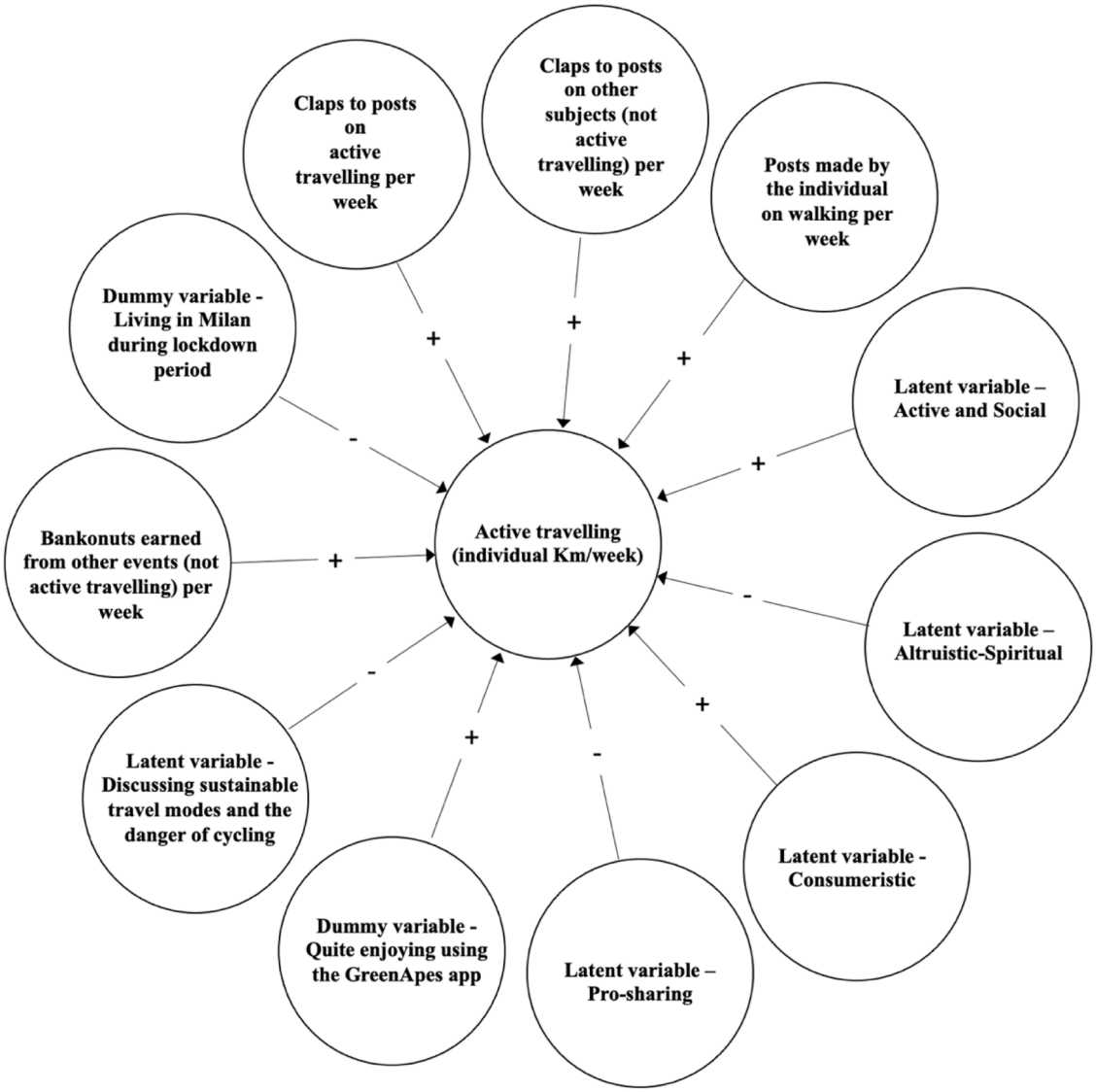

Fig. 5. Variables' direction.

continued citizen-focused behavioural changes around the themes of mobility, energy and consumption reduction and community participation. To achieve this aim, we developed a conceptual framework to interpret the relationship between the amount of active travel and metrics quantifying engagement in the DSM environment such as the number of posts, comments and participation in physical events promoted digitally in this environment. The conceptual framework also represented the relationship between lifestyles, attitudes and influence from family and friends of DSM participants and engagement in active travel monitored using the DSM app.

The conceptual framework was empirically operationalised using sequential exploratory factor analyses to identify latent variables from underlying indicators of individual lifestyles, attitudes, and social influence; and a random-effect Poisson regression to account for the panel nature of the app usage data and active travel data monitored by the app.

Our results show that broader engagement with the DSM app (number of claps to posts, posts made, rewards earned by participating in non-active travel events) is positively correlated with the monitored level of active travel.

Furthermore, lifestyles, TPB attitudes and behavioural controls, and social influence significantly explained the variability in cycling or walking as measured by the app. In particular, amongst the interesting relations that were uncovered and warrant further study, are:

- A negative correlation between monitored active travel and the Altruistic-Spiritual lifestyle
- A positive correlation between monitored active travel and the Consumeristic lifestyle
- A negative correlation between monitored active travel and the Pro-sharing attitude (where pro-sharing are those individuals are those who are likely to share goods and services, including car trips).

The results of this study are, essentially, exploratory in nature, and provide novel insights which can be tested on a larger, representative population to generate population inferences.

Future research should analyse the causality nexus between the relationships identified, using an appropriate experimental design for the deployment of the app and its features.

A particular aspect that deserves further investigation through the design of the experiment, in the context of the effectiveness of DSM approaches to promote sustainable living, is the use of non-monetary rewards. The perfect correlation between active travel distance and rewards gained by SharingMi participants to participate in active travel

events did not allow this analysis. As the concept of digital social markets relies on the use of non-monetary rewards, this is a quite pressing piece of research.

Additionally, since very few socioeconomic characteristics were disclosed in this study (for privacy reasons), we believe that it is important in future studies to obtain such information as these variables enable the analyst to better understand the preference heterogeneity.

Finally, future studies would benefit from monitoring the individuals before the DSM deployment. This would ensure that we have a baseline on how people behaved before the DSM intervention and would enable us to extend the analysis to potential shifts from previously used modes of transport.

Declaration of Competing Interest

The Authors declare that there is no conflict of interest.

Author contributions

Francesco Manca: Conceptualisation, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing. Nicolò Daina: Conceptualisation, Methodology, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing. Aruna Sivakumar: Conceptualisation, Methodology, Writing - Review & Editing, Supervision, Project administration. Jayne Wee Xin Yi: Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing. Konstantinos Zavistas: Investigation, Writing - Review & Editing, Resources. Giuliana Gemini: Investigation, Writing - Review & Editing, Resources. Irene Vegetti: Investigation, Writing - Review & Editing, Resources. Liam Dargan: Investigation, Writing - Review & Editing. Francesco Marchet: Investigation, Writing - Review & Editing, Resources, Data Curation.

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Appendix

Table A1

Table A1
Table of nomenclature.

Abbreviation	Definition
conf.int.	Confidence interval
CO2-eq	Carbon dioxide equivalent
DSM	Digital social market
EFA	Exploratory factor analysis
ICT	Information and communication technology
KMO	Kaiser-Meyer-Olkin
Obs	Observed
PEB	Pro-environmental behaviour
RLI	Reflexive Layers of Influence
Sim	Simulated
Std.dev.	Standard deviation
TPB	Theory of Planned Behaviour

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