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Understanding the influence of new and emerging data forms on mobility behaviours and related health outcomes

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ABSTRACT

Introduction: Transport and health are complex, evolving and interacting systems, which are increasingly influenced by new and emerging data forms. In this study we address the research question, *"How could New and Emerging Data Forms improve understanding of mobility behaviours, and the related health outcomes, of different population subgroups?"*
Methods: We build on an existing causal loop diagram (CLD) of the transport-health system to include the influence of New Data & Technologies, through a novel online Delphi approach to system dynamics modelling.
Results: We present an improved CLD of the transport-health system and have identified the potential influence that Persuasive & Monitoring Technologies could have on transport-related health, including insights on the characteristics for representing and assessing them.
Conclusions: The findings presented in this study can improve the design of holistic future-focused transport, health and data policies and the application of system dynamics to these areas, and as such are of relevance to researchers, policy makers and system dynamics practitioners.

1. Introduction

Both transport and health are complex systems that can be understood and influenced by new and emerging forms of data (Grant-Muller et al., 2018). Transport influences public health through various mechanisms of different magnitudes and timescales (Khreis et al., 2019; Glazener et al., 2021; Widener and Hatzopoulou, 2016). Provision of transport services and the individual use of particular modes affect levels of (and exposure to) air pollution, physical activity, personal injury and traffic collisions, which give rise to disease burdens. Transport is also a mechanism for the transmission and spread of a variety of infectious diseases (such as COVID-19). Well-being and mental health can also be strongly affected by the ability to move around and the conditions (e.g. comfort, security, safety) of the movement, in numerous ways. The exposure itself is spatio-temporally specific. The impacts (both positive and negative) on health occur over different time scales, and are dependent on socio-demographics, existing health, infrastructure features and behaviours. There are proven connections between mobility and numerous diseases, including cancers, lung and heart conditions and dementia (Woodcock et al., 2009). On the other hand, active forms of transport can be positively linked to health outcomes and low carbon mobility has potential to also reduce local air pollution (Macmillan and Mackie, 2016). More recently, the complex interactions between transport and health have been emphasised by the COVID-19 pandemic. Global hypermobility has allowed the disease to spread rapidly across the world (Musselwhite et al., 2020), whilst reduced traffic during lockdown has resulted in significant

; CLD, Causal Loop Diagram; SD, System Dynamics.

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increases in local air quality (Ropkins and Tate, 2021). Public transport has been seen as a key vector for transmission of the COVID-19 virus, leading to changes in travel behaviour towards both private car and active modes (Zhang et al., 2021).

Transport and mobility are undergoing a period of great change as a result of new technologies and changing behaviours and attitudes. For example, within the context of smart cities, enabling technologies, connectivity and data processing can inform and shape sustainability goals, with transportation being a critical domain (Abu-Rayash and Dincer, 2021). More recently, the impact of COVID-19 on available transport options and physical distancing may cause a further paradigm shift, though to what extent is uncertain. On the one hand the observed trends away from public transport may continue, and increase existing inequalities (Lee et al., 2021). On the other hand, there has been a unique learning opportunity for ways to promote sustainable mobility (Griffiths et al., 2021).

Set within a backdrop of policy to encourage the use of more sustainable forms of transport, such as active and public modes, understanding of the implications of these changes (both generally and specific to COVID-19) and the multiple ways that new data technologies (such as persuasive and monitoring apps) can influence mobility behaviours, is paramount. They can be introduced as a persuasive instrument, influencing the user to adopt more healthy and sustainable transport behaviours (e.g. through rewards or gamification, new social organisation, personalisation, real-time interaction) (Bopp et al., 2016; Andersson et al., 2018). Secondly, once a user engages with such an app, there is evidence to suggest that users undergo self-quantifying reflection of their behaviours (regardless of extrinsic rewards) and evolves their behaviour appropriately (Brazil and CAULFIELD, 2013; Huang et al., 2018, De Kruijf et al., 2018). Finally, the technologies are a data-source for richer, contextually specific, high resolution data beyond the conventional, allowing improved understanding of:

1) Mobility behaviours. (Boss et al., 2018; Toole et al., 2015);
2) The individual health influences, trade-offs between different types of influences and variation e.g. between key sub-groups of the population and by geographies (Guo et al., 2019); and,
3) The development of analytical and appraisal tools, techniques and methods for use in supporting more customised transport and public health practice and policy. Cavoli et al. (2015) identified limitations in traditional datasets linking transport and health that could have policy implications. One solution could be merging these with new and emerging data forms (Harrison et al., 2020; Grant-Muller et al., 2021)

Previous work has addressed the problem that policies designed to influence the health outcomes of one transport mechanism may also have an influence on health outcomes associated with a different transport mechanism (Harrison et al., 2021). This work builds on that as we believe that understanding the contribution of New & Emerging Data Forms (NEDF) and related technologies could be key in designing transport and health related policies that would avoid (or minimise) such complex and co-dependent problems, leading to the research question:

> "How could New and Emerging Data Forms improve understanding of mobility behaviours, and the related health outcomes, of different population subgroups?"

We adopt a system dynamics approach to addressing this question, creating a causal loop diagram through a novel online Delphi approach to group model building. Group model building is a standard approach in system dynamics, where a range of diverse experts and stakeholders are gathered in a workshop (sometimes multiple workshops) to identify consensus and conflict in system characteristics and behaviours. Although the online approach was designed due to travel restrictions arising from COVID-19, it has many advantages going forwards: a wider pool of global experts can be engaged, there is less pressure on their time and greater flexibility for engagement and a lower environmental impact as it negates the need for travel.

In the next section (2) of this paper we introduce a novel online Delphi approach to develop a causal loop diagram (CLD) that addresses the research question. In section 3 we present and discuss our results, including the participation, the iterations on the CLD and the characterisation of a policy scenario related to the introduction of persuasive and monitoring technologies. Finally, in section 4 we summarise our findings and contribution to the understanding of interactions between transport and health in a digital era, and the evaluation of interventions with the potential to improve population health.

2. Methodology

System Dynamics (SD) modelling is an important tool in capturing behaviours and understanding changes in complex systems over time. As such, it is ideal for exploring cross-sectoral impacts of transport schemes. It has been used extensively in the understanding of both transport (Shepherd, 2014) and health (Atkinson et al., 2015), and has had numerous applications in the understanding of transport-health interactions (Harrison et al., 2021). By its nature, SD traditionally operates at a highly aggregate level, as the focus is on the overall system rather than individual elements. As new technologies and NEDF are introduced, new opportunities open up for SD modelling to generate more detailed understanding of nuances within systems, thus leading to greater insights of influences and sensitivities within that system. For instance smart mobility which relies on 'big' data (Vecchio et al., 2019), or the relative potential of a smart city approach to sustainable urban mobility (Melkonyan et al., 2020).

In system dynamics, Causal Loop Diagrams (CLDs) capture the key variables and relationships that characterise a problem being addressed. The fundamental concepts of CLDs are:

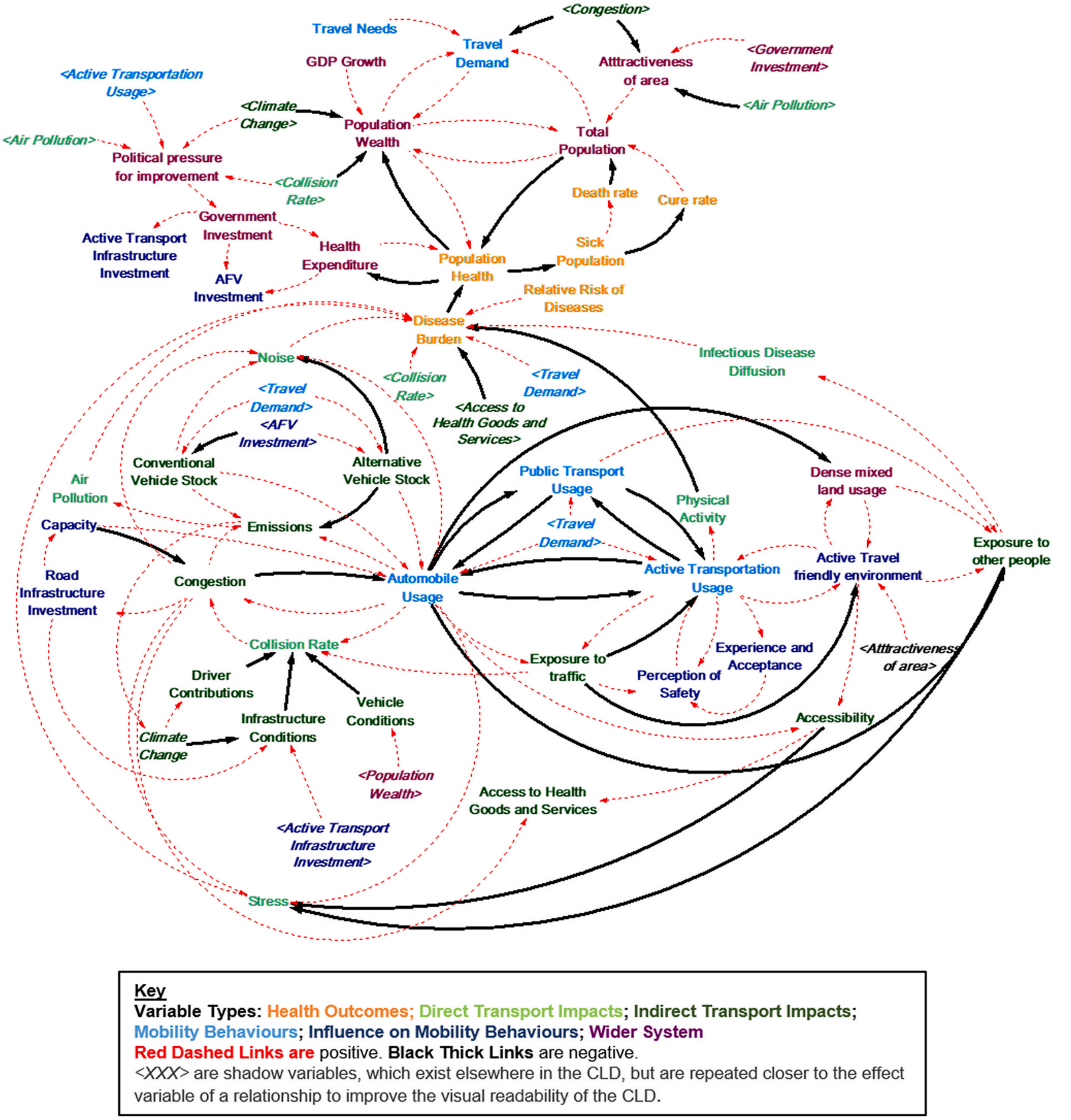

Fig. 1. CLD of transport-health as presented in the Survey (an earlier version of that presented in Harrison et al. (2021), prior to some minor edits following peer review).

- The values of the variables within the system change over time according to their relationship (link) with other variables, which can be either positive or negative.
  - o Positive Link: A change in one variable leads to a change in the *same* direction to the next variable, i.e. an increase (or decrease) in the initial variable leads to a corresponding increase (or decrease) in the other. For instance, the link between ‘Emissions’ (the cause) and ‘Air Pollution’ (the effect) is positive, meaning an increase in emissions would lead to an increase in air pollution.
  - o Negative Link: a change in one variable leads to a change in the *opposite* direction in the next variable, i.e. an increase (or decrease) in the initial variable leads to a corresponding decrease (or increase) in the other.
- Links are considered together as closed feedback ‘loops’: a chain of individual linked variables that start and end with the same variable, and do not contain the same variable twice.
- The behaviour of the system overall is determined by the feedback ’loops’ within the system.
- The CLD can be used for qualitative analysis but also as the basis of a quantified simulation model

CLDs are usually developed through literature review and engagement with stakeholders. Indeed, the most representative models would require group model building with a range of different stakeholders representing many points of view. This would usually be carried out at an in-person workshop, where the agreements and conflicts can be identified. Prevented from doing so due to the COVID-19 restrictions, in this study we adopted a remote approach to group model building, using an online Delphi expert survey. Although necessitated by the pandemic, the potential benefit of the methodology developed goes beyond removing the need for travel as it provides an opportunity to engage with wider range of global expertise than an in-person workshop, as well as reducing their personal time commitments and travel related environmental impacts. The Delphi technique has long been used as a forecasting tool (Rowe and Wright, 1999) and for achieving convergence of opinion relevant to this field of study (Paydar et al., 2021). Luna-Reyes and Andersen (2003) suggest that a Delphi approach would allow a researcher to develop a good understanding of critical issues under discussion, and to obtain parameters and policies to include in a SD model. Vennix and Gubbels (1992) used elements of a Delphi approach as 'knowledge elicitation cycles' to refine a preliminary conceptual model of patient flow within health care prior to a group workshop, a methodology also employed in a study of supply chain management (Angerhofer and Angelides, 2000). Most others have used the results of a Delphi survey to then develop a system dynamics model in a wide variety of situations, such as the tea-industry (Mohapatra et al., 1984), ICT development (Chen et al., 2012), tourism (Tan et al., 2018) and city resilience (Marana et al., 2019). In the arena of transport, Rees et al. (2017) developed a SD model of transport system change based on 'cause and effect' statements expressed by a Delphi panel. Elsewhere, Delphi surveys have been used in SD model validation (e.g. Marandure et al. (2020), Sandra et al. (2020) and Horschig et al. (2016)).

We follow a similar method to Vennix and Gubbels (1992) in that a preliminary CLD is presented to experts as part of the Delphi process. The CLD was originally developed through a systematic literature review regarding the use of SD in transport and health (Harrison et al., 2021). In that study, 23 papers were identified that met the inclusion criteria; requiring a) a focus on interactions between transport systems or mobility behaviours and public health, and b) reporting on and presenting an original system dynamics model or causal loop diagram. There were seven papers focusing on air quality, four on road safety, seven on active transport, four on multiple aspects and one on road noise. These were then reviewed in detail and used to construct an overview CLD of transport-health, as shown in Fig. 1. In addition to the creation of the preliminary CLD, the review also identified three areas of development that we address in this study:

- Detailed appreciation of the transport system and mobility behaviours
- Characterisation of specific health outcomes
- Inclusion of new data and technologies

2.1. Identification of participants

192 potential experts in transport, health and data were identified through journal/report authorship, position conference presentation, editorial boards and committee membership in relevant areas of health, transport & mobility, and new data. In order to encourage participation in the survey, participants were to be offered remuneration for their time and commitment (£75 as an e-voucher or charitable donation). As such, there were limits on total participants, so a further review was carried out for suitability, identifying those who had experience in at least two out of the three expert areas and a more thorough assessment of their potential contribution was undertaken, alongside ensuring a good balance between the participants research field, region and background (academia, consultancy, policy etc.). We originally identified a budget for 30 individuals and assumed a 20–40% response rate. Therefore, 84 individuals were invited to participate. There is no prescribed minimum number of participants for qualitative research, as it is dependent on the saturation level and resources available (Baker and Edwards, 2012). Few Delphi studies have included less than ten participants and small numbers of experts from a defined field of study have been shown to produce reliable results (Akins et al., 2005). Luna-Reyes and Andersen (2003) suggest 8–12 a good number in a focus group from which to develop an SD model. In group model building, the aim is to gather representative views of different stakeholders, so the representation is more important than the specific number. As numbers were limited by budget, invitations were sent in three waves, with the engagement in each wave

Table 1
Number of individuals identified and then contacted in each survey wave. Note that individuals can have more than one area of expertise.

		Initial List	Final List	Wave 1	Wave 2	Wave 3
Expertise Area	**Health**	108	44	3	29	12
	New Data	56	44	3	18	23
	Mobility	118	78	6	39	33
Region	**UK**	93	28	6	13	9
	Europe	41	24	0	9	15
	North America	27	18	0	13	5
	Other	31	14	0	9	5
Background	**Academia**	109	60	5	38	17
	Business/Consultancy	22	16	1	5	10
	Public/third sector	61	8	0	1	7
Total Individuals in each list/wave		**192**	**84**	**6**	**44**	**34**

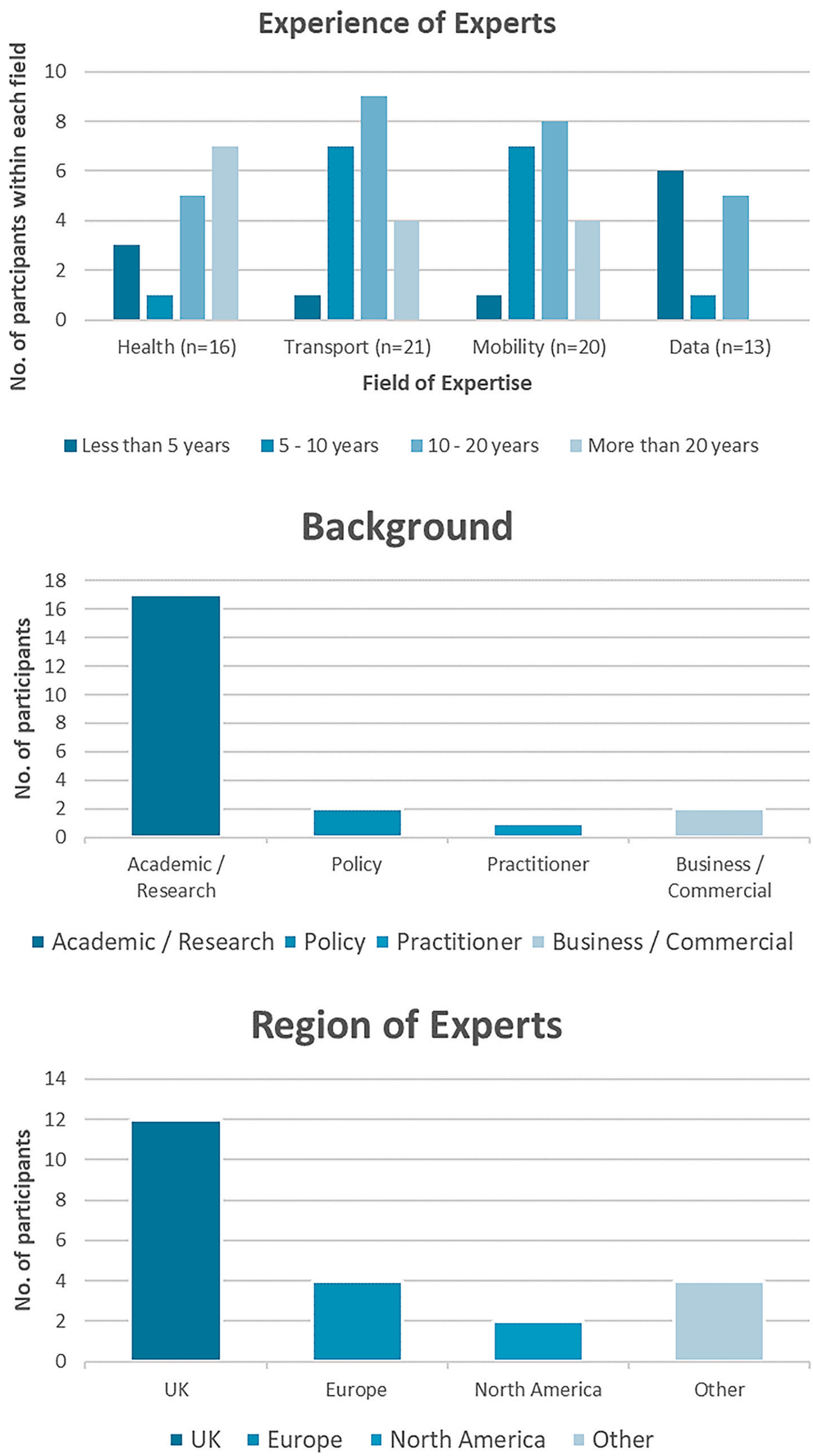

Fig. 2. Stage 1 participants.

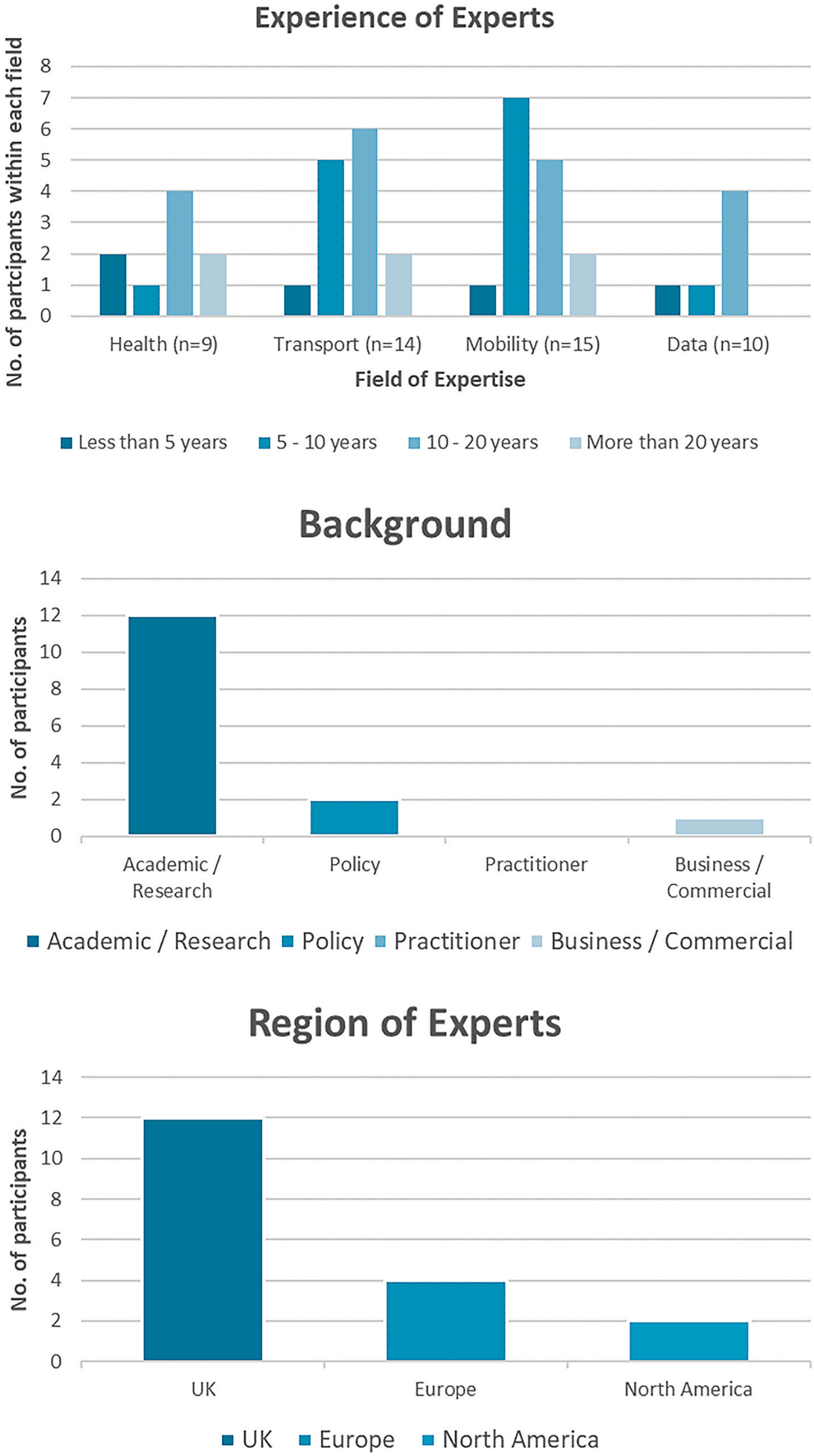

Fig. 3. Stage 2 participants.

determining the numbers of the next in order to achieve our target number of participants (see Table 1). Overall, we received a commitment to participate from 26 experts (31%), of which 22 (26%) completed the first survey and 16 (19%) also completed the second survey. We recognise that this is lower than our target of 30 individuals, but remains within our assumed response range (16–34) and above the recommended minimum number of a focus group or Delphi survey. Furthermore, the final number of individual participants was less important to us than obtaining a balanced range of representation, with at least half of 26 participants having a specialism in each of the expertise areas (as shown later in Figs. 2 and 3). Thus we are confident that our survey design remains valid.

2.2. Stage 1 survey

The purpose of the first stage was to present the preliminary CLD of the transport-health system (Fig. 1) and ask for expert opinion on how it can be improved. Participants were shown the CLD and provided with some basic information on the nature of CLDs in order to aid their understanding. The following question sections focused on the operational areas of the CLDs and participants were invited to respond to those sections that they felt confident in answering. Finally, participants were asked on the area/nature of expertise and years of experience. A copy of the survey is available as supplementary information for this paper.

The questionnaire was designed with streamed elements and specific questions directed to those with expertise in health, transport or mobility and new forms of data to take advantage of that expertise. In each section (other than data), participants were asked to focus on the relevant variables in order to rank them in order of importance, identify what they felt were the five strongest relationships (including their time horizon) and indicate any inaccurate or missing variables or relationships. They were also asked to identify diseases most associated with transport impacts and about relevant population sub-group characteristics. Participants confident in health outcomes were additionally questioned on some specific definitions.

As there were no 'new data & technologies' variables included in the initial CLD, the questions posed to those who were confident in this area were on: the most significant influences that new data and technologies would have on the CLD; suggestions for new variables and relationships; ranking of four specific forms of data (GPS Tracking, Internet Multimedia, Network Connections, Smart Ticketing Transactions); and which technologies were associated with them.

2.3. Stage 2 survey

The results of Stage 1 were used to improve the CLD and incorporate new data and technologies, (detail in Section 3). This was presented back to the participants in stage 2 and they were given the opportunity to suggest further amendments or agree it as a reasonable representation of the transport health system. If the participant required further changes to the CLD, they were invited to outline any inaccurate or missing variables or relationships. Following this, their opinion was sought on the characterisation of the policy scenario of the introduction of persuasive and monitoring technologies that a simple quantified version could address. A copy of the survey is available as supplementary information for this paper.

2.3.1. Policy scenario: Introducing persuasive and monitoring technologies

Persuasive and Monitoring Technologies (PMT) gather data on temporal spatial movements, identification of travel modes, levels of activity, and/or interaction with other devices. Such technologies can have a wide range of characteristics and objectives, though in this work we focus on mobility behaviour and related health outcomes. For example, the hardware platform hosting the technology could be a mobile phone or some form of wearable, such as a smart watch or wristband. They may rely on different types of underlying software and connectivity. On a mobile phone, this could be an app utilising the components within the phone such as gyroscope or GPS and connecting to other devices through a range of telecommunications: blue tooth, local area connections, and WiFi. Wearable technologies may rely on similar components, but these need to be purposefully built in for tracking individual movements. On either platform, PMTs can be either interactive or passive. Interactive PMTs require the user to engage with the data (though a user interface), possibly with some form of explicit rewards or gamification in place, in order to understand and adjust their mobility behaviours. In the case of passive PMTs the user would not be expected to view or even be aware of the data (although consent should be given for its collection). This latter option are can be particularly suited for wearables for those who cannot use or do not have access to mobile phones. In both cases the collected data can be analysed to understand trends in mobility behaviours, response to the data and/or other policy interventions. Previous research (Harrison et al., 2020, 2021) has highlighted the value of new and emerging data forms (NEDF) in designing and monitoring new influencing technologies, particularly in detecting the accrual of marginal changes in activity. Furthermore, analysis of the Stage 1 results suggested that these technologies may have a particularly significant influence on transport-related health. Participants were asked to rank eight policy objectives in order of importance, identify the sensitivity of population sub-groups to the changes in mobility behaviours and health outcomes in relation to the policy, significant influences of the policy on mobility behaviours or health outcomes, and specific variables.

3. Results

3.1. Stage 1 participation

The first wave of participants were contacted in early October 2020 and the final wave in mid-November 2020. It was closed to all participants in early December 2020. The response rate for Wave 1 was 4 (out of 6), Wave 2 was 12 (out of 44) and Wave 3 6 (out of 34) which was 22 (out of 84) overall. Although this was below our target 30 participants, we had insufficient further time available within the project to release a fourth wave of invites. We had obtained a good representation of our expertise areas that was within the assumed response range and above the accepted minimums. However, as shown in Fig. 2, the representation across the expert groups is reasonable. Most participants answered the transport (n = 21) and mobility sections (n = 20), almost three quarters answered the health outcome section (16) and over half the wider system (n = 14) and data (n = 13) sections. Participants with the longest experience in any subject area was health outcomes, and the overall least experience was data and technologies (with no one having more than 20 years). This may be somewhat reflective of how established the respective fields are. Over half of participants were UK based, with the remainder being spread between other regions, and most were from an academic background (n = 17).

3.2. Stage 2 participation

The second stage survey was released to all stage 1 participants in mid-December 2020 and closed at the end of January 2021.16 (out of 22) of the total participants completed this stage of this survey. Although this is further still from our target number, it is still within our assumed range, above assumed minimum and we have retained a reasonable representation across experts. In this stage, most of these participants were confident in transport (n = 14) and mobility behaviours (n = 15), over half in health (n = 9) and data (n = 10). Background data for one participant not available. The lengths of experiences and background are representative of the whole stage 1 group, though the dominance of UK is less so.

3.3. Stage 1 revisions

The revisions were based on analysis of the data gathered in the Stage 1 survey. Qualitative data (free text answers) from all sections of the survey were subjected to a thematic coding process (using NVivo software), whereas quantitative data (ranking, relevance, identification of strongest relationships, disease associations) were statistically analysed. From the ranking of variables, the most important variables in each category were identified. A number of variables, which were ranked low and/or had no further supporting qualitative evidence for importance were removed from the original CLD or incorporated into larger mechanistic variables representing sub-systems. Based on the identification of the strongest existing relationships in the original CLD, a number of relationships that were not identified as being amongst the strongest and had no further supportive qualitative evidence for inclusion were removed. From the identification of missing or inaccurate relationships, the suggestions of new variables and their relationships, and from supportive qualitative data, 103 amendments and additions were made to the original CLD. A full list of these changes is available in Appendix 1.

The most significant changes from the preliminary CLD is the combination of some variables and relationships into sub-groups we call modules that represent important mechanisms that will be developed in more detail on further analysis of the data and supporting literature. We developed one of these, New Data and Technologies, from the coded qualitative data from the New Data and Technologies section answers, as this was a key objective of our research.

We recognise through this work that both the transport and health systems separately, as well as the transport-health system as a whole are complex and multi-dimensional, making it impractical, if not impossible, to capture every variable and relationship. In this work, an objective was to identify what the most significant variables and relationships were which should be represented.

Finally, qualitative analysis of the data showed that representation of socio-demographic population sub-groups was not obvious in the original CLD. Though social equity is an important consideration, there is not an explicit variable in the CLD. CLDs, and the System Dynamic methodology are often aggregated, however, certain characteristics can be accounted for, by considering variables to be 'subscripted' by these characteristics. Even if the sub-groups may be 'hidden' in the aggregate high-level CLD, these should be considered to be represented in each relevant variable. Based on the responses from stage 1, the following characteristics were identified as being the most significant and should be considered, where as subscripted functions of certain variables:

- Age
- Socio-economic status
- Underlying health conditions & disabilities
- Sex
- Ethnicity

So, for example, the module 'Population Health, Wellbeing and Disease' could be considered separately for each of these subgroups, and mixtures thereof. A comparison of these would allow for assessment of the level of social equity relevant to any particular scenario. It is noted that this approach is more tangible with a quantified model, should one be developed from this CLD.

3.4. Stage 2 revisions

Of the 16 participants who responded to Stage 2, half of them (n = 8) agreed that the Revised CLD and New Data and Technologies CLD were reasonable representations of the most significant variables and relationships within the transport-health system. Of these, six participants suggested further minor changes to the Revised CLD, and four suggested minor changes to the New Data and Technologies CLD.

Most of these changes were additional relationships or clarifications. The most significant further revisions of the revised CLD was the refinement of the definitions of population health and mental-health/wellbeing and consideration on how to represent social justice/equality. For the New Data & Technologies CLD, suggestions were made to better consider Connectivity.

3.5. Final revised CLD

Fig. 4 shows the finalised main CLD, which is further explained in the glossary provided in Appendix 2. The time frame of interest is relatively short term – we consider the development of new data and technologies over the last ten years and approximately ten years in the future, therefore spanning the approximate period 2010–2030. The reason for this limited time frame is that we recognise that this had been (and set to be) a period of significant change within both transport systems and in particular in relation to the development of technology to provide transport-relevant data. As such, the assumptions we make are time-limited and it is necessary to draw our boundaries and focus on the elements of most interest here.

In the CLD, we have combined groups of variables into ten mechanistic modules in order to capture the most significant relationships. The New Data & Technologies module is not included in any feedback loops but does influence a number of variables and modules (see detail in next section). We have identified negative relationships with *Stress*, *Emissions*, *Noise*, *Collision Rate*, *Exposure to Other People* and *Infectious Disease Diffusion*, meaning that an increase in new data & technologies can lead to a decrease in these transport impacts. All these are, in turn, directly negatively related to *Population Health, Wellbeing & Disease* – which would therefore increase. *Exposure to Other People* also has an indirect negative link (though *Infectious Disease Diffusion*). On the other hand, there are positive relationships with *Economic Growth*, *Sustainable Policy Decisions*, *Active Travel Physical Activity*, *Diversity of Travel Needs and Demand*, *Positive Individual & Cultural Experience and Perceptions of Active Travel and Public Transport*, *Infrastructure, Infrastructure, Technology & Individual Contributions to Good Travelling Conditions*, and *Accessibility*. In these cases, an increase in uptake in society new data & technologies could lead to an increase in these variables (or variables contained with the modules). The first three of these are directly positively linked to *Population Health, Wellbeing and Disease*, whereas the remainder have indirect positive links. Through these observations, we can suggest that in answering our research question, that new and emerging data forms (and their related technologies) can improve health outcome related to mobility behaviours. We accept, however that the contribution is complex, as demonstrated by the significant number of relationships and feedback loops within the CLD. Further work will be required to identify those that are most significant.

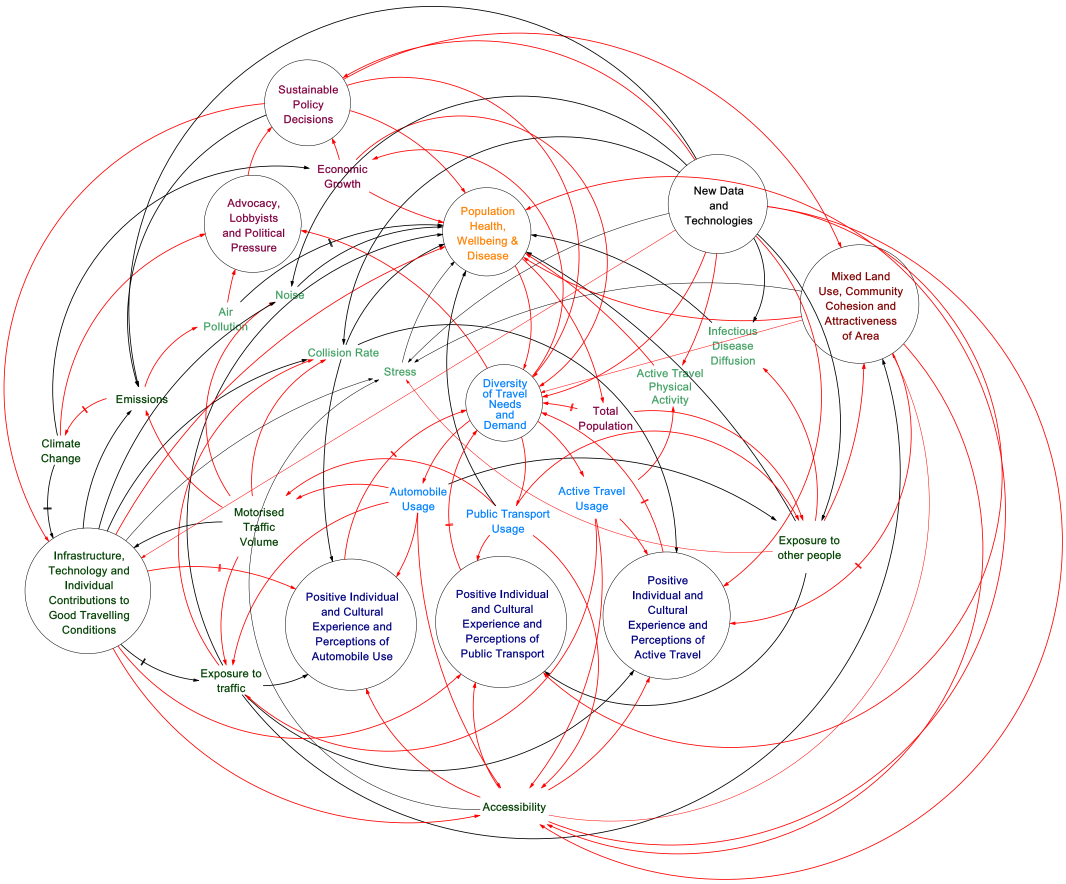

Fig. 4. Final CLD

3.6. Final new and emerging data CLD

The majority of participants suggested that data could be used in the understanding of mobility behaviour, both for real time monitoring and assessing behavioural change. In addition it could be used to identify differences between different (and at risk) groups and use of green spaces. Data could also be used for health monitoring, sharing best practise and modelling COVID-19 spread. For individuals, data can be used to persuade (targeted) behaviour change or to provide real-time information. There were various suggestions of the technologies that this data could be harvested from. Six participants suggested mobile phone data: *GPS tracking*, *Social Media* and *Call Data Records*. Wearable technologies could be used for both health and mobility tracking. Smartcards could also be used to understand changes in Public Transport use. Four existing variables in the main CLD were selected that new data and technologies would have a significant influence on by more than one participant: *Active Travel Use* (related to *Physical Activity*), *Infectious Disease Diffusion*, *Exposure to other People* and tele-working (part of *E-Activities*).

The New and Emerging Data CLD is shown in Fig. 5, again with further detail available in Appendix 2. As with the main CLD this has short time frame and as such, there are number of technology developments likely to impact on transport-health interactions, such as advanced *Connected and Automated Vehicles* and *Mobility as a Service*, that are beyond scope, though these are included as they are in their infancy at present.

The influence of the New Data & Technologies CLD on the wider CLD has been discussed in the previous section, where we identified that they could improve health outcomes related to mobility behaviours. In Fig. 5, we can see the further detail on this. For example, *Use of Persuasive and Monitoring Technologies* (PMT), which are positively influenced by *Mobile Phone Ownership & Use*, have a negative relationship with *Infectious Disease Diffusion* (i.e. an increased use of PMT will decrease disease diffusion – for example COVID tracing apps). PMT also have positive relationships with *Active Travel Physical Activity* (e.g. STRAVA encourages active travel) and Influencing *Sustainable Mobility Behaviours* (e.g. mobility apps with positive incentivisation). We explore the use of PMT, as an example of a specific policy related to New & Emerging Data, which can be explored using our CLD, in more detail in the next section. Another example is the increase in *E-Activities*, arising from improvement in *Network Connectivity & Internet of Things*. This in turn has negative association with both *Stress* and *Exposure to Other People* (meaning they can be decreased – thus improving health outcomes), and a positive influence on *Diversity of Travel Needs and Demand* (meaning it can increase – and is indirectly positively linked to health outcomes). Focusing on the influence on the *Understanding of Mobility Behaviours*, through the variable of that name, there are seven positive links within this CLD, therefore we can assume that understanding can be increased. Six of these are from different types of data (Traffic Network, Urban Monitoring, Social media, GPS, Network and Ticketing), whereas the final influence comes from the *Use*

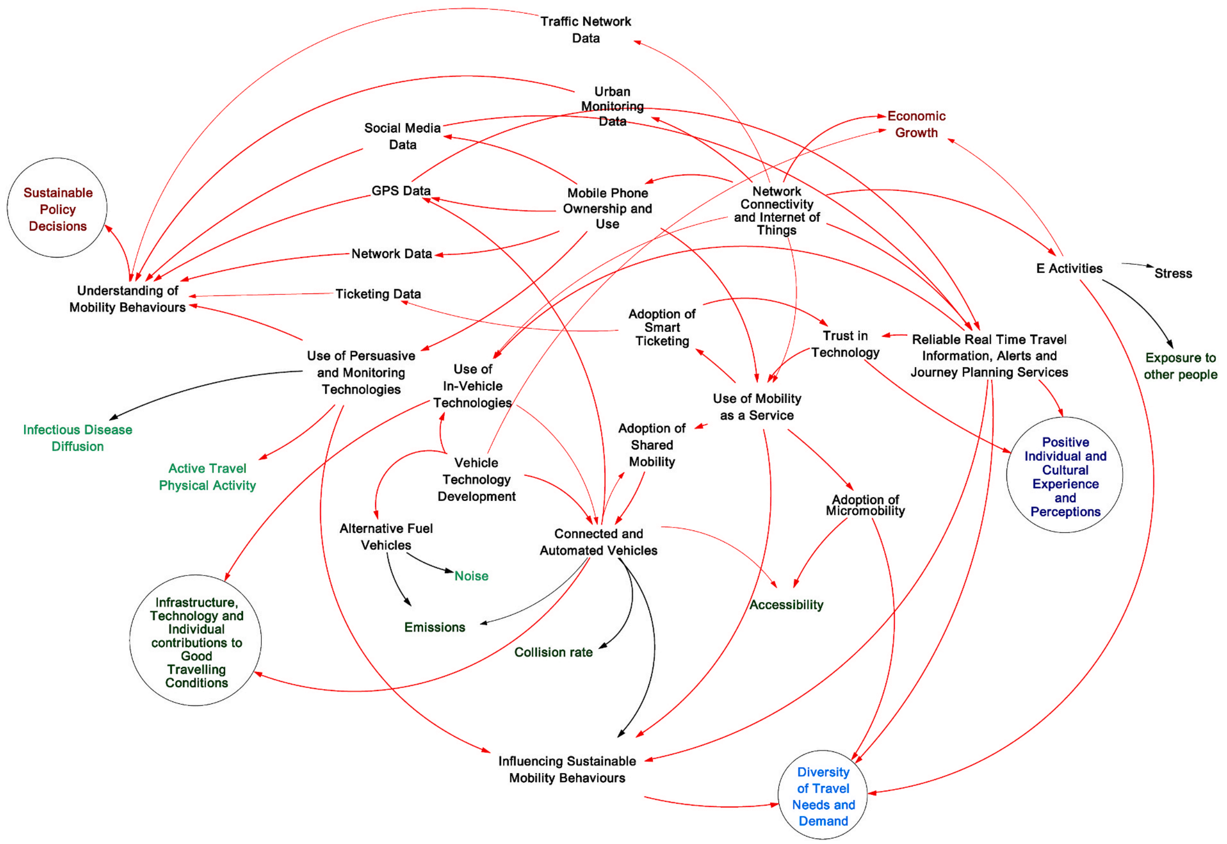

Fig. 5. New data & technologies module CLD

of Persuasive and Monitoring Technologies.

3.7. Persuasive and monitoring technologies (PMT) policy

With the CLDs finalised, we wish to demonstrate how a specific policy may be explored using the CLD and in the context of our research question. As described previously, Persuasive and Monitoring Technologies (PMT) are generally associated with mobile phones (as applications) or wearable technologies (e.g. smart watches). We asked our participants to consider what a policy to introduce them would entail and how it could be represented in the CLD. Based on the responses, the characteristics of these policies that can be used for assessment using the CLD are detailed in the following sections.

3.7.1. Policy objectives

The most important policy objectives for PMTs identified by the participants were Increasing Physical Activity and Increasing Social Equity. One participant noted that "increasing physical activity cannot be the objective but means to improve physical and mental health". This is a valid observation as indeed physical activity is a means to improve health, however, in line with the terminology used within the CLD, the objective of PMT that is of interest to this research is about direct transport impact of *Active Travel Physical Activity*, which then influences *Population Health, Wellbeing & Disease*. *Transport System Efficiency* (absorbed into the module *Infrastructure, Technology & Individual Contributions to Good Travelling Conditions*) also was ranked highly, with five participants ranking it as most important. Other suggestions for policy objectives offered by the participants included ethical aspects like inclusion and fairness, which will be included in the social equity and consideration of population sub-groups. As explained in Section 3.3, five population characteristics are considered: age, socio-economic status, underlying health conditions, sex and ethnicity. Thus, in the case of PMT, an objective would be to increase the equity between these groups in the output variables, such as those in the module *Population Health, Wellbeing & Disease*.

3.7.2. Population sub-groups – mobility behaviours

The participant responses suggest that the groups that would be most sensitive to changing their mobility behaviour due to PMT would be younger professionals, potentially in an urban area. Gender, Ethnicity and Underlying Health Conditions were generally seen as not important.

3.7.3. Population sub-groups - health outcomes

The sub-groups characteristics identified by the participants that should be considered as having the greatest potential health benefits from engaging with PMT are age (the eldest and the youngest), those with underlying health conditions and of lower Socio-Economic Status.

3.7.4. Significant influences of PMT

As previously explained, PMTs have a wide range of characteristics, utilising different technologies, with differing objectives and can be either passive or interactive. We have identified the objectives – improving *Population Health, Wellbeing & Disease* through *Active Travel Physical Activity,* and increasing Social Equity thereof. We were also interested in capturing which existing variables within the CLD that the uptake and use of PMT could have a strong influence on. Any social or behavioural assumptions regarding this influence is subject to the given definition of PMT and existing structure of the CLD, or explicitly stated otherwise by participants. There were two variables in the CLD that were identified by at least half of participants that the uptake and use of PMT would have a significant influence on: *Active Travel Physical Activity* and *Understanding of Mobility Behaviours*. Eight participants suggested that a significant influence PMTs could have on mobility behaviours or health outcomes would be to increase physical activity through increased walking, cycling and micro-mobility. Influences related to *Understanding of Mobility Behaviours* were identified as having a significant influence by seven participants. Firstly, PMT were seen as having the ability to inform individuals of their options – in terms of mode, time, cost, health and environmental impact. A number of comments related to the insights into one's own behaviour and thus the improvement of self-awareness and influence motivation. Related to this, two participants specifically mentioned the use of alerts to persuade people to change their behaviour either long term for more environmentally/health conscience or for short term situations such as poor air quality. Aside from individuals understanding, three participants commented on the use of data from PMT for monitoring population behaviour change for either smart cities or better urban design. Other influences include potentially reduced and safer driving, shifting working hours, altered pricing structures, better public transport and privacy concerns.

Based on the findings above and the features of the Final CLD(s), we have established that the *Use of PMT* can improve *Understanding of Mobility Behaviours* through the provision of data, and the higher uptake of PMT the more data that is available, therefore there understanding can be improved further. In terms of being specific to particular population groups, the level of understanding will be dependent on the provision of individual personal and socio-demographic data that can be linked to the mobility behaviour.

Influence on health outcomes related to mobility behaviours have been described within Sections 3.5 and 3.6. In relation to PMTs, a main policy objective has been to increase Physical Activity (related to active travel), which in turn will positively influence *Population Health, Wellbeing & Disease*. This is shown by the positive relationship in the CLD between *Use of PMT* and *Active Travel Physical Activity*. PMTs will appeal to different population sub-groups, with younger urban professionals being most likely to change their mobility behaviours, partly due to being more acquainted with (and adaptive to) new technologies, but also as they may be more able to engage in physical activity and being in an urban environment there may be better connectivity. However, these are not the sub-groups who may benefit most though improvement in health outcomes brought about by changes in mobility behaviour. Those that are may also be classed as vulnerable (age-related vulnerabilities, underlying health conditions and low socio-economic status), and those with lower levels of access to new technologies such as PMT, hence to the new data that could benefit them (either directly to themselves or via provision to authorities to understand their behaviours). In order to achieve the policy objective of increasing social equity (e.g. *Population Health, Wellbeing & Disease* for each population subgroup), methods to allow these groups to participate in PMT, through education and the provision of accessible technologies, may be required.

4. Conclusion

The innovation in this work in the evaluation of interventions to improve transport-related health outcomes arises from three areas. Firstly, in this work we have addressed the research question:

> "How could New and Emerging Data Forms improve understanding of mobility behaviours, and the related health outcomes, of different population subgroups?"

In response to this question we have developed a causal loop diagram (CLD) of the transport-health system that includes the influence of New Data & Technologies. This builds on previous work (Harrison et al., 2021), which was the first attempt to develop a comprehensive CLD of transport-health through literature review of existing studies. Here, we have not only enriched that preliminary CLD through engagement with experts in transport and health, but have also sought the inclusion of experts in new data and technologies, in order to include the important and previously overlooked influences on transport and health. We have identified important relationships that characterise how NEDF (such as *GPS Data* or *Social Media Data*) influence the *Understanding of Mobility Behaviours. Public Health, Wellbeing and Disease* is likely to be improved through both positive and negative, direct and indirect links to New Data & Technologies. Differences between sub-groups can be captured through considering variables and modules being subscripted by five characteristics (age, socio-economic status, underlying health conditions, sex and ethnicity). The CLD will require further development in future work, in particular that of the modules and understanding of differences between sub-groups, but can then be quantified to build a simulation model to study the impacts of policies and influences of NEDF on the system. There is also the potential to consider wider cross-sectoral sustainability issues and interactions (eg energy, environment, safety, security, society). However, although we have drawn boundaries and assumptions for our purposes, the current CLD is not redundant for future research. It can be used at any point as a starting point for those who wish to focus on specific areas of the transport-health system, and the influence of new data and technologies, taking different assumptions and altering the CLD as appropriate through their own methods. In fact, one advantages of the CLD developed is the incorporation of modules to represent complex sub-systems that can be developed in future work.

Secondly, we have also identified the potential influence that introducing persuasive & monitoring technologies could have on this system, and what the characteristics for representing and assessing them could be, which is summarised in Table 2.

We consulted with experts on specific impacts and objectives of Persuasive and Monitoring Technologies, in relation to the CLD(s) and on specific population sub-groups. The results of this can be used to extract and simplify the key elements of the CLD(s) to understand these policies in more detail, to develop a simulation model that could forecast their impacts and inform the development of sustainable cities.

Finally, a novel Delphi approach to group model building of a CLD has been developed and illustrated here. Unlike previous related studies, we carried this out online and encouraged explicit engagement in the variables and relationships of the CLD from the participants, rather than focus on high-level discussion of the concepts contained therein. Although this approach was recognised as complex for the individuals involved, we gained some valuable insights on how to present group model building to individuals online and in future applications would seek to limit the use to a more focused or less complex problem. Nevertheless, we believe that the methodology developed can serve as a prototype for researchers who wish to adopt a system dynamics approach to socio-technological development and policy research that may allow them to engage with a wider range of experts than many funding resources may usually allow.

In conclusion, we believe that the findings and discussions presented in this study will be of interest to a broad group of researchers or policy makers concerned with designing holistic future-focused transport, health and data policies, as well as system dynamics practitioners.

Table 2
Characteristics of introducing persuasive and monitoring technologies.

Characteristics	Persuasive & Monitoring Technologies
Policy Objectives	• Physical Activity • Social Equity
Population most sensitive to changing mobility behaviours	• Younger urban professionals
Population with greatest potential health benefits	• The eldest and the youngest • Those with underlying health conditions • Lower Socio-Economic Status
Most significant influence in CLD	• Active Travel Physical Activity • Understanding of Mobility Behaviours

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A conflict of interest

A conflict of interest may exist when an author or the author's institution has a financial or other relationship with other people or organizations that may inappropriately influence the author's work. A conflict can be actual or potential. At the end of the text, under a subheading 'Disclosure Statement', all authors must disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations within three (3) years of beginning the work submitted that could inappropriately influence (bias) their work. Examples of potential conflicts of interest which should be disclosed include employment, consultancies, stock ownership, honoraria, paid expert testimony, patent applications/registrations, and grants or other funding.

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Author statement

Gillian Harrison: Conceptualisation, Methodology, Verification, Formal analysis, Investigation, Writing – Original Draft, Writing – Review & Editing, Visualisation. Susan Grant-Muller: Conceptualisation, Methodology, Writing – Review & Editing, Supervision, Project administration, Funding acquisition. Frances Hodgson: Conceptualisation, Methodology, Writing – Review & Editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jth.2022.101335.

Appendix 1

List of changes from preliminary to revised CLD from Stage 1 analysis.

Removed Variables and Relationships	New Variables and Relationships	Representation in revised CLD
Health Outcomes		
Cure Rate Death Rate Disease Burden Relative Risk of Disease Sick Population	Population Health	Incorporated into 'population health', mechanistic sub-system variable.
Population Health (−)> Health Expenditure*	n/a	Represented by indirect link through Economy and Sustainable Policy Decisions
Population Health (−)> Population Wealth*	n/a	Identified as inaccurate or unimportant (*renamed Economy)
n/a	Population Health (+) > Diversity of Travel Needs and Demand	The influence of underlying health conditions and disabilities on transport choices was identified as missing from the original CLD
Direct Transport Impacts		
Physical Activity	Active Travel Physical Activity	For clarity, in the updated CLD this is termed 'Active Travel Physical Activity', as it is meant to represent just the additional (or reduced) activity arising from mobility behaviours. Underlying levels of physical activity are considered within demographic inputs and any changes in non-AT physical activity are outside the scope of the model.
Stress	Mental Health	Analysis of the qualitative data showed strongly that a more appropriate variable would be 'Mental Health'. This allows for the incorporation of positive impacts on mental health (eg from improved wellbeing), as well as the negative impacts of stress.
Air Pollution (−)> Attractiveness of Area	n/a	Identified as unimportant
Collision Rate (+)> Congestion	n/a	Identified as unimportant
n/a	Active Travel Physical Activity > Mental Health	Identified as important missing link

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(*continued*)

Removed Variables and Relationships	New Variables and Relationships	Representation in revised CLD
n/a	Collision Rate(−)> Mental Health	Identified as important missing link
n/a	Collision Rate (−)> Positive Individual and Cultural Experience and Perceptions of Active Travel*	Identified as an important missing link
n/a	Collision Rate (−)> Positive Individual and Cultural Experience and Perceptions of Automobile use*	Identified as an important missing link
n/a	Noise (−)> Mental Health	Identified as important missing link
Indirect Transport Impacts		
Access to health goods and services	Accessibility	Incorporated into definition of accessibility
Alternative Fuel Vehicle Stock Congestion Driver Contributions Infrastructure Contributions Vehicle Conditions	Infrastructure Technology and Individual Contributions to Good Travelling Conditions	New mechanistic variable for which a sub-system is being developed, that will represent a range of variables related to travelling conditions,
Alternative Fuel Vehicle Stock Conventional Vehicle Stock	Motorised vehicle traffic volume	Better representative of impacts originally related to automobile usage to also include Public Transport usage
Accessibility (−) > Stress	Accessibility (+) > Wellbeing	Identified as an inaccurate relationship
Automobile Usage (+) > Congestion	Motorised vehicle traffic volume (+)> Infrastructure Technology and Individual Contributions to Good Travelling Conditions	Automobile usage identified as better as indirect link via motorise traffic volume
Automobile Usage (+)> Noise	Motorised Vehicle Traffic Volume (+)> Noise	Indirect link though 'Motorised Traffic Volume
Exposure to traffic(−) > Active Transportation Usage	Exposure to traffic(−) > Positive individual and cultural experience and perceptions of Active Travel	This link incorporated into new mechanistic variable
n/a	Wellbeing	Identified as important missing variable
n/a	Accessibility (+) > Positive individual and cultural experience and perceptions	Identified as important missing link
n/a	Exposure to other people (+) > Mixed land use, community cohesion and attractiveness of area	Identified as important missing link (via community cohesion and giving a indirect + link to mental health via wellbeing)
n/a	Exposure to other people (−) > Positive individual and cultural experience and perceptions of public transport	Identified as important missing link (related to commuting overcrowding)
n/a	Exposure to Traffic (−)> Mental Health	Identified as important missing link
n/a	Infrastructure Technology and Individual Contributions to Good Travelling Conditions (+)> Accessibility	Identified as important missing link (via infrastructure conditions and congestion)
n/a	Infrastructure Technology and Individual Contributions to Good Travelling Conditions (−)> Exposure to traffic	Identified as important link (through congestion, which is part of the mechanism)
n/a	Infrastructure Technology and Individual Contributions to Good Travelling Conditions (+)>Positive individual and cultural experience and perceptions	Identified as important missing link (via infrastructure conditions)
n/a	Wellbeing (+)> Mental Health	Identified as important missing link
Mobility Behaviours		
Travel Needs Travel Demand	Diversity of Travel Needs and Demand	Mechanistic sub-group variable that represents a combination of the two individual variables Travel needs and Travel demand within one definition (see glossary)
Active Transportation Usage	Active Travel Usage	Identified as being a more widely accepted term
Active travel usage > Political pressure*	n/a	Now indirect link through travel demand (*variable renamed advocacy, lobbyist and political pressure)
Active Travel usage (−) > Automobile Usage Active Travel usage (−) > Public Transport usage Automobile Usage (−) > Active Travel usage Automobile Usage (−) > Public Transport usage Public Transport usage (−) > Active Travel usage Public Transport usage (−) > Automobile Usage	n/a	Relationships between usage of different modes now represented by mechanistic sub-group variable travel needs and travel demand (see glossary), and will consider identified inaccurate relationships between active travel and public transport
Automobile Usage (+)> Congestion* Automobile Usage (+) > Emissions Automobile Usage (+)> Stress*	Automobile Usage (+) > Motorised Traffic Volume (−)	Now represented indirectly through motorised traffic volume and incorporated into Infrastructure Technology and Individual Contributions to Good Travelling Conditions (*stress renamed mental health)
Automobile Usage (+) > Collision Rate		Now represented indirectly through motorised traffic volume
Travel Demand (+)> Population Wealth	n/a	Identified as unimportant
n/a	Active Travel usage > accessibility	Identified as an important link

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(*continued*)

Removed Variables and Relationships	New Variables and Relationships	Representation in revised CLD
n/a	Automobile Usage(+) > Positive individual and cultural experience and perceptions of automobile use	Identified as important to reflect the similar feedback experiences as active travel
n/a	Public Transport usage (+)> Accessibility	Identified as an important missing link
n/a	Public Transport Usage (−)> Mental Health	Identified as important missing link due to stress of overcrowded commuting
n/a	Public Transport Usage (+)> Positive individual and cultural experience and perceptions of public transport use	Identified as important to reflect the similar feedback experiences as active travel
Influence on mobility behaviours		
Active Travel Friendly Environment	Mixed land use, community cohesion, attractiveness of area	Incorporated into new mechanistic variable that represents impacts of land use, planning and community
Active travel friendly environment > Exposure to other people	n/a	Identified an unimportant
Active Travel infrastructure investment Alternative Fuel Vehicle investment Capacity Road infrastructure investment	Infrastructure Technology and Individual Contributions to Good Travelling Conditions	Incorporated into new mechanistic variable for which a sub-system is being developed, that will represent a range of variables related to travelling conditions.
Perception of safety Experience and acceptance	Positive individual and cultural experience and perceptions of Active Travel	Incorporated into new mechanistic variable that captures the influences of experience and perceptions regarding active travel
n/a	Positive individual and cultural experience and perceptions of Automobile use	New mechanistic variable that captures the influences of experience and perceptions regarding automobile use, which it was identified as important to include, similar to active travel.
n/a	Positive individual and cultural experience and perceptions of Public Transport use	New mechanistic variable that captures the influences of experience and perceptions regarding public transport use, which it was identified as important to include, similar to active travel.
n/a	Positive individual and cultural experience and perceptions (+) > Diversity of Travel Needs and Demand	Important link identified
Wider System		
Active Travel infrastructure investment Alternative Fuel Vehicle investment Government Investment Healthcare expenditure Road infrastructure investment	Sustainable Policy Decisions	New mechanistic variable to better represent the influence of political decisions beyond investment
Attractiveness of Area Dense mixed Land Use	Mixed land use, community cohesion, attractiveness of area	Incorporated into new mechanistic sub-group variable to represent impacts of land use, planning and community
GDP Growth Population Wealth	Economic Growth	Identified as a better term to represent its meaning and incorporate GCP growth
Political pressure for improvement	Advocacy, Lobbyists and political pressure	New mechanistic sub-group variable to represent a wide range of mechanisms of political pressure
Attractiveness of area(+) > total population	n/a	Identified as unimportant
Dense mixed land use (+)> exposure to people	n/a	Identified an unimportant
Total Population (−)> Population Health	n/a	Identified as inaccurate or unimportant
n/a	Total population (+) > exposure to other people	Identified as important missing link
n/a	Mixed land use, community cohesion, attractiveness of area (+)> Wellbeing	Identified as an important missing link (to represent the importance of community and nature).
New Data and Technologies		
n/a	New Data and Technologies	New mechanistic variable that represents the New Data and Technologies CLD
n/a	New Data and Technologies (+) > Active Travel Physical Activity New Data and Technologies (−) > Infectious Disease Diffusion New Data and Technologies (−) > Exposure to other people New Data and Technologies (+) > Positive individual and cultural experience and perceptions of Active Travel use New Data and Technologies (+) > Positive individual and cultural experience and perceptions of Public Transport use New Data and Technologies (+) > Diversity of Travel Needs and Demands New Data and Technologies (+) > Accessibility New Data and Technologies (−) > Collision Rate	Key links to variables within the main CLD from the New Data and Technologies sub-group CLD

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(continued)

Removed Variables and Relationships	New Variables and Relationships	Representation in revised CLD
	New Data and Technologies (−) > Noise New Data and Technologies (−) > Emissions New Data and Technologies (+) > Sustainable Policy Decisions	

Appendix 2

Transport-Health CLD Glossary

Health Outcome Variables (orange)

All health outcome variables are incorporated into one mechanistic sub-group variable **'Population Health'.** This represents the complex relationships between heath outcome variables including disease burden, relative risks and death rates, as well as physical, mental and social wellbeing at population sub-group levels representing socio-economic and underlying health factors. (Kindig and Stoddart, 2003; WHO, 1948).

Direct Transport Impact Variables (light green)

Air Pollution**:** The level of air pollution arising from motorised traffic that specific demographic sub-groups are exposed to in the local area.

Noise: Nuisance levels of background noise arising from motorised traffic that specific demographic sub-groups are exposed to in the local area.

Collision Rate: The rate of occurrence of road traffic collisions resulting in injury or death between motorised vehicles and/or active travellers in the local area.

Stress: A measure of mental tension arising from external (environmental, social, psychological) factors.

Active Travel Physical Activity: The amount of physical activity related to active travel being carried out by specific demographic sub-groups of the population.

Infectious Disease Diffusion: The rate of diffusion of infectious air-bourne disease between individuals within the local area.

Indirect Transport Impacts (dark green)

Climate Change: Changes in seasonal weather and occurrence of extreme weather events due to rises in global temperature.

Emissions: Greenhouse gases and local air pollutants emitted by motorised vehicles in the local area.

Infrastructure, Technology and Individual Contribution to Good Travelling Conditions: A mechanistic sub-group variable that represents a sub-system of related variables not significant to include as individual variables. This variable includes the following:

- conditions of road and pathway infrastructure,
- competence of drivers of motorised vehicles to drive safely and efficiently
- level of maintenance of vehicles to be at a safe and efficient standard
- efficiency and capacity of the road network, including congestion
- the introduction of disruptive transport technologies that could have significant effect on the transport system, eg connected and automated vehicles, mobility-as-a-service, individual drones, hyperloop etc

Motorised traffic volume: the flow of motorised vehicles using the road network (automobiles, public transport, two-wheelers and commercial).

Exposure to traffic: the exposure of individuals travelling in the network by any mode to traffic operating in that network.

Accessibility: the ability for individuals within specific population sub-groups to be able access key goods and services such as employment, education, healthcare, retail & leisure, green spaces.

Exposure to other people: the likelihood of individual of a specific population sub-group of being in close proximity to other individuals within the local area.

Mobility Behaviours (light blue)

Automobile Usage: the volume of trips made by automobile by specific population sub-groups.

Public Transport Usage: the volume of trips made by public transport by specific population sub-groups.

Active Travel Usage: the volume of trips made by walking or cycling by specific population sub-groups.

Diversity of Travel Needs and Demand: A mechanistic sub-group variable representing the range in trip motivation, requirements and limitations (including pricing/costs, stock availability) of specific population sub-groups regarding their mobility and their choice of making a trip by a specific mode.

Influences on Mobility Behaviours (dark blue)

Positive Individual and Cultural Experience and Perception of Automobile Usage/Active Travel Usage/Public Transport Usage: a mechanistic sub-group variable representing various feedbacks that increase or reduce favour for this mode of transport by specific population sub-groups within the local area, such as the lived experience of an individual (that could have both short and long term impacts), and the influence of the acceptance of that mode within the wider society brought about through the visibility and volume of other users, collision rates and/or media reports. This sub-system has a strong influence on travel needs and demand related to that specific mode.

Wider System Variables (purple)

Mixed Land Use, Community Cohesion and Attractiveness of Area: a mechanistic sub-group variable representing the role of community cohesion, dense mixed land use, urban sprawl and attractiveness of the local area.

Sustainable Policy Decisions: a mechanistic sub-group variable representing the decisions made by policymakers on where and how investments are made and the implementation of policy schemes within the local area in order to achieve a sustainable outcome, and also the regulatory decision imposed by national governments that may impact on the local area. Policies could be (though are not limited to) the following: road infrastructure, healthcare, active travel, alternative fuels, land use planning.

Advocacy, Lobbyists and Political Pressure: a mechanistic sub-group variable, which represents various groups which may influence political decisions.

New Data and Technologies

New Data and Technologies: a mechanistic sub-group variable that represents the New Data and Technologies CLD, and incorporates:

1. New mobility-related technologies, services and practices, such as smartphones (and applications), travel information services, connected and automated vehicles, shared micro-mobility, teleworking, mobile phone ownership, in-vehicle technologies and persuasive technologies
2. The highly grained spatial temporal individual level data arising from these new technologies (such as GPS, social media and network data) that can be analysed and developed to improve the understanding of mobility behaviours of specific population subgroups within the local area.

New Data and Technologies CLD Glossary

Adoption of Micro-mobility: the volume of use of micro-mobility services such as bicycles, e-bikes, and e-scooters.

Adoption of Shared Mobility: the volume of use of shared mobility services, were uses do not own the mode of transport they are using, such as shared automobiles and micro-mobility.

Adoption of Smart Ticketing: the volume of users who purchase tickets for public transport through digital platforms such as mobile phone applications or online.

Alternative Fuel Vehicles: the number of motorised vehicles within a fleet that are not reliant on a conventionally fuelled powertrain, such as electric battery or hydrogen fuel cell vehicles.

Connected and Automated Vehicles: the number of motorised vehicles that can be driven (all or in part) without a human driver and are reliant on data sharing within the “internet of things”.

GPS Data: Global Positioning System Data that tracks individual spatial and temporal movements.

Influencing Sustainable Mobility Behaviours: the amount of influence on the mobility choices and behaviours of individuals to adopt sustainable forms of travel.

Mobile Phone Ownership and Use: the prevalence of mobile phone ownership and use within a population and by specific subgroups within the local area.

Network Connectivity and Internet of Things: the quality of network provision within the local area, accessibility by individuals within specific sub-groups and variety of devices connected to the network and sharing data.

Network Data: Data that arises from the individual connections to mobile phone networks on a spatial and temporal level.

Reliable Real Time Travel Information Alerts and Journey Planning Services: The level of consistency and accuracy of data provided to individuals within the local area of real-time road network information and travel conditions that allows users to effectively plan journeys by various forms of transport.

Social Media Data: Data arising from the use of social media (eg Twitter, Facebook) that can be analysed to track events and attitudes of individuals within the local area.

E-Activities: The ability of specific sub-groups within the population to access and engage in activities online at home using network connections. These activities include home-working, education, grocery shopping, social and leisure activities.

Traffic Network Data: Data monitoring the traffic network, such as road use, vehicle type, footfall. Although this may largely be from traditional sources, the volume and may be increased via network connectivity and IoT.

Trust in Technology: the level of trust of individuals within specific sub-groups within the population of the local area that the technology which they use is consistent and accurate.

Understanding of Mobility Behaviours: the knowledge about the movement and transport choices of individuals within specific sub-groups within the population of the local area that can allow policy makers and transport operators to plan appropriately for sustainable transport.

Urban Monitoring Data: the volume of sensors and associated technologies within a local area that can monitor the state of the environment, such as air quality.

Use of In-Vehicle Technologies: The volume of use of new technologies within vehicles through data sharing on the internet of things that allow the user to plan journeys and drive more efficiently.

Use of Mobility as a Service Applications: the volume of use of mobile phone applications that allow the user to plan a journey and choose transport options.

Use of Persuasive and Monitoring Technologies: the volume of use of technologies that gather data on temporal spatial movements, identification of transport modes, levels of activity, and/or interaction with other devices. This data can be used by the individual to understand and adjust their mobility behaviours.

Vehicle Technology Development: the level of development of innovative and more efficient powertrain technologies.

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