Forthcoming at *Information Systems Research*

Information Systems Research for Smart Sustainable Mobility: A Framework and Call for Action

Wolfgang Ketter*
University of Cologne & Erasmus University, ketter@wiso.uni-koeln.de

Karsten Schroer
University of Cologne, karsten.schroer@uni-koeln.de

Konstantina Valogianni
IE Business School, konstantina.valogianni@ie.edu

Transportation is a backbone of modern globalized societies. It also causes approximately one third of all EU and US greenhouse gas emissions, represents a major health hazard for global populations and poses significant economic costs (e.g., due to traffic congestion). However, rapid innovation in vehicle technology, mobile connectivity, computing hardware and AI-powered information systems heralds a deep socio-technical transformation of the sector. The emergence of connected, autonomous, shared and electric (CASE) vehicle technology has created a digital layer that resides on top of the traditional physical mobility system. The resulting layered modular architecture is similar to that seen in other cyber-physical systems. Yet, it also comes with several characteristics and challenges that are unique to the domain of mobility and require entirely new solution approaches. While other management and domain-specific research disciplines have started to embrace the new opportunities for research resulting from this deep structural change, the Information Systems (IS) community's involvement in smart mobility research has been marginal. Yet, we argue that our field's uniquely multi-disciplinary, data-driven and socio-technical research lens puts it in a strong position to address many of the large-scale societal challenges encountered in the mobility sector. Therefore, we make the case for IS research to play an active role in delivering a smart sustainable mobility ecosystem that is beneficial to users, mobility providers and the environment. We contribute a research framework to direct IS research efforts while providing a shared understanding of the smart sustainable mobility domain. We also present seven IS research opportunities along the dimensions of this framework and propose concrete angles of attack which we hope will spur an impactful and structured research agenda in the area.

Key words: CASE vehicles, smart sustainability mobility, digital platforms, IS for Social Good, Green IS

---

* Contact author; authors are in alphabetical order

1. Introduction

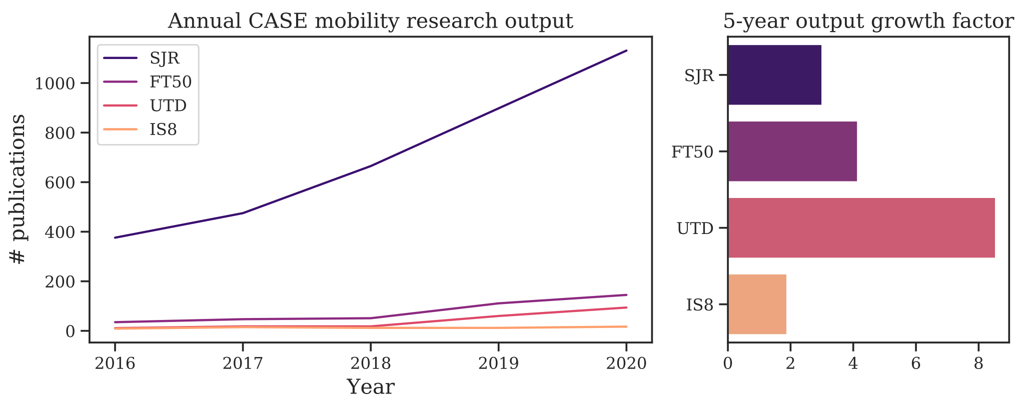
Transportation is a backbone of modern globalized societies and is changing fast. Rapid innovation in vehicle technology (Ba et al. 2013), connectivity, mobile technology (Hafermalz et al. 2020) and AI-powered information systems (Nishant et al. 2020), among others, heralds what is probably the deepest and most comprehensive transformation the industry has seen since the release of the first production car, Ford's Model T, in 1908 (Sperling 2018). To this date, however, most mobility ecosystems around the world still operate on an uncoordinated, inefficient and unsustainable basis (Bruun and Givoni 2015). Most traditional forms of transportation contribute to climate change, produce hazardous pollution (World Health Organization 2005), cause bodily harm (World Health Organization 2018) and/or are a major source of inefficiency (Cramton et al. 2018, Cheng et al. 2020). Yet, many technology-enabled solutions that can remedy these societal issues are already at our disposal or are just around the corner.

Researchers agree that tomorrow's mobility system[1] will likely be based on a multi-modal portfolio of connected, autonomous, shared and electric (CASE) mobility resources, i.e., vehicles (Burns 2013, Sperling 2018). These emerging vehicle technology themes could enable society to achieve a more favourable trade-off between the societal costs and the individual benefits of physical mobility (Bruun and Givoni 2015). Most scholars argue that, if implemented in an uncoordinated fashion, these CASE vehicle technologies may do more harm than good. Sperling (2018) paints a dystopian "doom and gloom" scenario in which autonomous vehicles lead to increased use of road-based transport versus transit options, worsening congestion and urban sprawl. Technological innovations in mobility, like many other human inventions, seem to be a double-edged sword; a wicked problem with multiple interdependencies and inherent complexities requiring data-driven system-level solution approaches (Ketter et al. 2016b).

[1] Throughout this article we use the term mobility interchangeably with transportation. Our definition of mobility only refers to physical mobility (as defined in Lyytinen and Yoo (2002)) of goods and people. Broader aspects such as social mobility or labor mobility are outside the scope of this article.

Indeed, the wider research community has recognized these challenges. Yet, we find that the IS community, with some exceptions (Greenwood and Wattal 2017, Babar and Burtch 2020, Zhang et al. 2020), has been a relatively silent observer of the intensifying discourse on CASE mobility. We base this conclusion on a comprehensive literature search of leading mobility (Scimago Journal Rank (SJR) Transportation Q1 Basket), management and IS journals (FT 50 list, UT Dallas list, IS Basket of 8) over the past five years, the results of which we have visualized in Figure 1. We find that the IS contribution is relatively small in absolute terms. While this may be due to a difference in size of the respective research communities, a trend analysis of research output growth reveals that our community's premier journal basket (IS Scholars' Basket of 8) is the journal category with the lowest relative growth in annual research output over the past five years.

Figure 1 Smart mobility research output of domain- and management/IS-focused journal baskets.



Note. See Online Appendix A for methodology and data tables.

We attribute this apparent lack of involvement of our community to the highly interdisciplinary, nascent and complex nature of the field. Yet, it is precisely this complexity coupled with the increasingly digitalized and data-driven nature of the mobility domain that holds great opportunity for IS and calls for a much stronger involvement of our discipline. With ubiquitous information flows from sensors and mobile devices in spatio-temporal resolution, we have an abundance of information at our disposal which remains to be leveraged. We propose a comprehensive research framework and agenda that will guide IS research endeavours in utilizing this new breadth of information to the benefit of users, mobility providers and the environment. IS researchers are uniquely positioned to address Smart Sustainable Mobility challenges for two reasons. First, IS research can draw on a powerful methodology toolbox comprising advanced technical methods including algorithmic and mechanism design (Bichler et al. 2010), machine learning and econometrics (Abbasi et al. 2015, Adomavicius et al. 2013, Barfar and Padmanabhan 2017, Dlugosch et al. 2020, Greenwood and Wattal 2017). Second, IS researchers combine technical skills with deep expertise in large-scale behavioral and experimental studies and experience in analysing social aspects of various phenomena (Babar and Burtch 2020, Burtch et al. 2018, Oestreicher-Singer and Zalmanson 2013, Osterwalder et al. 2005). It is this unique socio-technical lens (Sarker et al. 2019) that differentiates IS researchers from other fields (who might have either technical or social expertise) and enables them to confront large-scale societal challenges head on (Ketter et al. 2016a). For example, IS research already plays a highly active role in driving sustainability in the domains of energy (Dedrick 2010, Melville 2010, Watson et al. 2010, Seidel et al. 2013, Ketter et al. 2018) and emissions management (Corbett 2013), where expertise in social and technical aspects is required.

Our commentary is structured as follows: We start by synthesizing current thinking on the future of mobility and illustrate how four core innovations in vehicle technology (CASE) may result in both intended and unintended consequences for the mobility sector and its adjacent sectors. We then explain why a Smart Sustainable Mobility future is not an inevitable outcome of technological innovation and why achieving it requires careful management and guidance. We proceed by arguing that IS can provide exactly this. We support our argument with a research framework. Building on the developed framework, we formulate and detail seven core research opportunities for IS. We end with a conclusion and call to action for our community.

2. Scoping Smart Sustainable Mobility: A Challenge of Societal Scale

For the purpose of this commentary, mobility is defined to comprise physical mobility (i.e., transportation) of goods and people. We consider a mobility system to be smart and sustainable if it can leverage, learn from, and act upon data, information and technology in such a way that a sustainable balance between user preferences, business needs and the environment is struck.

Although there are obvious interdependencies between smartness and sustainability, we consider both concepts to be distinct. Smartness refers to the digital nature of a mobility system which enables real-time information exchange, coordination and automation (as afforded by CASE vehicle technology). Sustainability extends beyond important environmental aspects (e.g., Watson et al. 2010, Seidel et al. 2018) to socio-economic sustainability (safety, resource allocation efficiency, user satisfaction, scope for profitable business models, etc.). Sustainability can only be achieved if the coordination and automation opportunities offered by a smart system are leveraged. It then follows that a mobility system can be smart without being sustainable (meaning the system is digital and automated but not geared toward sustainability) but not the other way round (i.e., to be sustainable, the mobility system must necessarily be smart).

There is evidence to suggest that the current mobility system fails to deliver on both smartness and sustainability objectives. As an illustration, consider the following three social negatives of traditional physical mobility consumption. First, conventional combustion-driven mobility is energy intensive and produces greenhouse gas. It thus contributes substantially to the global greenhouse gas emission balance sheet, with an estimated 27-28% of EU[2] and US[3] greenhouse gas emissions attributable to transportation. As such, the sector represents a key lever in the fight against climate change. We will refer to this social negative as SN1 – Climate Impact. Second, road traffic is a major health and safety hazard. Transport-related pollutant emissions that arise from hydrocarbon combustion threaten the health and well-being of urban populations (World Health Organization 2005). Roughly 1.3m people die in traffic accidents each year across the globe (World Health Organization 2018) (social negative SN2 – Health & Safety Impact). Third, road transport is space intensive and inefficient. In Los Angeles, America's most congested metropolis, commuters spend 102 hours in peak traffic per year (INRIX Research 2018). Congestion has become a significant social and economic cost (Cramton et al. 2018), while road and parking infrastructure takes up a

[2] https://www.eea.europa.eu/data-and-maps/indicators/transport-emissions-of-greenhouse-gases/transport-emissions-of-greenhouse-gases-11

[3] https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

significant share of space in urban environments (social negative SN3 – Economic Impact). Below, we provide summary for clarity:

SN1 – Climate Impact: climate impact of mobility related to energy intensity of a vehicle and carbon emissions of the associated fuel (gas or electricity production)

SN2 – Health & Safety Impact: health and safety hazards inherent to transportation usage (i.e., health impact of pollutant emissions and road accidents)

SN3 – Economic Impact: economic inefficiencies of transportation (i.e., social impact and economic cost of time lost due to congestion, search for parking spaces, etc. and/or poor access to transportation)

New vehicle technologies, some of which have been developed to address exactly these challenges, promise to improve the sector's sustainability footprint. The transportation community has brought forward diverse visions on the future of mobility technology (e.g, Burns 2013, Sperling 2018). Four common themes emerge from this research – mobility is likely to become connected (C), autonomous (A), shared (S) and electric (E). We adopt the acronym CASE to describe these four distinct technological developments (Sperling 2018)[4]. The concept encapsulates a comprehensive body of research related to economic, strategic, operational and system aspects surrounding electrical vehicles (EVs) (e.g, Papadopoulos et al. 2013, Masoum et al. 2015), autonomous vehicles (AVs) (e.g, Wadud et al. 2016, Maciejewski and Bischoff 2017), shared vehicles (e.g, Firnkorn and Müller 2015, Shaheen and Cohen 2007) or a combination of the three (SAEVs) (e.g, Chen et al. 2016, Dlugosch et al. 2020). We also include a fourth observed attribute – *connected* – which we find important to distinguish particularly given the effect of connected vehicles on the availability of and access to information (Mahmassani 2016). To varying extents, CASE technology can be applied to all kinds of mobility resources including public transport (electric autonomous buses), micro-mobility (shared e-bikes and e-scooters) and even aviation (e.g., autonomous and electric vertical take-off and landing pods). For clarity, we explicitly define the dimensions of CASE below:

[4] Other acronyms like ACES are also sometimes used

Connected (C): real-time digital signal exchange and communication capabilities of vehicle resources in a ubiquitous computing sense. When connected, the vehicle can interface with other actors and assets in the mobility system as part of a wider internet of things (IoT) allowing for real-time vehicle- and system-level status monitoring and control/coordination (Batty et al. 2012, Qi and Shen 2018).

Autonomous (A): the ability of any type of vehicle to operate without external assistance, which requires all intelligence to be contained *within* the vehicle. Six levels of automation ranging from no automation (L0), assisted driving (L1), feet-off driving (L2), hands-off driving (L3), eyes-off driving (L4) and full automation (brains-off) (L5) are typically distinguished (SAE 2018). We consider L5 to be fully autonomous. Autonomy can be enhanced by connectedness (C), i.e., via communication with other smart and connected vehicles (vehicle-to-vehicle) or smart infrastructure (vehicle-to-infrastructure) (Mahmassani 2016).

Shared (S): the simultaneous and/or sequential use of vehicle assets by a pool of users for transportation purposes. Sharing can take many forms and can range from models similar to renting (e.g., subscription car access like zipcar) to more archetypical sharing models like BlaBlaCar (private ride sharing) (Sundararajan 2016, Eckhardt et al. 2019).

Electric (E): vehicle propulsion via an electric motor. Two main pure electric vehicle propulsion technologies exist. These are (1) battery electric vehicle (BEV) technology, which draws on a battery pack as the only source of energy supplying one or several on-board electric motors, and (2) fuel cell electric vehicle (FCEV) technology, which uses a fuel cell to convert chemical energy (typically from hydrogen) to electricity, which powers onboard electric motor(s).

CASE mobility technology holds great promise in addressing the three social negatives (SN) of mobility. Importantly, CASE technology, if adopted and utilized in a coordinated effort, represents a core prerequisite and enabler of Smart Sustainable Mobility. Yet, research has also revealed a range of potential adverse effects that may arise from uncoordinated adoption and use of CASE. We synthesize these views in Table 1 where we show how each SN might either be alleviated

(↓) or aggravated (↑) by new CASE technology. It becomes apparent that the risk of unintended consequences (i.e., a worsening of one or multiple SNs) may be substantial. Thus, CASE technology may afford and result in a smart mobility system, but not necessarily one that is also sustainable (i.e., a system in which unintended consequences are effectively managed and avoided). Delivering on both smartness and sustainability objectives is complex and can only be described as a "wicked problem".

Table 1 Possible Societal Implications of CASE Vehicle Technology

Technology	Intended Consequences	Unintended Consequences
Connected (C)	– Lower energy consumption through coordination, optimized routing and flow (Wadud et al. 2016) (↓ SN1) – Reduced congestion through real-time coordination and routing (Batty et al. 2012, Qi and Shen 2018) (↓ SN3) – Enhanced safety through early warning and crash avoidance systems (Mahmassani 2016) (↓ SN2)	– Increased demand for road-based transport for convenience and life-style reasons (Mahmassani 2016) (↑ SN1 & SN3)
Autonomous (A)	– Lower energy consumption as a result of de-emphasized performance, eco-driving, improved traffic flow and routing (Burns 2013, Wadud et al. 2016) (↓ SN1) – Reduced congestion through real-time coordination and routing (Mahmassani 2016) (↓ SN3) – Enhanced safety through heavily reduced scope for human error (Mahmassani 2016, Wadud et al. 2016) (↓ SN2) – Reduced space utilization (e.g., for inner-city parking) (Sperling 2018) (↓ SN3)	– Increased demand for road-based transport due to improved cost-competitiveness against other options (esp. when shared), therefore, higher energy demand and congestion (Axhausen 2017) (↑ SN1 & SN3) – Empty rides between pick-up and drop-off resulting in further growth in energy demand and congestion (Wadud et al. 2016) (↑ SN1 & SN3) – Longer commutes being accepted as a result of higher convenience of autonomous transport, therefore, urban sprawl and further traffic and energy demand increase (Sperling 2018) (↑ SN1 & SN3)
Shared (S)	– Reduced specific energy consumption through higher vehicle utilization (higher trips per vehicle and passengers per trip) (Firnkorn and Müller 2015) (↓ SN1) – Reduced congestion and space utilization due to fewer vehicles on the road (Firnkorn and Müller 2015) (↓ SN3)	– Higher demand for road-based transport due to improved cost competitiveness of shared mobility over e.g. transit, therefore more traffic and higher energy intensity (Axhausen 2017, Sperling 2018) (↑ SN1 & SN3)
Electric (E)	– Lower energy intensity due to higher efficiency of electric propulsion versus combustion engine technology (Pelletier et al. 2016) (↓ SN1) – Zero emissions possible if fueled entirely with renewable electricity (Pelletier et al. 2016) (↓ SN1)	– Uncoordinated vehicle charging may over-strain the electric grid and/or require substantial infrastructure investment (Valogianni et al. 2019) (↑SN1)

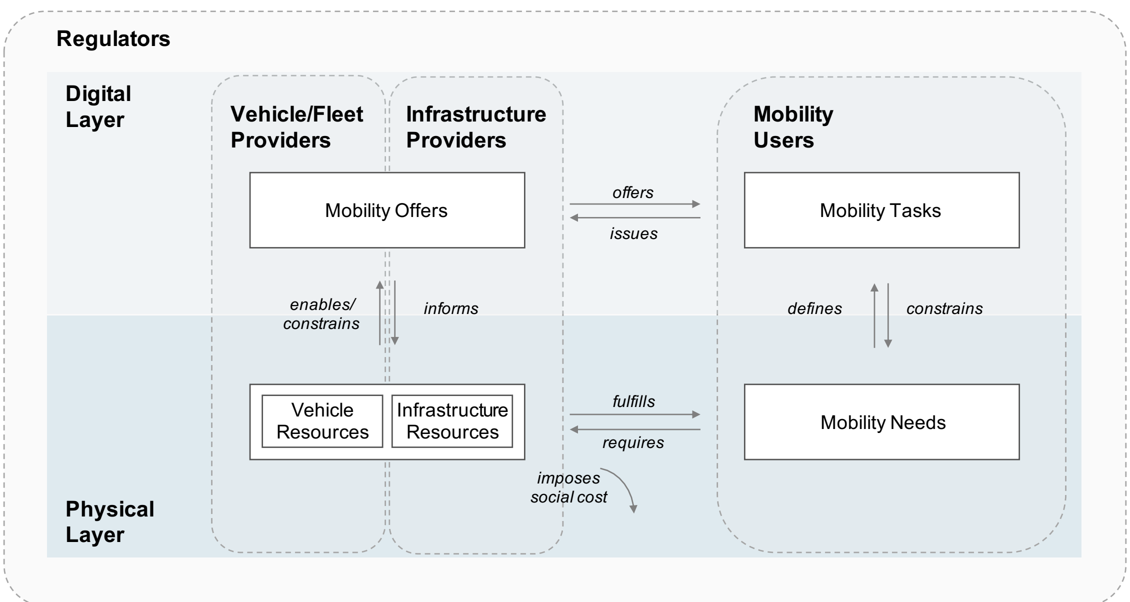
↓ = alleviates/improves; ↑ = aggravates/worsens; SN1 = Climate Impact; SN2 = Health & Safety Impact; SN3 = Economic Impact

However, CASE vehicle technology also provides the necessary tools to effectively address the wickedness of Smart Sustainable Mobility. For example, ubiquitous data flows from connected vehicles and mobile devices in spatio-temporal resolution provide real-time transparency on the mobility ecosystem. Computational technologies exist that can store and process the resulting data quantities in real time. Connected mobility allows for the broadcasting of instructions, price signals or allocation decisions in real-time. Autonomous technology can ensure flexible and rational execution of such instructions. Finally, shared and electric mobility, if coordinated well, enable an overall more efficient and less resource intensive transport system. In the following section, we describe the integral role that we foresee for IS as a discipline and for its scholars in facilitating the journey toward Smart Sustainable Mobility.

3. The IS perspective on Smart Sustainable Mobility: A Framework

As highlighted by Yoo et al. (2010), the digitization of services, such as mobility, gives rise to a *layered modular architecture* in which an information-based digital layer exists on top of the traditional physical layer. This *layered modular architecture* (Yoo et al. 2010) is the key assumption underlying our mental model of CASE-based future mobility as illustrated in Figure 2. Here, the

Figure 2 Framework for an IS-enabled Smart Sustainable Mobility System.



traditional physical layer ("network and device layer" as per Yoo et al. (2010)) consists of mobility resources (i.e., vehicles), physical infrastructures (roads, parking spots, charging points, the electricity grid, communication networks) and user mobility needs. An information-based instance of this ecosystem resides in the digital layer. The digital layer relies on real-time status information from its underlying physical layer as well as on information exchange with it ("service and content layer" as per Yoo et al. (2010)). The latter is facilitated via ubiquitous sensing and communication technology inherent to connected (C) mobility.

In Figure 2, we have also superimposed the stakeholders active in different areas of both physical and digital layers. Mobility Regulators are responsible for establishing a Smart Sustainable Mobility regulatory framework that facilitates and incentivizes system-beneficial and sustainable consumption of mobility, while providing guidance on system architecture, privacy, ethical questions and other aspects of societal relevance. A second stakeholder class is comprised of vehicle/fleet operators or providers (taxi drivers, fleet operators, public transport companies, logistics providers, etc.) who provide Mobility Offers to meet demand originating from a third class of actors, the Mobility Users (private users, online retailers, etc.). In addition, Infrastructure Operators are responsible for supplying and maintaining the right amount of Smart Sustainable Mobility Infrastructure Resources (e.g., EV charging poles, smart parking lots, road infrastructure, electricity grid capacity, etc.) such that physical Mobility Tasks can be executed to effectively meet Mobility Needs. Finally, Mobility Users express their Mobility Needs in the form of digital-layer Mobility Tasks that can be matched with corresponding Mobility Offers as published digitally by Vehicle Operators.

Figure 2 emphasizes the reliance of Smart Sustainable Mobility on a digital and a physical layer. Despite its similarities with digital or cyber-physical systems such as cloud computing and IoT-based production or supply chain systems (e.g., gas pipelines), Smart Sustainable Mobility has distinct characteristics that require unique IS-driven solution approaches. Differences include (1) the considerably higher Sustainable Development Goals (SDG) implications, expanding beyond environmental to health and social/economic (traffic and electricity disruptions, accidents, etc); (2) the much more diverse and combinatorial nature of (physical) resources that is inherent to mobility and leads to (3) a much higher degree of coordination complexity. Digital or cyber-physical systems do not have the same necessity for matching demand and supply in real time. The storage capabilities in such cyber-physical systems (e.g., gas storage) differentiate such systems from Smart Sustainable Mobility systems. In addition, while cyber-physical systems such as gas pipelines, have equally severe mission critical implications (see for example the Colonial Pipeline Cyberattack[5]), Smart Sustainable Mobility failures can result in major interruptions of service level, delays in transportation of goods (including vital items) and health hazards from increased risk of accidents. Finally, (4) the Smart Sustainable Mobility domain is set apart by the larger and more diverse stakeholder landscape in mobility that requires high decision autonomy due to complex preference structures and high dimensionality of the decision spaces. Table 2 further details the unique differentiators of Smart Sustainable Mobility and provides examples.

Our layered modular framework accounts for these key differentiators of Smart Sustainable Mobility versus digital and cyber-physical systems. To illustrate this point it may be instructive to consider a concrete example of the user experience in an IS-enabled and digitalized mobility system. Imagine a user who wishes to travel from her current location in the suburbs to a destination in the city center (Mobility Need). Since she does not own a vehicle she issues a Mobility Task; e.g., via an app-based interface provided to her by the mobility platform operator ("service and content layer"). She receives various Mobility Offers with varying characteristics (mode, route, travel time, price, departure time, etc.) that all match her Mobility Task. The app interface indicates that she could save a considerable portion of her trip cost if she opts for an off-peak time slot or a high-occupancy vehicle option. Since she is not in a rush, she opts for a shared bike located just around the corner (i.e., a Vehicle Resource) to cycle to the nearest subway station where she boards a subway train headed toward the city center. Upon her arrival, she selects an e-scooter at the subway exit that has been reserved for her and completes the last leg of her journey ("network and device layer"). On her return journey, she opts for a more convenient and slightly faster travel mode by selecting a pooled electric vehicle, which picks her up from her city location and drops

[5] https://www.reuters.com/business/colonial-pipeline-ceo-tells-senate-cyber-defenses-were-compromised-ahead-hack-2021-06-08/

Table 2 Key differentiators of Smart Sustainable Mobility against other cyber-physical systems

	Cloud Computing	**Cyber-physical System**	**Smart Sustainable Mobility**	**Core SSM differentiators**
1. Societal Importance				
1.1 SDG implications	low	high	high	Besides environmental (CO_2 and pollution) and health (accidents) implications, SSM has also social/economic (access, congestion cost, etc.) implications.
1.2 System mission criticality	mild	severe	severe	Physical implications are severe (physical harm, journey delay, etc.). SSM accidents besides leading to interruption of mobility service, can lead to electricity interruptions, delays in transportation of vital goods and even health-related accidents (ambulances, etc.).
2. Nature of Resources				
2.1 Number of Resource Types	single	single	diverse	Resources are much more diverse, including road space, vehicles, vehicle space, grid capacity, etc.
2.2 Divisibility	almost continuous	almost continuous	discrete divisibility	Resources have discrete divisibility (such as journey increments, vehicle space, etc.), as opposed to almost continuous divisibility of cloud jobs or gas and other natural resources.
2.3 Combinatorics	individual	individual	combinatorial	Mobility resources are combinatorial with critical paths between different connecting modes/road segments, etc.
2.4 Storability	large-scale	large-scale	small-scale	Lack of large-scale storage opportunities (e.g., of mobility demand or of electricity for charging) in SSM requires real-time matching of demand and supply
3. Complexity of Coordination				
3.1 Dimensionality	temporal	spatio-tenporal	spatio-tenporal	Decision on when and where to provide mobility service.
3.2 Time Horizon	close to real-time	close to real-time	Continuous/real-time	Requirement for online coordination of mobility requests due to lack of storage.
3.3. Constraints	few	few	many	Multiple physical resource constraints (e.g., vehicle/road capacity, etc.) and individual preference constraints (time of departure/arrival, mode choice, price, CO2 emissions, etc.), as opposed to mainly capacity constraints.
4. Stakeholder Interface				
4.1 User Preference Structure	relatively homogeneous	relatively homogeneous	highly heterogeneous	Highly diverse mix of use cases (commuting, delivery, leisure trips, etc.) and segments (goods mobility, personal mobility) with heterogeneous preference sets.
4.2 Preference Elicitation and Learning	explicit	explicit	largely implicit	High dimensionality of decision space (mode, route, departure, etc.) may require extrapolation and implicit elicitation.
4.3 Decision Autonomy	low	medium	high	High automation of real-time choices required due to complexity (e.g., dynamic re-routing, automated pre-booking of connecting modes, etc.).

her off at home (having picked up and dropped off other passengers along the way). Her experience is seamless, uninterrupted and highly predictable. She experiences only minimal wait time and no congestion. Note that this is just one illustration of Smart Sustainable Mobility. Our framework generalizes beyond the area of urban road transport and comprises all forms of mobility resources including, for example, air travel or shipping. This is also a direct result of the CASE technology themes transcending into these sub-domains.

Facilitation of such a seamless Smart Sustainable Mobility experience is the purpose of the digital layer. Such facilitation requires the management of a large portfolio of heterogeneous CASE Vehicle Resources (such as shared bikes, demand-responsive transit or ride hailing vehicles to name a few), owned and operated by different platform participants as well as demand for these resources from heterogeneous sectors (e.g., personal mobility or goods mobility). It also requires the management of Infrastructure Resource constraints such as road space, electric grid capacity or available parking spots. The digital layer enables this management, allowing for real-time preference elicitation, predictive analytics, and automated planning and control in time and space. The heterogeneity of actors in our proposed framework is another characteristic of layered modular architectures (Yoo et al. 2010). Indeed, one can already observe in practice the first platforms that exhibit certain aspects of such a *layered modular* ecosystem. Examples include Uber and BlaBlaCar (Sundararajan 2016), which provide platforms for peer-to-peer ride hailing and ride sharing respectively. Our proposed framework exceeds the somewhat narrow scope of these existing mobility platforms. We define a Smart Sustainable Mobility System as an ecosystem that consolidates and manages many different types of Vehicle Resources, Infrastructure Resources and system participants from diverse sectors, coordinating them against system-level objectives, and drawing on the layered modular architecture attributes (Yoo et al. 2010). In the following section, we further detail the individual components of this IS-enabled Smart Sustainable Mobility System.

3.1. Physical Layer

The dimensions of the physical layer are presented in the bottom half of Figure 2. We distinguish two types of resources: (1) distributed Vehicle Resources, which can be any vehicle type that affords mobility services to the user population and (2) distributed Infrastructure Resources, which comprises the physical environment in which vehicles operate. These resources are consumed when fulfilling distributed Mobility Needs, such as personal travel, goods mobility or even energy services via the battery storage of an electric vehicle. We use the attribute *distributed* to indicate variability across both a temporal as well as a spatial dimension. Specifically, Vehicle Resources are any connected, autonomous, shared and electrical (CASE) mobility mode that can provide a mobility or transportation service to users. Our framework allows for the fact that some Vehicle Resources may exhibit only a selection of the four CASE attributes. For instance, micro-mobility options such as shared bikes or e-scooters might not have autonomous capabilities. We do, however, find that some form of *connectedness* and real-time information exchange between physical Vehicle Resources and the digital layer must be guaranteed. Our framework allows for ownership of Vehicle Resources by different stakeholders, including private owners or large-scale professional fleet operators. Infrastructure Resources are any type of infrastructure required to fulfill Mobility Needs via Vehicle Resources. Examples include road segments, parking spots, charging stations or electricity grid capacity. We explicitly also consider the environment as a type of infrastructure resource that is being consumed as part of a mobility service (e.g., by emitting CO_2 emissions). Ownership of Infrastructure Resources may be diverse. For example, non-professional private owners of single charging points or parking spots may coexist with large scale network and infrastructure operators.

3.2. Digital Layer

An information-based representation of Vehicle Resources, Infrastructure Resources and Mobility Needs resides in the digital layer of the smart mobility framework. Supply is represented as Mobility Offers that are enabled or constrained by the availability of physical Vehicle Resources (e.g. available units, remaining state of charge, etc.) as well as Infrastructure Resources (e.g. free-flow road capacity, number of charging spots, electricity grid capacity, emission limits, CO_2 targets), both of which must be considered when formulating Mobility Offers. Conversely, Mobility Offers can be used to plan, organize or reallocate Physical Resources. For example, a substantial presence of EV car-sharing providers in a region might require enhancements of the local charging infrastructure (downward arrow in Figure 2).

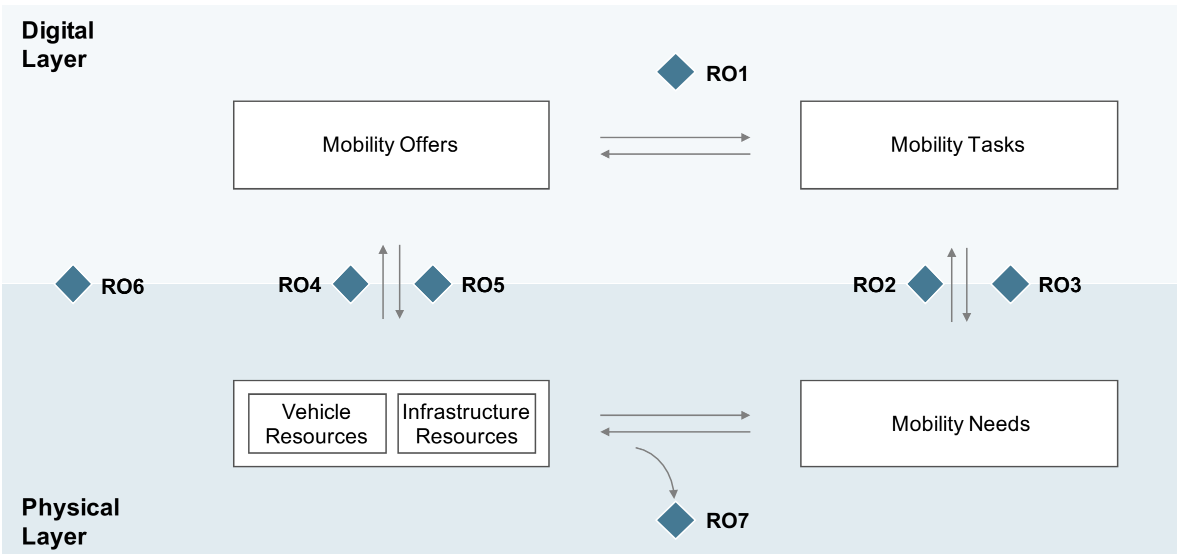
Mobility Tasks are defined by physical Mobility Needs (i.e., preferences). A user may request personal mobility, energy flexibility, logistics or other services in an on-demand fashion. These needs and preferences are encoded in Mobility Tasks in the digital layer. Operators and owners of mobility resources will be able to access these encoded requests and make (tailored) offers. Similarly, Mobility Tasks can incorporate information on the availability of resources and may have to be adapted to a scarcity in supply of these resources. This will necessarily involve some form of demand response on the user side such as (1) time shifting, (2) route shifting, (3) mode shifting or (4) foregoing the intended mobility request (e.g., by substituting with IS-enabled remote options such as online shopping or telework technologies). A matching of both sides is conducted in the digital layer. In addition, Mobility Tasks can affect and shape Mobility Needs. For example, while a user might have an intrinsic preference for a self-driving taxi, such a need and its associated Mobility Task might not (yet) be available (e.g., as a result of technology immaturity). Future technological innovation in Mobility Resources, Offers and Tasks that include self-driving taxis will allow for such a need to be satisfied; hence, the Mobility Task constrains the Mobility Needs that can be fulfilled.

It is easy to see the requirement for data-driven information systems in this exchange both in terms of preference elicitation and modeling on the supply and demand side as well as in terms of real-time matching of preferences at the interface of offers and tasks. As such, the digital layer serves as a coordination layer that enables matching between various mobility options and mobility demand under the given system capacity constraints such as fleet size, and battery-, road-, and electricity grid-capacity.

4. IS research opportunities toward smart mobility

We have argued that Information Systems Research can be an instrumental facilitator of smart sustainable mobility. We now specify this role by formulating seven concrete IS research opportunities (ROs) for the IS community in this domain. These opportunities build on the capabilities of CASE technology and can be mapped onto the dimensions of our framework (see Figure 3). Each research opportunity, as well as our proposed framework, is applicable to all four CASE technology themes or combinations thereof, e.g., connected and electric without autonomy features. Naturally, the presence of all four CASE technological themes might increase the complexity of the required solutions.

Figure 3 **IS Research Opportunities (ROs) toward Smart Sustainable Mobility.**



Note. **RO1**: Designing Real-time Coordination Mechanisms for Smart Sustainable Mobility Environments; **RO2**: Learning and Automating Heterogeneous Smart Sustainable Mobility User Choice Structures; **RO3**: Developing Incentive Designs and Nudging Strategies for Smart Sustainable Mobility Demand Response; **RO4**: Designing & Evaluating AI-Powered Real-Time Decision Support for CASE Mobility Resource Planning and Operations; **RO5**: Developing and Evaluating Digitally-Enabled Smart Sustainable Mobility Business Models; **RO6**: Human-AI collaboration in Smart Sustainable Mobility Systems; **RO7**: Investigating Intended and Unintended Consequences of Smart Sustainable Mobility Interventions

Addressing the ROs will enable IS to directly contribute to making future mobility both smart and sustainable, thus resolving the three social negatives (negative climate, safety and economic impacts) of incumbent transportation systems. For example, RO1 (Designing Real-time Coordination Mechanisms for Smart Sustainable Mobility Environments) could alleviate environmental (SN1) and economic (SN3) negatives, while RO7 can evaluate the impact of new technologies and policies on all three social negatives, and so on. We present the details per each RO below, and summarize their characteristics in Table 3.

4.1. RO1: Designing Real-time Coordination Mechanisms for Smart Sustainable Mobility Environments

At the heart of the Smart Sustainable Mobility challenge lies a resource allocation problem. Mobility users overutilize capacity-constrained resources such as road space, emission limits or parking contributing to the three social negatives of mobility (Cramton et al. 2018). Therefore, an important element in the digital layer of the smart mobility ecosystem is the efficient matching of resources with demand toward a certain objective. While traditional coordination literature typically optimizes for a narrow definition of social welfare that neglects many externalities, coordination in a Smart Sustainable Mobility system must go beyond individual social welfare objectives and focus on alleviating the social negatives SN1, SN2, leveraging the presence of one or more CASE technology themes.

Real-time matching of Mobility Tasks and Offers that also successfully serves to alleviate these social negatives is complex because of the high-dimensionality of the decision spaces (time horizons, modes of mobility, budget constraints, sustainability constraints, etc.). Additionally, the matching entity (e.g., platform) has to solve combinatorial allocations with dynamically evolving preferences and spaces. Traditional optimization approaches that exhibit the usual NP-hardness characteristics quickly become intractable in these high-dimensional combinatorial spaces. Therefore, heuristic AI-powered algorithms (such as Deep Learning) that derive near-optimal allocation decisions might prove powerful to address such challenges (Karaenke et al. 2019). In contrast to traditional real-time matching problems, system criticality is an additional factor to consider in Smart Sustainable Mobility domains. For example, in a Smart Sustainable Mobility system the social, environmental and financial costs of failures are immense. Because of the special nature of the Smart Sustainable Mobility system (see Table 2), the allocation and matching must happen in almost real-time so that customers have uninterrupted service (e.g., matching a request to a mobility or electricity service); therefore, solutions with low computational complexity are required. Challenges related to aligning dimensionality, combinatorics, and computational performance to achieve a practical coordination design can open new paths for future work.

Summarizing, we see tremendous research opportunities around **designing real-time coordination mechanisms for Smart Sustainable Mobility environments** that arise from the above-described challenges. Specific research questions that can guide IS research efforts here include: *What possible coordination approaches capable of fulfilling design guidelines (scalable, real-time, practical, alleviating SNs) exist and how do they compare?*; *Are there trade-offs between design guidelines, and if so how can they be managed?*; *How can the designed approaches be tested ex ante for robustness under close-to-real-world conditions?*; *How does mechanism design impact human/algorithmic behavior?*

The IS field has developed a rich portfolio of contributions in this regard that provide an excellent starting point. Auctions and other smart market-based coordination approaches (Bichler et al. 2010) have been investigated in depth both from a mathematical and a behavioral point of view in application domains such as server capacity allocation (Bapna et al. 2008a), grid computing (Bhargava and Sundaresan 2004), combinatorial auctions (Scheffel et al. 2011), and labor markets (Hong et al. 2016), as well as auctions specialized in electric mobility (Kahlen et al. 2018, Valogianni et al. 2019), shared mobility (Lam 2016) or road pricing (Cramton et al. 2018). However, when designing comprehensive smart market mechanisms for a mobility ecosystem, where vehicles are connected, autonomous, shared and electric, one can appreciate that complexity increases. Each of the framework dimensions represent constraints and influence stakeholder objectives differently, making their management in a smart ecosystem far from trivial. As discussed, due to the complexities of the required coordination in a system with many agents (large-scale, combinatorial), alternatives to traditional analytical solutions may be needed. Testing and benchmarking of different design concepts in large-scale (agent-based) simulations may be fruitful to achieve a consensus on the preferred mechanism design. The Multi-Agent Transport Simulation (MATsim) (Horni et al. 2016) is an example of such a framework - one that could be leveraged for competitive benchmarking of design approaches (Ketter et al. 2016b). In addition, accounting for behavioral characteristics in such mechanisms is of paramount importance for the success of a mechanism. The latter is a unique competency of IS research, which has not only studied the mechanisms themselves but also behavioral attributes that affect behaviors within a mechanism's incentive framework (Cason et al. 2011, Kannan et al. 2019, Lu et al. 2019a,b, 2016). Note that this established an important link to RO2 (see below), which deals with preference learning and automation in high-dimensional transportation domains. Building on this body of knowledge, IS researchers are uniquely positioned to drive forward, in an iterative fashion, the design of efficient matching instruments and mechanisms. The IS community has expertise both in terms of tools required to address this challenge effectively, and in terms of understanding the complexity posed by interdependencies between physical and digital layers in dynamic environments.

4.2. RO2: Learning and Automating Heterogeneous Smart Sustainable Mobility User Choice Structures

Bounded rationality (Simon 1979), excessive transaction costs (Balduzzi and Lynch 1999), and cognitive overload (Schwartz 2016) can result in suboptimal individual decision making and subsequent welfare loss. In high-frequency, high-dimensional Smart Sustainable Mobility environments these issues are particularly relevant. Thus, to achieve the desired real-time coordination as envisioned in RO1, human preferences must be better understood and their decisions supported through IS/IT. Only then can the full potential for alleviating the SNs of mobility be leveraged. Practically speaking, understanding user preferences is key in the translation of physical Mobility Needs to digital Mobility Tasks (upward relationship in Figure 3). For example, learning customer preferences about autonomous ride-sharing in the center of a metropolitan area helps the ride-sharing platform operator allocate the required resources and offer a seamless and uninterrupted service to customers (mitigating SN1, SN2 and possibly SN3). Preference learning is also crucial for identifying the impact of CASE technologies or Mobility Tasks on consumer behavior, i.e. for understanding how Mobility Tasks shape Mobility Needs (downward relationship in Figure 3).

Dynamic customer modeling and choice automation can provide these insights and tools. As such, RO2 is targeted at **learning and automating heterogeneous Smart Sustainable Mobility**

user choice structures in a high-velocity, high-dimensional Smart Sustainable Mobility system. Specific questions to direct IS research in this area include: *How can multi-dimensional and high-frequency data be used to elicit implicit user preferences in high-dimensional Smart Sustainable Mobility environments?*; *How can consumer choice models be designed to be adaptive to dynamically evolving Smart Sustainable Mobility environments?*; *How should (semi- and/or adjustably-) automated IT artefacts be designed to act upon learned preferences on a user's behalf?*

IS research has longstanding experience in customer modeling and preference elicitation in domains such as B2B auctions (Bapna et al. 2008c, Lu et al. 2016) online environments (McKinney et al. 2002, Yang et al. 2019), purchasing behavior (Bemmaor and Glady 2012), online security (Yang and Padmanabhan 2010), or electricty systems (Peters et al. 2018), among others. Research has looked at causal modeling of current and emerging consumer preference trends and predictive modeling and forecasting of future consumer preferences. Both are necessary for downstream decision support tools that help users navigate the complexities of the above-mentioned domains. Smart Sustainable Mobility environments, however, come with a few notable differences (see also Table 2): First, users can exhibit highly heterogeneous and dynamic preference sets depending, for example, on specific travel use cases and other (local) state variables (e.g., local vehicle supply, outside options, weather, etc.). Second, the choice space in mobility is exceedingly large in scale. Users can choose between different departure times, travel modes and routes. Finally, this large set of high-dimensional decisions continues to dynamically evolve as CASE technologies reach maturity and new vehicle types emerge. These novelty characteristics make new preference learning and choice automation approaches necessary.

Therefore, while previous choice modeling research experience may provide a strong basis, significant adaptations to Smart Sustainable Mobility are required. For example, large spatio-temporal datasets that can be used to analyze user patterns in a rapidly changing mobility and energy domain are increasingly abundant and include sensor data, electricity consumption data, mobile GPS traces and geo-tagged transaction data that provide a novel level of granularity of human offline behavioral patterns in the city and its transportation system (Zhang et al. 2020). Explanatory preference modeling powered by these large-scale datasets can uncover drivers of user preferences in unprecedented detail; however, as opposed to previous work, it now requires a combination of data mining and geo-spatial analytics techniques combined with econometric and statistical analysis. As CASE technology proliferates dynamically, understanding the root cause of evolving consumer needs will be a fruitful avenue for IS research and can provide a basis for formulating utility functions required for choice automation. Second, scalable predictive models (Peters et al. 2018) that can dynamically and cost-effectively (Zheng and Padmanabhan 2006) forecast mobility needs in the different CASE application fields are needed. For example, segmenting user clusters using unsupervised learning techniques and predicting user behaviour such as willingness to pay (Bapna et al. 2008b) and price elasticity (Cohen et al. 2016) is an important step in leveraging big mobility data. Predicting mobility needs or combined electricity and mobility needs, however, requires consideration of both temporal and geographic dimensions; this aspect generates significantly more complexity compared to other environments, such as e-commerce. For example, Schroer et al. (2022) and Willing et al. (2017) draw on location analytics techniques to develop statistical mobility demand forecasting models that predict car sharing demand in time and space. Such dynamic spatio-temporal forecasting methods remain highly relevant as contextual contingencies of the mobility ecosystem evolve and play to our IS researchers' strengths in predictive analytics and (spatial) decision support systems (Keenan and Jankowski 2019).

Accurate customer models are also required when assisting customers in making more efficient decisions by broadening the customer decision spectrum, minimizing information asymmetry barriers and managing bounded rationality issues. In a real-time data-driven world in which a large volume of operational decisions must be made, decision support tools such as recommender agents become necessary enablers of demand response (Adomavicius et al. 2009). IS researchers can capitalize on expertise in choice automation support using advanced machine learning, such as the algorithms implemented in recommender systems (Qiu and Benbasat 2009, Adomavicius et al. 2013, Collins et al. 2009), marketing applications (Chica and Rand 2017), smart business networks (Collins et al. 2010), etc.

While not deeply researched in mobility, demand automation is a common notion in the domain of electronic market-based systems such as electricity systems, where it has received some attention from IS research (Watson et al. 2010, Gottwalt et al. 2011, Peters et al. 2013). For example, Valogianni and Ketter (2016) propose a decision support system for consumers combined with a central demand response module that develops effective pricing strategies for different user groups. For applications in Smart Sustainable Mobility, which are subject to a variety of novel challenges and complications (see Table 2), new choice automation frameworks must be developed accordingly.

4.3. RO 3: Developing Incentive Designs and Nudging Strategies for Smart Sustainable Mobility Demand Response

Apart from understanding high-dimensional, heterogeneous customer preferences (RO2) and matching them with available supply in an optimal manner (RO1), there may be a need to more actively shape consumer demand by encouraging certain desired demand response in the user population. For example, in the event of increased demand for autonomous vehicles in the center of a metropolitan area, prices of alternative modes such as shared bikes could be dynamically discounted thus shifting demand to such outside options while mitigating SN1 and SN3. In general, demand response can take place in terms of (1) time-shifting[6], (2) route-shifting, (3) mode-shifting or (4) curtailing (Vickrey 1969). Previous research has shown that strategic incentive design (Guda and Subramanian 2019, Cohen et al. 2016) and non-financial contextual design choices (e.g., Tiefenbeck et al. 2018) can be effective in evoking desired behavioral patterns. The latter approach has commonly become known as nudging and subsumes diverse techniques such as reminders, personalized defaults, rankings, gamification, etc. (Thaler et al. 2013).

We argue that there is a large but under-researched potential for putting such techniques to use in the domain of mobility. Therefore, this research opportunity is directed at **developing effective incentive designs and nudging strategies for Smart Sustainable Mobility demand response**. Research questions that can guide efforts in this area include: *How should effective mobility demand response interventions be designed to steer user behavior in a system-beneficial*

[6] time-shifting can refer to both mobility and electric charging actions

manner (e.g., via time-,route- or mode-shifting)?; *Are financial incentive schemes effective in eliciting user demand response in time and space, and if so, what are the boundary conditions?*; *Can traditional nudging techniques influence user behavior toward desired outcomes in high-dimensional spatio-temporal choice spaces like Smart Sustainable Mobility?*; *Which design criteria constitute successful nudging interventions in Smart Sustainable Mobility?*

In terms of examining financial incentive schemes, IS can draw on a wide body of research on revenue maximization and incentive design (Guda and Subramanian 2019, Cohen et al. 2016). Some early empirical implementations (e.g. Uber surge pricing), although solely profit focused, are also available for empirical investigation. Research on data-driven dynamic tariff designs, by which an agent issues tariffs and observes the market response, are a novel and promising route as well. Near-optimal tariff designs are found by continuously updating tariffs while balancing the cost of exploration with the benefits from exploiting profitable tariffs, for example by using a reinforcement learning approach (Peters et al. 2013). Importantly, empirical investigation and demonstrations of these mechanisms are needed.

We also see research opportunities in non-financial demand response strategies that leverage behavioral nudges. While not yet well-researched in mobility (likely as the result of the above-mentioned challenges), experiences from the energy domain hint at the potential of such approaches. For example, Tiefenbeck et al. (2018) demonstrate that users can be nudged towards more energy conservation simply by removing salience bias through real-time feedback on their consumption behavior, while Costa and Kahn (2013) show that energy conservation nudge-effectiveness is heterogeneous and depends strongly on individual ideology. In a similar vein, Adena and Huck (2020) explore the potential negative long-term effects of excessive nudging, e.g., by means of too-frequent reminders and asks. Nudging is also a promising research field in mobility and may further augment price-based strategies. Other non-financial incentives comprise the provision of viable alternatives to mobility. Examples include “telework” incentives or “global teams initiatives” that aim to reduce travel. All these require a deep understanding of IT capabilities and human mobility behavior in order to yield the desired outcomes without compromising goals such as productivity or well-being, to name a few.

A particular challenge of research on incentive schemes and nudging in smart mobility systems, as opposed to prior work, is the sheer size of the option space, which is a result of the non-binary nature of mobility choices (see Table 2). Users have flexibility both in space (route, mode) and time (departure, arrival). Any incentive or nudging structure should play to both dimensions to achieve the desired outcome of reducing SNs of mobility. For example, to avoid congestion, any pricing schemes should be differentiated both across regions and time periods to accurately reflect supply and demand (Cramton et al. 2018), while on-demand workers in ride hailing networks can also be incentivized via prices to relocate to certain high-demand regions at certain points in time (Guda and Subramanian 2019, Bimpikis et al. 2019). In addition, highly heterogeneous and dynamic user utilities might make user-specific tailoring of incentives and nudges necessary. For example, travel during rush hour might be avoidable for some users but not for others. Theoretical and empirical research on such spatio-temporal financial and non-financial incentive schemes is highly promising and strongly aligned with IS research methods and tools. Note that (quasi-)experimental research designs must be carefully crafted to isolate the causal effect of certain incentives in these high-dimensional choice spaces. IS research expertise in experimental design and causal inference places our community at the center of addressing the challenges presented here.

4.4. RO4: Designing & Evaluating AI-Powered Real-Time Decision Support for CASE Mobility Resource Planning and Operations

As mobility systems become smarter, transportation information flows (supply and demand data, traffic flow data, price data, etc.) are increasingly abundant (see for example open mobility data standards such as the Mobility Data Specification (MDS)[7]). While this creates unprecedented transparency on the status of fleets, traffic flows, etc. it also results in the need to leverage these data streams for better strategic and operational decision making.

[7] https://github.com/openmobilityfoundation/mobility-data-specification

In short, as argued previously, digitalization of mobility affords better and real-time coordination and can help remedy the SNs of mobility. Yet, this comes at the cost of higher operational and strategic intricacies for managers of mobility service systems (Abbasi et al. 2016, Beverungen et al. 2019). Therefore, a clear research opportunity for IS research lies in **designing and evaluating AI-powered real-time decision support for CASE mobility resource planning and operations**. The following exemplary research questions might guide IS research efforts in shaping the agenda here: *Which strategic and operational complexities arise for supply-side actors in Smart Sustainable Mobility environments?*; *How can IS support and automate these decision challenges?*; *What is the value of incorporating ever more abundant (real-time) data-feeds in the strategic and operational decision making process?*

On the strategic level, mobility asset investment decisions are conditioned on expectations of future technology adoption scenarios, changing consumer behavior, and the state of the system (supply, demand, prices) among other factors and are therefore subject to uncertainty. Decisions on how many vehicles to purchase, the level of vehicle autonomy and other capabilities, how many parking spots to create or how many charging points of which capacity to place where within a given region are dependent on expectations of future adoption rates, of the nature and dynamics of consumer behavior (which can often be endogenous to the investment decisions) and on assumptions of how these fleets and infrastructure resources will be managed. Standard optimization approaches quickly become intractable in such volatile, high-dimensional environments, with many interdependencies originating in the sheer size of the optimization problem (see Table 2). Large-scale data-driven simulation that uses heuristics to achieve near-optimal results has been shown to be highly successful in these cases (Valogianni et al. 2020). The unprecedented granularity and availability of data afforded by CASE technology enables a new, data-driven and simulation-based approach to vehicle and infrastructure provisioning to which IS can make significant contributions. Such simulation studies, especially agent-based simulation frameworks, also allow for joint evaluation against multiple objectives. This is important as Smart Sustainable Mobility involves trade-offs between firm-level objectives such as sustainability (i.e., the SNs of mobility) and profitability.

At the operational decision level, newly available data streams offer new scope for machine learning and optimization. The vast volumes of data being generated by all entities participating in the CASE-based Smart Sustainable Mobility ecosystem (customers, vehicles, smart infrastructure equipment such as traffic lights, vehicle charging points, etc.) enable advanced spatio-temporal predictions of near-term demand and supply of CASE resources such as vehicles, electricity required to charge the vehicles, price levels of different inputs, etc. IS researchers can address this research opportunity by capitalizing on deep expertise in predictive analytics (Shmueli and Koppius 2011) in domains such as healthcare (Bardhan et al. 2015, Singh et al. 2018), cybersecurity (Abbasi et al. 2015), presidential elections (Barfar and Padmanabhan 2017), detecting financial fraud (Abbasi et al. 2012), and forecasting economic regimes (Ketter et al. 2009), among others. Yet, the peculiarities of the Smart Sustainable Mobility sphere (see Table 2) lead to a number of specific challenges. Effective decision support systems will usually have a wider scope as they involve multiple uncertainties (e.g., demand and supply in time and space) for which prediction or stochastic algorithms must be devised. Exploring the influence of prediction errors and their interactions (in case of multiple prediction models) is crucial. Additionally, operational decisions must be made at high frequency and/or with very different time horizons (e.g., weeks-ahead vs. real-time) which can create challenges.

4.5. RO5: Developing and Evaluating Digitally-Enabled Smart Sustainable Mobility Business Models

A Smart Sustainable Mobility transition will be successful or, indeed, possible if profitable business models can be conceived that spur private sector adoption and engagement while ensuring societal benefits related to alleviating the SNs of mobility. In this vein, a crucial research opportunity pertains to the creation of such **digitally-enabled Smart Sustainable Mobility business models** that build on the capabilities of CASE technology to create societal value (Osterwalder et al. 2005). Indeed, CASE technology may open up completely new application fields for vehicle resources and mobility, where the social negatives SN1, SN2, SN3 can be alleviated. For example, Vehicle Resources can now be used not only to transport people but also for goods delivery, electricity services and a myriad of further use-cases, many of which are yet to be discovered (in-vehicle commerce and services to name just one example).

Smart Sustainable Mobility business models are enabled through information systems that help manage the complexities associated with the real-time management of these (possibly) multi-purpose vehicle resources (Table 2). Specific research questions that may be useful in developing and evaluating different business model options include: *What are viable IS-enabled business models that build on the affordances of CASE mobility technology?*; *How can Smart Sustainable Mobility business models strike an effective balance between efficiency (utilization and profitability), sustainability and customer satisfaction?*; *How resilient and robust are such business models under different Smart Sustainable Mobility scenarios?*

IS research can, in close collaboration with practitioners, contribute to identifying, testing and evaluating these new business model options. Existing business model archetypes may have to be substantially adapted and/or combined to fit the Smart Sustainable Mobility paradigm due to several unique characteristics of this operating environment. First, the previously discussed multi-use characteristics of mobility assets that require ongoing trade-off analyses between the possible markets in which the asset can create value (personal mobility, goods mobility, etc.) may require operating multiple business models in parallel. Yet, if these trade-offs can be managed effectively, new levels of asset utilization, profitability and sustainability may be achieved. For example, a CASE vehicle may transport people during rush hour, perform last-mile parcel delivery in low-demand periods and provide energy services to the grid when connected to a charging station (Kahlen et al. 2018). Second, providing Smart Sustainable Mobility services will require heterogeneous inputs (electricity, parking space, road usage) many of which do and/or increasingly will exhibit high-frequency supply changes in time and space. Managing these inputs such that cost and sustainability targets are achieved is a major operational decision challenge for mobility providers. Finally, business objectives are increasingly multi-dimensional and extend beyond profitability. This involves continuously trading-off potentially conflicting goals.

Taking an IS Design Science (Hevner and Gregor 2013), empirical (Oestreicher-Singer and Zalmanson 2013) or mixed methods approach (Fürstenau et al. 2019), and drawing on the extant literature in the fields of digital platforms and smart service systems (Beverungen et al. 2019), IS can enable the operations of increasingly more complex business models. Methodologically, such work may combine big data analytics, large-scale simulation and/or field tests. In many cases the prototyping of IS decision support tools that are needed for the operation of such data-driven and highly complex business models may be needed (see RO4). Some interesting early work has emerged along these lines. For example, Brandt and Dlugosch (2020) develop a two-stage data-driven framework for ex-ante assessment of operational policies of shared mobility providers. Finally, early examples that build on the capabilities of CASE and combine different business models are emerging. Specifically, Kahlen et al. (2018) present an EV fleet management concept that explicitly considers the trade-off between providing mobility and electricity services in a profit-maximizing manner. While promising, a lot of opportunity for future work exists that further develops existing business models and explores new business model instantiations in a continuously evolving Smart Sustainable Mobility ecosystem.

4.6. RO6: Human-AI collaboration in Smart Sustainable Mobility Systems

Smart sustainable mobility systems are operating and evolving with the help of the latest AI methods such as location-based analytics, object recognition using deep learning, dynamic price adjustments, intelligent agents for preference elicitation and decision support, to name a few. Thus, a major question arises: how to facilitate a successful collaboration between human users or decision makers and AI? This question is relevant for all digital-physical intersections, which is why we position RO6 as an overarching RO within our framework (see Figure 3)

Trust in AI-based systems in a Smart Sustainable Mobility environment is crucial, as a lack of or partial trust is not expected to enable the ecosystem to reach its full potential and satisfy objectives such alleviating the social negatives SN1, SN2, SN3. At the same time, AI-based systems adoption is challenging, since the domain is nascent, and many of the utilized AI-based applications might be seen as intrusive (e.g., the controversial issue of recording user location by Uber´s algorithms [8]) or flawed (e.g., accidents caused by autonomous cars [9]). Literature has shown that when algorithms make mistakes, humans trust them less as opposed to humans who have made similar mistakes (Dietvorst et al. 2015). Especially with regard to autonomy, an active dialogue has been developed in the academic community about minimizing the flaws of autonomous vehicles and the responsible entities in case of an accident[10]. In addition, users might be hesitant to adopt AI-based apps that record their preferences in order to offer optimized routing or electric-vehicle charging recommendations. Concerns such as intrusiveness, reliability, bias, or simply resistance to change might arise and require the expertise of IS researchers – who combine social sciences paradigms and technical expertise (Sarker et al. 2019) – to be addressed.

Specifically, Research Opportunity 6, which lies at the intersection of the physical and digital layer of the Smart Sustainable Mobility framework, is concerned with **investigating Human-AI collaboration in Smart Sustainable Mobility systems**. Examples of research questions are: *What design attributes increase human trust toward AI-based applications in Smart Sustainable Mobility systems?; How should privacy-preserving AI-based systems be designed so that they are not perceived as intrusive in Smart Sustainable Mobility platforms?*

IS researchers have already taken some important steps toward exploring human-AI interaction (Berente et al. 2019) and collaboration (Fügener et al. 2021, Breuker et al. 2016, Fügener et al. Forthcoming) in other domains; hence such expertise can be capitalized in Smart Sustainable Mobility environments. IS researchers have also developed expertise in developing AI-based systems (Zhu et al. 2021, Pfeiffer et al. 2020, Wang et al. 2018, Meyer et al. 2014, Sahoo et al. 2012), as well as managing such complex intelligent systems (Ahsen et al. 2019, Du et al. 2014, Chen et al. 2011). However, as opposed to other cyber-physical systems, Smart Sustainable Mobility environments exhibit unique characteristics that require new research contributions (see Table 2). Most importantly, the mission criticality of such systems necessitates human-AI collaboration robustness and

[8] https://www.npr.org/sections/thetwo-way/2017/08/29/547113818/uber-ends-its-controversial-post-ride-tracking-of-users-location?t=1586959206306

[9] https://www.theguardian.com/commentisfree/2018/jul/15/crucial-flaw-of-self-driving-cars-always-need-human-involvement

[10] https://www.moralmachine.net

trust that exceeds levels seen in other domains. Therefore, AI acceptance and human-AI collaboration need to be studied carefully in a Smart Sustainable Mobility context. Tools to achieve the thorough study of human-AI collaboration can be field experiments (similar to the one presented by Cherchi (2017)) or interventions using AI-based artifacts (e.g., Koroleva et al. (2014)).

4.7. RO7: Investigating Intended and Unintended Consequences of Smart Sustainable Mobility Interventions

Mobility is a public good and subject to regulation. We realize that the comprehensive transformation of a sector toward smart sustainability, such as is anticipated for the mobility sector, requires a strong foundation in public policy and underlying management approaches. The IS community has made deep contributions in the domains of energy and sustainability (Watson et al. 2010, Melville 2010, Ketter et al. 2016b, Corbett and Mellouli 2017), health (Bardhan et al. 2015, Singh et al. 2018) and other areas of high societal relevance. We believe that IS research can be a key facilitator of the Smart Sustainable Mobility transition, not only by developing required decision support tools or coordination mechanisms (as argued in RO 1 through 6), but also by informing policy discussions with hard, causal evidence obtained from rigorous empirical investigation. Therefore, we propose an additional RO that is concerned with **investigating intended and unintended consequences of Smart Sustainable Mobility interventions (as described in Table 1)**. Concrete research questions underlying this opportunity might include: *What are the system- and user-level impacts of new mobility technology, policy or IS artefact introduction?*; *Does a new technology/policy innovation alleviate or aggravate SNs of mobility and under which conditions?*; *What are the temporal and spatial dynamics of macro-level effects?*; and; *What are the implications of these ex-post empirical findings for shaping the ongoing Smart Sustainable Mobility transition with future technologies, policies and managerial approaches?*

Research on the societal impact of technology is deeply rooted in IS (Greenwood and Wattal 2017, Burtch et al. 2018, Babar and Burtch 2020). Furthermore, the IS discipline's prowess in big data analytics for causal inference (Abbasi et al. 2016) – particularly within the economics of IS community – means that our discipline has all the necessary tools at its disposal to engage with this research opportunity. In the evaluation of the social cost of new mobility technologies, IS can contribute extensively by informing policy decisions that are targeted at mitigating unintended consequences of CASE technology (see Table 1), while actively promoting the desired effects. For example, Greenwood and Wattal (2017) investigate the impact of ride hailing platforms on alcohol-related traffic deaths and demonstrate that a significant reduction in drunk driving-related fatalities was achieved. In a similar vein, Babar and Burtch (2020) investigate the heterogeneous effects of ride hailing platforms on public transport. They show that the degree of substitution or complementarity depends on a set of contextual factors and they formulate concrete policy recommendations showing how public transport authorities can benefit from ride hailing platform introduction. Pelechrinis et al. (2016) find that the introduction of bike sharing platforms replaces some car traffic and thus alleviates traffic and parking pressure. While the above cited studies use highly aggregated data (e.g., monthly or quarterly), increasingly ubiquitous real-time geo-tagged datasets will enable ever more fine-grained empirical investigation. This will allow IS scholars to investigate societal implications of CASE technology (beyond the current IS focus on instantiations of the sharing economy such as ride hailing and ride sharing) in unprecedented detail and to provide considerably more targeted policy and managerial recommendations. There are several challenges endemic to the domain of Smart Sustainable Mobility that make causal analyses difficult. Real-world experimentation is difficult and possibly unethical in Smart Sustainable Mobility environments. Therefore, researchers will rely mostly on observational data sources. With highly granular spatio-temporal mobility data feeds, the detail at which causal inference can be credibly achieved is far superior to what is observed in traditional natural experiment-based causal inference literature. This insight provides opportunity for truly actionable managerial and policy advice beyond the macro-level insights. Yet, when modeling at such granular levels new challenges arise. For example, user utility (and choice) in mobility will heavily depend on local state conditions (e.g., supply of vehicles, weather) and trip purpose (Table 2), which must be taken into account and controlled for. Additionally, effects such as spatial spillovers can make causal analysis challenging when working at low levels of aggregation.

5. Smart Sustainable Mobility Research - Current IS Engagement and Barriers to Entry

We now look at where the current state of IS research in Smart Sustainable Mobility research stands with regards to the previously developed Research Opportunities. We have argued that IS has been a relatively silent observer of the recent uptake in Smart Sustainable Mobility research. Here, we explore in more detail why this might be the case, focusing on possible barriers to entry that have thus far prevented wide-spread IS engagement with the field. For this purpose we perform an in-depth review of the IS Basket of 8 papers identified in the initial key-word-based cross-disciplinary survey of the literature (see Figure 1). The results of this analysis are presented in Appendix B. Several insights are to be highlighted.

First and foremost, extant IS research in Smart Sustainable Mobility is limited. Out of the 65 initial papers, only 22 (34%) deal with Smart Sustainable Mobility topics at their core. Second, out of these remaining Smart Sustainable Mobility-related IS papers, most focus on just two out of the seven research objectives (ROs) we propose in this work: RO5 – Developing and Evaluating Digitally-Enabled Smart Sustainable Mobility Business Models and RO7 – Investigating Intended and Unintended Consequences of Smart Sustainable Mobility Interventions. The rest (8 papers) are distributed more or less equally among the remaining five ROs. Third, there is a large methodological emphasis on empirical methods (specifically econometrics and interview-based qualitative case studies). Decision support systems for Smart Sustainable Mobility applications are rarely proposed, although we have identified such work as crucial in driving the transition toward Smart Sustainable Mobility. Finally, the naturally data-intensive empirical research pieces included in our sample are primarily reliant on proprietary data sources with only 6 papers using public or synthetic data.

Throughout this commentary we have argued that the domain's nascent, complex and interdisciplinary nature are the key reasons for a lack of IS engagement in the field. The review of current IS research confirms many of these suspicions. Nascency implies a lack of domain knowledge in the IS community, creating educational barriers to entry. Indeed, the (limited) extant IS research tends to focus on just two out of the seven ROs we put forward, indicating a lack of awareness of other research opportunities. This commentary is targeted at removing exactly this barrier.

Complexity and interdisciplinary nature suggests a need for methodological prowess in tackling Smart Sustainable Mobility research opportunities. We have argued extensively throughout this article that IS has all the prerequisites to thrive in these environments, as has been demonstrated in other complex domains such as healthcare and cyber-security. Yet, we also observe that extant Smart Sustainable Mobility work is mostly empirical in nature, meaning it is about understanding phenomena rather than providing data-driven and analytics-focused solution frameworks. There clearly is a lack of research on decision support systems that help practitioners navigate complexity in mobility. Again, we attribute this to the nascency and complexity of the field, as well as a possible lack of familiarity with design science and machine-learning-driven methodologies. In this research commentary, we provide actionable ROs that can guide IS researchers with limited prior domain knowledge to leverage their extensive analytical skillset for meaningful contributions to Smart Sustainable Mobility.

In addition to nascency and complexity, we find that extant Smart Sustainable Mobility research can be resource-intensive – particularly with regard to requiring access to large-scale real-world datasets. Indeed, as we point out above, most of the empirically-focused papers we have reviewed draw from proprietary data sources. In cases where public data is used, the data is not typically geo-tagged and relatively coarse, preventing micro-level analyses envisioned in this commentary. This creates a third adoption barrier for IS researchers interested in Smart Sustainable Mobility research. We believe, however, that granular mobility data is increasingly becoming available. Four observations support this argument: (1) First, open standards that facilitate easier mobility data sharing at scale are becoming the norm. Examples of some of the most common standards include: General Bikeshare Feed Specification (GBFS[11]), General Transit Feed Specification (GTFS[12]) or

[11] https://github.com/NABSA/gbfs

[12] https://developers.google.com/transit/gtfs/reference/

the Mobility Data Specification (MDS[13]). Such standards are already used by many operators (often in combination with open APIs) and their use can even be mandated by local transport authorities as part of open mobility data initiatives (see e.g., LA). (2) Second, empirical evidence also confirms that there already are a number of mobility platform operators that readily share real-time mobility data streams through openly accessible APIs[14]. These sources are available to researchers even today and first research leveraging such datasets has emerged (e.g., Demircan et al. 2022b,a). (3) Third, there are also third-party market research companies[15] that provide real-time data streams including history of most major shared mobility platforms - even those for which open APIs cannot be readily found/queried. While these datasets are not publicly available (yet), they nonetheless provide a viable source of data. (4) Finally, in case real-world data cannot be obtained, large-scale open-source simulation platforms are available that provide realistic synthetic transportation environments and are widely used in the transportation literature. An example would be MATSim (Horni et al. 2016).

6. Conclusion

Throughout this commentary, we have made the case for IS research to actively shape the future of mobility toward an information-driven Smart Sustainable Mobility ecosystem. We have based this argument on advances in vehicle technology (connected, autonomous, shared and electric (CASE) mobility), which not only provide access to an unprecedented breadth of digital information but also enable real-time analysis and management of the mobility system. We argue that an active management of physical vehicle resources, infrastructure resources and mobility needs is required to promote the positive climate, health & safety and economic effects of CASE mobility, while

[13] https://github.com/openmobilityfoundation/mobility-data-specification

[14] As an illustrative example, the following GitHub repository provides a (non-exhaustive) list of (openly accessible) mobility sharing platform APIs including instructions on how to query them `https://github.com/ubahnverleih/WoBike`

[15] e.g., fluctuo (https://fluctuo.com) or remix (https://www.remix.com/solutions/shared-mobility)

mitigating unintended consequences of this technology (see Table 1). Given the unique characteristics of the envisioned next generation transportation system that clearly set it apart from other cyber-physical systems, a new research agenda is needed to which the IS community can make significant contributions. By laying out a vision for an IS-enabled smart mobility system we have proposed a framework which can help structure this agenda (see Figures 2 and 3). We have also proposed seven concrete IS research opportunities along this framework for which we discussed promising IS research questions, approaches and methodologies. We summarize the core results of these discussions in Table 3. Despite a previously limited involvement in Smart Sustainable Mobility research, the IS community has all the necessary tools at its disposal to play a pivotal role in the knowledge creation necessary to address the presented research opportunities and pave the way for a successful transition toward sustainable smart mobility. We hope that this work may spur interest in our community to contribute to this exciting agenda and to seize a unique opportunity to positively impact our environment, our economy and our societal welfare at large.

Table 3 Summary of proposed IS Research Opportunities (ROs) in Smart Sustainable Mobility

Research Opportunity	Exemplary Research Questions	IS Research Traditions*	Novelty Characteristics
RO1 – Designing Real-time Coordination Mechanisms for Smart Sustainable Mobility Environments	– What possible coordination approaches capable of fulfilling design guidelines (scalable, real-time, practical, alleviating SNs) exist and how do they compare? – Are there trade-offs between design guidelines, if so how can they be managed? – How does mechanism design impact human/algorithmic behavior?	Behavioral, Design, Economics of IS	1. **Combinatorial nature** of resources 2. **High dimensionality** of decision spaces including time, space, modes, etc. 3. **Real-time** characteristics of the mechanisms may prohibit standard optimization-based approaches (due to NP-hardness) 4. **System criticality** and requirement for resilience/robustness to extreme events
RO2 – Learning and Automating Heterogeneous Smart Sustainable Mobility User Choice Structures	– How can high-frequency data be used to elicit implicit user preferences in high-dimensional mobility environments? – How can mobility preference models be adaptive to dynamically evolving environments? – How should mobility choice automation systems be designed?	Behavioral, Design	1. Highly **heterogeneous and dynamic user preference sets** 2. **Large-scale choice and action space** 3. **Interdependence** of **preferences and** diverse set of system/personal **state variables/constraints** 4. Dynamically **evolving environments**
RO3 – Design of Mobility Demand Response Incentives and Nudging Strategies	– Are financial incentive schemes effective in eliciting user demand response in mobility, and if so, what are the boundary conditions? – Can nudging techniques influence user behavior toward desired outcomes in spatio-temporal choice spaces?	Behavioral, Design	1. **Large-scale choice and action space** making targeted behavioral steering difficult 2. **Heterogeneity in user response** to incentives due to highly heterogeneous utilities
RO4 – Designing Real-Time Decision Support for CASE Mobility Asset Operations	– Which strategic/operational complexities arise for supply-side actors in Smart Sustainable Mobility environments? – What is the value of incorporating abundant (real-time) data-feeds in the strategic/operational decision making process? – How can IS support and automate these novel decision challenges?	Design	1. High **number of uncertainties** 2. **Heterogeneous decision horizons** (days-ahead procurement, real-time bidding,etc.) leading to multi-stage decision problem 3. High frequency (real-time) and granularity (high spatial resolution) resulting in **very large problem instances**
RO5 – Developing and Evaluating Digitally-Enabled Smart Sustainable Mobility Business Models	– How can new IS-enabled business models be designed around the affordances of CASE mobility technology such that a balance between efficiency (utilization and profitability), sustainability and customer satisfaction is struck? – How resilient and robust are these business models under different Smart Sustainable Mobility scenarios?	Design	1. **Multi-use assets** with more than one possible use case (human/goods transport, energy services, etc.) 2. **Multi-resource requirements & constraints** (electricity, road and parking space, etc.) with high-frequency supply changes in time and space 3. **Multi-objective business models** beyond profit maximization (sustainability objectives become relevant) requiring active trade-off management
RO6 – Human-AI collaboration in Smart Sustainable Mobility Systems	– What design attributes increase human trust toward AI-based applications in Smart Sustainable Mobility systems? – How should privacy-preserving AI-based systems be designed so that they are not perceived as intrusive in Smart Sustainable Mobility platforms?	Behavioral	1. **System criticality** requires successful and robust human-AI collaboration 2. **Privacy concerns** to be addressed via privacy-preserving data handling and system design
RO7 – Investigating Intended and Unintended Consequences of Smart Sustainable Mobility Interventions	– What are the system- and user-level impacts of new mobility technology, policy or IS artefact introduction? – Does a new technology/policy innovation alleviate or aggravate SNs of mobility and under which conditions? – What are the implications for shaping the ongoing transition to Smart Sustainable Mobility?	Economics of IS	1. More and more **tightly controlled** user-level **mobility data** (privacy concerns) and corresponding requirement for modeling based on anonymized, non-user-level and (possibly) aggregated data 2. Need for **modeling time and space** and associated causal inference challenges 3. Controlling for **high-dimensional choice and action space**

* IS Research Traditions according to Abbasi et al. (2016)

Acknowledgments

The author team would like to gratefully acknowledge the detailed and constructive reviews received by Prof. Ahmed Abbasi (Senior Editor), Prof. Gautam Pant (Associate Editor) and the two anonymous reviewers. Their in-depth comments and thoughtful suggestions during multiple review rounds have contributed to a much stronger paper and we very much appreciate their time and effort.

References

Abbasi A, Albrecht C, Vance A, Hansen J (2012) Metafraud: a meta-learning framework for detecting financial fraud. *MIS Quarterly* 1293–1327.

Abbasi A, Sarker S, Chiang RH (2016) Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems* 17(2):1–32.

Abbasi A, Zahedi F, Zeng D, Chen Y, Chen H, Nunamaker Jr JF (2015) Enhancing predictive analytics for anti-phishing by exploiting website genre information. *Journal of Management Information Systems* 31(4):109–157.

Adena M, Huck S (2020) Online fundraising, self-image, and the long-term impact of ask avoidance. *Management Science* 66(2):722–743.

Adomavicius G, Bockstedt JC, Curley SP, Zhang J (2013) Do recommender systems manipulate consumer preferences? a study of anchoring effects. *Information Systems Research* 24(4):956–975.

Adomavicius G, Gupta A, Zhdanov D (2009) Designing intelligent software agents for auctions with limited information feedback. *Information Systems Research* 20(4):507–526.

Ahsen ME, Ayvaci MUS, Raghunathan S (2019) When algorithmic predictions use human-generated data: A bias-aware classification algorithm for breast cancer diagnosis. *Information Systems Research* 30(1):97–116.

Axhausen KW (2017) Towards an AV future: Key issues. *Future Urban Mobility Symposium 2017* (Singapore), URL `http://dx.doi.org/https://doi.org/10.3929/ethz-b-000169534`.

Ba S, Lisic LL, Liu Q, Stallaert J (2013) Stock market reaction to green vehicle innovation. *Production and Operations Management* 22(4):976–990.

Babar Y, Burtch G (2020) Examining the Heterogeneous Impact of Ride-Hailing Services on Public Transit Use. *Information Systems Research* .

Balduzzi P, Lynch AW (1999) Transaction costs and predictability: Some utility cost calculations. *Journal of Financial Economics* 52(1):47–78.

Bapna R, Goes P, Gupta A (2008a) Auctioning vertically integrated online services: Computational approaches for real-time allocation. *Journal of Management Information Systems* 25(3):65–98.

Bapna R, Jank W, Shmueli G (2008b) Consumer surplus in online auctions. *Information Systems Research* 19(4):400–416.

Bapna R, Jank W, Shmueli G (2008c) Price formation and its dynamics in online auctions. *Decision Support Systems* 44(3):641–656.

Bardhan I, Oh Jh, Zheng Z, Kirksey K (2015) Predictive analytics for readmission of patients with congestive heart failure. *Information Systems Research* 26(1):19–39.

Barfar A, Padmanabhan B (2017) Predicting presidential election outcomes from what people watch. *Big Data* 5(1):32–41.

Batty M, Axhausen KW, Giannotti F, Pozdnoukhov A, Bazzani A, Wachowicz M, Ouzounis G, Portugali Y (2012) Smart cities of the future. *European Physical Journal: Special Topics* 214(1):481–518.

Bemmaor AC, Glady N (2012) Modeling purchasing behavior with sudden "death": A flexible customer lifetime model. *Management Science* 58(5):1012–1021.

Berente N, Gu B, Recker J, Santhanam R (2019) Managing AI. *Call for Papers, MIS Quarterly* .

Beverungen D, Breidbach CF, Poeppelbuss J, Tuunainen VK (2019) Smart service systems: An interdisciplinary perspective. *Information Systems Journal* 29(6):1201–1206.

Bhargava HK, Sundaresan S (2004) Computing as utility: Managing availability, commitment, and pricing through contingent bid auctions. *Journal of Management Information Systems* 21(2):201–227.

Bichler M, Gupta A, Ketter W (2010) Designing smart markets. *Information Systems Research* 21(4):688–699.

Bimpikis K, Candogan O, Saban D (2019) Spatial pricing in ride-sharing networks. *Operations Research* 67(3):744–769.

Brandt T, Dlugosch O (2020) Exploratory data science for discovery and ex-ante assessment of operational policies: Insights from vehicle sharing. *Journal of Operations Management* (May 2019):1–22.

Brandt T, Feuerriegel S, Neumann D (2018) Modeling interferences in information systems design for cyber-physical systems: Insights from a smart grid application. *European Journal of Information Systems* 27(2):207–220.

Breuker D, Matzner M, Delfmann P, Becker J (2016) Comprehensible predictive models for business processes. *MIS Q.* 40(4):1009–1034.

Bruun E, Givoni M (2015) Sustainable mobility: Six research routes to steer transport policy. *Nature* 523(7558):29–31.

Burns LD (2013) Sustainable mobility: A vision of our transport future. *Nature* 497(7448):181–182.

Burtch G, Carnahan S, Greenwood BN (2018) Can you gig it? an empirical examination of the gig economy and entrepreneurial activity. *Management Science* (April 2020):5497–5520.

Cason TN, Kannan KN, Siebert R (2011) An experimental study of information revelation policies in sequential auctions. *Management Science* 57(4):667–688.

Chen HM, Schütz R, Kazman R, Matthes F (2017) How Lufthansa Capitalized on Big Data for Business Model Renovation. *MIS Quarterly Executive* 16(1):19–34.

Chen TD, Kockelman KM, Hanna JP (2016) Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transportation Research Part A: Policy and Practice* 94:243–254.

Chen YD, Brown SA, Hu PJH, King CC, Chen H (2011) Managing emerging infectious diseases with information systems: reconceptualizing outbreak management through the lens of loose coupling. *Information Systems Research* 22(3):447–468.

Cheng Z, Pang MS, Pavlou PA (2020) Mitigating traffic congestion: The role of intelligent transportation systems. *Information Systems Research* 31(3):653–674.

Cherchi E (2017) A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transportation Research Part A: Policy and Practice* 100:88–104.

Chica M, Rand W (2017) Building agent-based decision support systems for word-of-mouth programs: a freemium application. *Journal of Marketing Research* 54(5):752–767.

Cohen P, Hahn R, Hall J, Levitt S, Metcalfe R (2016) Using Big Data to Estimate Consumer Surplus: The Case of Uber. *NBER Working Paper Series* 1–42.

Collins J, Ketter W, Gini M (2009) Flexible decision control in an autonomous trading agent. *Electronic Commerce Research and Applications* 8(2):91 – 105.

Collins J, Ketter W, Gini M (2010) Flexible decision support in dynamic inter-organisational networks. *European Journal of Information Systems* 19(4):436–448.

Corbett J (2013) Designing and using carbon management systems to promote ecologically responsible behaviors. *Journal of the Association for Information Systems* 14(7):339–378.

Corbett J, Mellouli S (2017) Winning the SDG battle in cities: how an integrated information ecosystem can contribute to the achievement of the 2030 sustainable development goals. *Information Systems Journal* 27(4):427–461.

Costa DL, Kahn ME (2013) Energy conservation ”nudges” and environmentalist ideology: Evidence from a randomized residential electricity field experiment. *Journal of the European Economic Association* 11(3):680–702.

Cramton P, Geddes R, Ockenfels A (2018) Set road charges in real time to ease traffic. *Nature* 560(2 August 2018):23–25.

Dedrick J (2010) Green IS: Concepts and issues for information systems research. *Communications of the Association for Information Systems* 27(1):173–184.

Demircan M, Ahadi R, Ketter W (2022a) Sustainability vs . Price : Analysis of Electric Multi-Modal Vehicle Sharing Systems under Substitution Effects. *ECIS 2022 Research Papers*, 162, URL https://aisel.aisnet.org/ecis2022_rp/162.

Demircan M, Schroer K, Fritze MP, Ketter W (2022b) To Differentiate Or Not To Differentiate ? The Role of Product Characteristics in the Sharing Economy. *ECIS 2022 Research Papers*, 164, URL https://aisel.aisnet.org/ecis2022_rp/164.

Dietvorst BJ, Simmons JP, Massey C (2015) Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General* 144(1):114.

Dlugosch O, Brandt T, Neumann D (2020) Combining analytics and simulation methods to assess the impact of shared, autonomous electric vehicles on sustainable urban mobility. *Information & Management* 103285.

Dremel C, Wulf J, Herterich MM, Waizmann JC, Brenner W (2017) Digital Transformation Often Requires Big Data Analytics Capabilities1 2. *MIS Quarterly Excecutive* 16(2):81–100.

Du AY, Das S, Gopal RD, Ramesh R (2014) Optimal management of digital content on tiered infrastructure platforms. *Information Systems Research* 25(4):730–746.

Eckhardt GM, Houston MB, Jiang B, Lamberton C, Rindfleisch A, Zervas G (2019) Marketing in the Sharing Economy. *Journal of Marketing* 83(5):5–27.

Firnkorn J, Müller M (2015) Free-floating electric carsharing-fleets in smart cities: The dawning of a post-private car era in urban environments? *Environmental Science and Policy* 45:30–40.

Frey A, Trenz M, Veit D (2019) Three differentiation strategies for competing in the sharing economy. *MIS Quarterly Executive* 18(2):143–156.

Fügener A, Grahl J, Gupta A, Ketter W (2021) Will humans-in-the-loop become borgs? merits and pitfalls of working with ai. *Management Information Systems Quarterly (MISQ)-Vol* 45.

Fügener A, Grahl J, Ketter W, Gupta A (Forthcoming) Cognitive challenges in human-ai collaboration: Investigating the path towards productive delegation. *Information Systems Research* .

Fürstenau D, Baiyere A, Kliewer N (2019) A dynamic model of embeddedness in digital infrastructures. *Information Systems Research* 30(4):1319–1342.

Gottwalt S, Ketter W, Block C, Collins J, Weinhardt C (2011) Demand side management-A simulation of household behavior under variable prices. *Energy Policy* 39(12):8163–8174.

Greenwood BN, Wattal S (2017) Show Me the Way to go Home: An Empirical Investigation of Ride-Sharing and Alcohool Related Motor Vehicle Fatalities. *MIS Quarterly* 41(1):163–187.

Guda H, Subramanian U (2019) Your Uber Is Arriving: Managing On-Demand Workers Through Surge Pricing, Forecast Communication, and Worker Incentives. *Management Science, Articles in Advance* (March):1–20.

Guo Y, Li X, Zeng X (2019) Platform Competition in the Sharing Economy: Understanding How Ride-Hailing Services Influence New Car Purchases. *Journal of Management Information Systems* 36(4):1043–1070.

Hafermalz E, Johnston RB, Hovorka DS, Riemer K (2020) Beyond ‘mobility’: A new understanding of moving with technology. *Information Systems Journal* .

Hanelt A, Busse S, Kolbe LM (2017) Driving business transformation toward sustainability: exploring the impact of supporting IS on the performance contribution of eco-innovations. *Information Systems Journal* 27(4):463–502.

Hevner AR, Gregor S (2013) Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly* 37(2):337–355.

Hong SJ, Bauer JM, Lee K, Granados NF (2020) Drivers of Supplier Participation in Ride-Hailing Platforms. *Journal of Management Information Systems* 37(3):602–630.

Hong Y, Wang C, Pavlou PA (2016) Comparing open and sealed bid auctions: Evidence from online labor markets. *Information Systems Research* 27(1):49–69.

Horni A, Nagel K, Axhausen KW (2016) *The Multi-Agent Transport Simulation MATSim* (London: Ubiquity Press).

INRIX Research (2018) Inrix Global Traffic Scorecard. Technical report.

Jensen T, Vatrapu R, Bjørn-Andersen N (2018) Avocados crossing borders: The problem of runaway objects and the solution of a shipping information pipeline for improving international trade. *Information Systems Journal* 28(2):408–438.

Jung D, Kim BC, Park M, Straub DW (2019) Innovation and policy support for two-sided market platforms: Can government policy makers and executives optimize both societal value and profits? *Information Systems Research* 30(3):1037–1050.

Kahlen MT, Ketter W, Dalen JV (2018) Electric Vehicle Virtual Power Plant Dilemma : Grid Balancing Versus Customer Mobility. *Production and Operations Management* 0(0):1–17.

Kannan KN, Pamuru V, Rosokha Y (2019) Using machine learning for modeling human behavior and analyzing friction in generalized second price auctions. *Available at SSRN 3315772* .

Karaenke P, Bichler M, Minner S (2019) Coordination is hard: Electronic auction mechanisms for increased efficiency in transportation logistics. *Management Science* 65(12):5884–5900.

Kathuria A, Karhade PP, Konsynski BR (2020) In the Realm of Hungry Ghosts: Multi-Level Theory for Supplier Participation on Digital Platforms. *Journal of Management Information Systems* 37(2):396–430.

Keenan PB, Jankowski P (2019) Spatial Decision Support Systems: Three decades on. *Decision Support Systems* 116(October 2018):64–76.

Ketter W, Collins J, Gini M, Gupta A, Schrater P (2009) Detecting and forecasting economic regimes in multi-agent automated exchanges. *Decision Support Systems* 47(4):307–318.

Ketter W, Collins J, Saar-Tsechansky M, Marom O (2018) Information Systems for a Smart Electricity Grid. *ACM Transactions on Management Information Systems* 9(3):1–22.

Ketter W, Peters M, Collins J, Gupta A (2016a) A Multiagent Competitive Gaming Platform to Address Societal Challenges. *MIS Quarterly* 40(2):447–460.

Ketter W, Peters M, Collins J, Gupta A (2016b) Competitive Benchmarking: An IS Research Approach to Address Wicked Problems with Big Data and Analytics. *MIS Quarterly* 40(4):1–53.

Klör B, Monhof M, Beverungen D, Bräuer S (2018) Design and evaluation of a model-driven decision support system for repurposing electric vehicle batteries. *European Journal of Information Systems* 27(2):171–188.

Koroleva K, Kahlen M, Ketter W, Rook L, Lanz F (2014) Tamagocar: Using a simulation app to explore price elasticity of demand for electricity of electric vehicle users. *Proceedings of the 35th International Conference on Information Systems (ICIS)* .

Lam AY (2016) Combinatorial Auction-Based Pricing for Multi-Tenant Autonomous Vehicle Public Transportation System. *IEEE Transactions on Intelligent Transportation Systems* 17(3):859–869.

Lu Y, Gupta A, Ketter W, Heck Ev (2016) Exploring bidder heterogeneity in multichannel sequential b2b auctions. *MIS Quarterly* 40(3):645–662.

Lu Y, Gupta A, Ketter W, van Heck E (2019a) Dynamic Decision Making in Sequential Business-to-Business Auctions: A Structural Econometric Approach. *Management Science* (June).

Lu Y, Gupta A, Ketter W, Van Heck E (2019b) Information transparency in business-to-business auction markets: The role of winner identity disclosure. *Management Science* 65(9):4261–4279.

Lyytinen K, Yoo Y (2002) Research commentary: The next wave of nomadic computing. *Information Systems Research* 13(4):377–388.

Maciejewski M, Bischoff J (2017) Congestion effects of autonomous taxi fleets. *Transport* 1–10.

Mahmassani HS (2016) 50th Anniversary Invited Article—Autonomous Vehicles and Connected Vehicle Systems: Flow and Operations Considerations. *Transportation Science* 50(4):1140–1162.

Masoum AS, Deilami S, Abu-Siada A, Masoum MA (2015) Fuzzy Approach for Online Coordination of Plug-In Electric Vehicle Charging in Smart Grid. *IEEE Transactions on Sustainable Energy* 6(3):1112–1121.

McKinney V, Yoon K, Zahedi F (2002) The measurement of web-customer satisfaction: An expectation and disconfirmation approach. *Information Systems Research* 13(3):296–315.

Melville N (2010) Information Systems Innovation for Environmental Sustainability. *MIS Quarterly* 34(1):1–21.

Meyer G, Adomavicius G, Johnson PE, Elidrisi M, Rush WA, Sperl-Hillen JM, O'Connor PJ (2014) A machine learning approach to improving dynamic decision making. *Information Systems Research* 25(2):239–263.

Mocker M, Fonstad NO (2017) How AUDI AG is Driving Toward the Sharing Economy. *MIS Quarterly Executive* 16(4):279–293.

Möhlmann M, Zalmanson L, Henfridsson O, Gregory RW (2021) ALGORITHMIC MANAGEMENT OF WORK ON ONLINE LABOR PLATFORMS: WHEN MATCHING MEETS CONTROL 45(4):1999–2022.

Nishant R, Kennedy M, Corbett J (2020) Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management* 53:102104.

Oestreicher-Singer G, Zalmanson L (2013) Content or community? a digital business strategy for content providers in the social age. *MIS Quarterly* 591–616.

Osterwalder A, Pigneur Y, Tucci C (2005) Clarifying business models: origins, present, and future of the concept. *Communications of the Association for Information Systems* 15(May):1–43.

Papadopoulos P, Jenkins N, Cipcigan LM, Grau I, Zabala E (2013) Coordination of the charging of electric vehicles using a multi-agent system. *IEEE Transactions on Smart Grid* 4(4):1802–1809.

Pelechrinis K, Li B, Qian S (2016) Bike Sharing and Car Trips in the City: The Case of Healthy Ride Pittsburgh, URL `http://dx.doi.org/10.2139/ssrn.2853543`.

Pelletier S, Jabali O, Laporte G (2016) 50th Anniversary Invited Article—Goods Distribution with Electric Vehicles: Review and Research Perspectives. *Transportation Science* 50(1):3–22.

Peters M, Ketter W, Saar-Tsechansky M, Collins J (2013) A reinforcement learning approach to autonomous decision-making in smart electricity markets. *Mach Learn* 92:5–39.

Peters M, Saar-Tsechansky M, Ketter W, Williamson SA, Groot P, Heskes T (2018) A scalable preference model for autonomous decision-making. *Machine Learning* 107(6):1039–1068.

Pfeiffer J, Pfeiffer T, Meißner M, Weiß E (2020) Eye-tracking-based classification of information search behavior using machine learning: evidence from experiments in physical shops and virtual reality shopping environments. *Information Systems Research* 31(3):675–691.

Qi W, Shen ZJM (2018) A Smart-City Scope of Operations Management. *Production and Operations Management* 0(0):1–14.

Qiu L, Benbasat I (2009) Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems* 25(4):145–182.

SAE (2018) J3016_201806: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. URL `https://www.sae.org/standards/content/j3016{\_}201806/`.

Sahoo N, Singh PV, Mukhopadhyay T (2012) A hidden markov model for collaborative filtering. *MIS quarterly* 1329–1356.

Sarker S, Chatterjee S, Xiao X, Elbanna A (2019) The Sociotechnical Axis of Cohesion for the IS Discipline: Its Historical Legacy and its Continued Relevance. *MIS Quarterly* 43(3):695–719.

Saxena D, Muzellec L, Trabucchi D (2020) BlaBlaCar: Value creation on a digital platform. *Journal of Information Technology Teaching Cases* 10(2):119–126.

Scheffel T, Pikovsky A, Bichler M, Guler K (2011) An experimental comparison of linear and nonlinear price combinatorial auctions. *Information Systems Research* 22(2):346–368.

Schroer K, Ketter W, Lee TY, Gupta A, Kahlen M (2022) Data-Driven Competitor-Aware Positioning in On-Demand Vehicle Rental Networks. *Transportation Science* 56(1):182–200.

Schwartz B (2016) *The Paradox of Choice: Why More Is Less, Revised Edition: Amazon.de: Barry Schwartz: Amazon.De* (Harper Perennial).

Seidel S, Chandra Kruse L, Székely N, Gau M, Stieger D (2018) Design principles for sensemaking support systems in environmental sustainability transformations. *European Journal of Information Systems* 27(2):221–247.

Seidel S, Recker J, vom Brocke J (2013) Sensemaking and Sustainable Practicing: Functional Affordances of Information Systems in Green Transformations. *MIS Quarterly* 37(4):1275–1299.

Shaheen S, Cohen A (2007) Growth in Worldwide Carsharing: An International Comparison. *Transportation Research Record: Journal of the Transportation Research Board* 1992:81–89.

Shmueli G, Koppius OR (2011) Predictive analytics in information systems research. *MIS Quarterly* 35(3):553–572.

Simon HA (1979) Rational Decision Making in Business Organizations. *THE AMERICAN ECONOMIC REVIEW* 22.

Singh VK, Shrivastava U, Bouayad L, Padmanabhan B, Ialynytchev A, Schultz SK (2018) Machine learning for psychiatric patient triaging: an investigation of cascading classifiers. *Journal of the American Medical Informatics Association* 25(11):1481–1487.

Sperling D (2018) *Three revolutions: steering automated, shared, and electric vehicles to a better future* (Washington, D.C., USA: Island Press).

Sundararajan A (2016) *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism* (Cambridge, MA: The MIT Press).

Tan FTC, Cahalane M, Tan B, Englert J (2017) How GoGet carshare's product-service system is facilitating collaborative consumption. *MIS Quarterly Executive* 16(4):265–277.

Thaler RH, Sunstein CR, Balz JP (2013) Choice Architecture. Sharfir E, ed., *The Behavioral Foundations of Public Policy*, chapter 25, 428–439 (Princeton, NJ, USA: Princeton University Press), ISBN 9780300122237, URL `http://dx.doi.org/10.2139/ssrn.1583509`.

Tiefenbeck V, Goette L, Degen K, Tasic V, Fleisch E, Lalive R, Staake T (2018) Overcoming Salience Bias: How Real-Time Feedback Fosters Resource Conservation. *Management Science* 64(3):1458–1476.

Valogianni K, Gupta A, Ketter W, Sen S, van Heck E (2019) Multiple vickrey auctions for sustainable electric vehicle charging. *Proceedings of the 40th International Conference on Information Systems (ICIS)* .

Valogianni K, Ketter W (2016) Effective demand response for smart grids: Evidence from a real-world pilot. *Decision Support Systems* 91:48–66.

Valogianni K, Ketter W, Collins J, Zhdanov D (2020) Sustainable electric vehicle charging using adaptive pricing. *Production and Operations Management* 29(6):1550–1572.

Vickrey W (1969) Congestion Theory and Transport Investment. *The American Economic Review* 59(2):251–260.

Wadud Z, MacKenzie D, Leiby P (2016) Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice* 86:1–18.

Wang Q, Li B, Singh PV (2018) Copycats vs. original mobile apps: A machine learning copycat-detection method and empirical analysis. *Information Systems Research* 29(2):273–291.

Watson RT, Boudreau MC, Chen AJ (2010) Information Systems and Environmentally Sustainable Development: Energy Informatics and New Directions for the IS Community. *MIS Quarterly* 24(4):665–694.

Weiss N, Schreieck M, Wiesche M, Krcmar H (2020) From Product to Platform: How can BMW compete with Platform Giants? *Journal of Information Technology Teaching Cases* 11(2):90–100.

Willing C, Klemmer K, Brandt T, Neumann D (2017) Moving in time and space – Location intelligence for carsharing decision support. *Decision Support Systems* 99:75–85.

World Health Organization (2005) Health effects of transport-related air pollution. Technical report, World Health Organization (WHO).

World Health Organization (2018) GLOBAL STATUS REPORT ON ROAD SAFETY. Technical Report 4, World Health Organization.

Wulf J, Mettler T, Brenner W (2017) Using a Digital Services Capability Model to Assess Readiness for the Digital Consumer. *MISQ Executive* 16(3):171–195.

Yang M, Ren Y, Adomavicius G (2019) Understanding user-generated content and customer engagement on facebook business pages. *Information Systems Research* 30(3):839–855.

Yang YC, Padmanabhan B (2010) Toward user patterns for online security: Observation time and online user identification. *Decision Support Systems* 48(4):548–558.

Yoo Y, Henfridsson O, Lyytinen K (2010) Research commentary—the new organizing logic of digital innovation: an agenda for information systems research. *Information systems research* 21(4):724–735.

Zhang Y, Li B, Krishnan R (2020) Learning individual behavior using sensor data: The case of global positioning system traces and taxi drivers. *Information Systems Research* 31(4):1301–1321.

Zheng J, Ren F, Tan Y, Chen X (2020) Optimizing two-sided promotion for transportation network companies: A structural model with conditional bayesian learning. *Information Systems Research* 31(3):692–714.

Zheng Z, Padmanabhan B (2006) Selectively acquiring customer information: A new data acquisition problem and an active learning-based solution. *Management Science* 52(5):697–712.

Zhu H, Samtani S, Brown RA, Chen H (2021) Adeep learning approach for recognizing activity of daily living (adl) for senior care: Exploiting interaction dependency and temporal patterns1. *MIS Quarterly* 45(2):859–896.

Appendix A: Literature Search Methodology and Results

A comprehensive literature search was conducted using the following search words: *car sharing*, *ride sharing*, *smart mobility*, *smart transport*, *electric mobility*, *electric transport*, *shared mobility*, *shared transport*, *sustainable mobility*, *sustainable transport*, *mobility-as-a-service* and *mobility-on-demand*. The publication counts presented in Tables 4 and 5 represent the number of unique hits across these search terms per journal basket and individual journal respectively.

Table 4 Publication count by journal basket 2016-2020

Basket	Acronym	2016	2017	2018	2019	2020
Scimago Journal Rank Transportation Q1 Basket	SJR	376	475	665	898	1131
FT50 Journal Basket	FT50	35	47	51	111	145
IS Basket of 8	IS8	9	15	12	12	17
UT Dallas Journal Basket	UTD	11	18	18	60	94
Total		**415**	**525**	**726**	**1014**	**1287**

Note: IS Basket of 8 includes MISQ Executive and JIT Teaching Cases

Table 5: **Publication count by individual journal 2016-2020**

Journal	Baskets	2016	2017	2018	2019	2020
Academy of Management Journal	FT50, UTD	0	1	1	1	1
Academy of Management Review	FT50, UTD	0	0	0	0	2
Accounting Review	UTD	0	0	0	1	0
Accounting, Organizations and Society	FT50	0	1	0	0	0
Administrative Science Quarterly	FT50, UTD	1	1	0	1	0
American Economic Review	FT50	1	0	1	4	0
Analytic Methods in Accident Research	SJR	0	0	0	2	3
Contemporary Accounting Research	FT50	0	0	0	0	1
Econometrica	FT50	0	0	0	0	0
Economics of Transportation	SJR	1	0	0	0	5
Entrepreneurship Theory and Practice	FT50	0	0	0	1	2
European Journal of Information Systems	IS8	0	0	3	0	3
Harvard Business Review	FT50	4	3	0	1	0
Human Relations	FT50	0	0	0	1	1
Human Resource Management	FT50	1	3	3	0	1
IEEE Transactions on Transportation Electrification	SJR	4	9	5	10	16
Information Systems Journal	IS8	2	1	1	3	0
Information Systems Research	FT50, UTD, IS8	1	1	1	5	8
International Journal of Physical Distribution and Logistics Management	SJR	0	0	0	0	0
International Journal of Sustainable Transportation	SJR	42	32	33	59	80
International Journal of Tourism Research	SJR	1	0	0	1	0
Journal of Accounting and Economics	FT50, UTD	0	0	0	0	0

Table 5: **Publication count by individual journal 2016-2020**

Journal	Baskets	2016	2017	2018	2019	2020
Journal of Accounting Research	FT50, UTD	0	0	0	0	0
Journal of AIS	IS8	0	0	0	0	0
Journal of Applied Psychology	FT50	0	1	0	1	0
Journal of Business Ethics	FT50	3	4	13	16	9
Journal of Business Venturing	FT50	0	2	0	1	2
Journal of Consumer Psychology	FT50	0	1	0	1	2
Journal of Consumer Research	FT50, UTD	2	1	1	5	1
Journal of Finance	FT50, UTD	0	0	0	0	0
Journal of Financial and Quantitative Analysis	FT50	0	0	0	0	0
Journal of Financial Economics	FT50, UTD	0	0	0	0	0
Journal of Information Technology [16]	IS8	1	1	3	0	4
Journal of International Business Studies	FT50, UTD	0	0	1	1	0
Journal of Management	FT50	0	2	1	3	4
Journal of Management Information Systems	FT50, IS8	1	3	1	2	4
Journal of Management Studies	FT50	2	0	1	4	3
Journal of Marketing	FT50, UTD	0	0	1	3	4
Journal of Marketing Research	FT50, UTD	0	1	0	1	2
Journal of Operations Management	FT50, UTD	0	0	1	0	1
Journal of Political Economy	FT50	0	1	1	1	2
Journal of Strategic Information Systems	IS8	1	1	2	0	3
Journal of the Academy of Marketing Science	FT50	1	2	0	6	4
Journal of Transport and Land Use	SJR	7	13	30	13	10
Journal of Transport Geography	SJR	40	32	61	66	100
Journal of Travel Research	SJR	2	1	2	10	11
Journal on Computing	UTD	0	0	1	1	1
Management Science	FT50, UTD	1	1	2	8	27
Manufacturing & Service Operations Management	FT50, UTD	0	3	4	11	21
Marketing Science	FT50, UTD	0	0	0	2	3
MIS Quarterly [17]	FT50, UTD, IS8	3	8	1	2	2
Mobilization	SJR	0	0	0	0	0
Operations Research	FT50, UTD	0	0	0	6	2
Organization Science	FT50, UTD	0	1	0	4	0
Organization Studies	FT50	0	0	0	0	0
Organizational Behavior and Human Decision Processes	FT50	0	0	0	0	0
Production and Operations Management	FT50, UTD	2	0	4	7	11
Quarterly Journal of Economics	FT50	0	0	1	0	0
Research Policy	FT50	6	2	9	9	9
Review of Accounting Studies	FT50	0	0	0	0	0
Review of Economic Studies	FT50	0	0	0	1	1
Review of Finance	FT50	0	0	0	0	0
Review of Financial Studies	FT50, UTD	1	0	0	0	0
Sloan Management Review	FT50	5	4	2	1	6

[16] Includes JIT Teaching Cases

[17] Includes MISQ Executive

Table 5: **Publication count by individual journal 2016-2020**

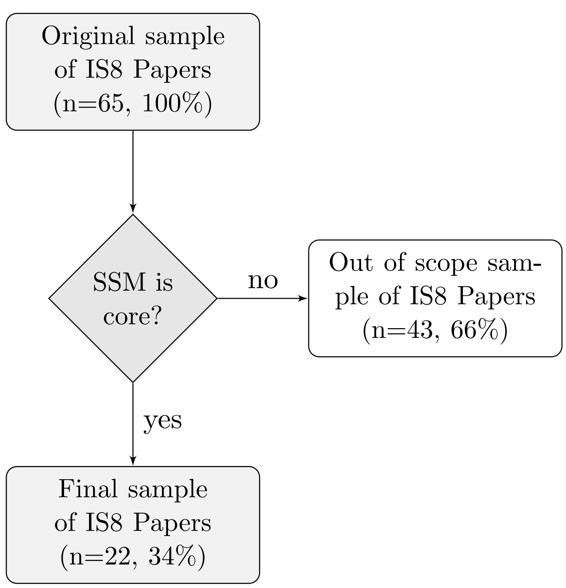
Journal	Baskets	2016	2017	2018	2019	2020
Strategic Entrepreneurship Journal	FT50	0	0	1	0	1
Strategic Management Journal	FT50, UTD	0	0	0	1	8
Sustainable Cities and Society	SJR	4	16	51	46	70
The Accounting Review	FT50	0	0	0	0	0
Tourism Management	SJR	5	6	5	9	8
Transport Policy	SJR	65	77	119	132	150
Transport Reviews	SJR	12	16	12	28	34
Transportation	SJR	53	64	84	111	103
Transportation Research Part A: Policy and Practice	SJR	45	69	62	124	156
Transportation Research Part B: Methodological	SJR	15	25	35	46	38
Transportation Research Part D: Transport and Environment	SJR	38	41	74	86	135
Transportation Research Part E: Logistics and Transportation Review	SJR	4	10	10	16	33
Transportation Research, Part C: Emerging Technologies	SJR	19	41	45	76	85
Transportation Science	SJR	10	10	12	16	23
Transportmetrica A: Transportation Science	SJR	7	1	7	15	21
Transportmetrica B	SJR	0	2	0	5	8
Travel Behaviour and Society	SJR	2	10	18	27	42

Appendix B: In-Depth Analysis of Basket of 8 Papers

The data tables presented in Appendix A represent the results of a keyword search. Here, we review the specific content per each paper in an attempt to identify which dimensions of the presented have seen initial research interest and which remain under-explored. Our focus is on IS Basket of 8 (IS8) papers, that represent the core literature corpus of the IS discipline.

We first apply an additional filter to sieve out papers that only tangentially deal with Smart Sustainable Mobility (SSM) topics. Such papers would still have made the original list given the relatively coarse key word-based selection criterion but are of little help here. We therefore review the abstracts as well as method and conclusion sections of the full sample of 65 Basket of 8 papers to eliminate such articles. Two main recurring reasons for exclusion emerge: (1) no or only tangential links to SSM, mainly in the form of examples or short in-text mentions, (2) case study from the domain of SSM but with more general scope. These are mainly studies focusing on the sharing economy and using seminal case studies such as Uber or BlaBlaCar. The results of the filtering procedure are shown in Figure 4.

Figure 4 Filtering Process



Next, we analyze the remaining papers in-depth. We review their methods, the data used and most importantly their contributions. We then classify these papers along the seven Research Opportunities laid out in the Commentary. In Table 6 we present the results.

Table 6: **IS8 Papers with core SSM contributions**

RO	Title	Authors	Outlet	IS Tradition	Method	Data
RO1	Avocados crossing borders: The problem of runaway objects and the solution of a shipping information pipeline for improving international trade	(Jensen et al. 2018)	JMIS	Design	activity theory	proprietary
RO2	Drivers of Supplier Participation in Ride-Hailing Platforms	(Hong et al. 2020)	JMIS	Economics of IS	discrete choice model	proprietary
	Learning Individual Behavior Using Sensor Data: The Case of GPS Traces and Taxi Drivers	(Zhang et al. 2020)	ISR	Economics of IS	structural equations modeling	proprietary
	In the Realm of Hungry Ghosts: Multi-Level Theory for Supplier Participation on Digital Platforms	(Kathuria et al. 2020)	JMIS	Economics of IS	econometrics (tree induction)	proprietary
RO3	Optimizing Two-Sided Promotion for Transportation Network Companies: A Structural Model with Conditional Bayesian Learning	(Zheng et al. 2020)	ISR	Economics of IS	structural equations modeling	proprietary
RO4	Design and evaluation of a model-driven decision support system for repurposing electric vehicle batteries	(Klör et al. 2018)	EJIS	Design	optimization	synthetic
	Modeling interferences in information systems design for cyberphysical systems: Insights from a smart grid application	(Brandt et al. 2018)	EJIS	Design	simulation	public
RO5	How AUDI AG Established Big Data Analytics in Its Digital Transformation	(Dremel et al. 2017)	MISQ(E)	Design	survey, interviews	proprietary
	Three Differentiation Strategies for Competing in the Sharing Economy	(Frey et al. 2019)	MISQ(E)	Design	survey, interviews	proprietary

Table 6: **IS8 Papers with core SSM contributions**

RO	Title	Authors	Outlet	IS Tradition	Method	Data
	How AUDI AG is Driving Toward the Sharing Economy	(Mocker and Fonstad 2017)	MISQ(E)	Design	survey, interviews	proprietary
	How GoGet CarShare's Product-Service System is Facilitating Collaborative Consumption	(Tan et al. 2017)	MISQ(E)	Design	survey, interviews	proprietary
	From Product to Platform: How can BMW compete with Platform Giants?	(Weiss et al. 2020)	JIT	Design	survey, interviews	proprietary
	BlaBlaCar: Value creation on a digital platform	(Saxena et al. 2020)	JIT	Design	survey, interviews	proprietary
	How Lufthansa Capitalized on Big Data for Business Model Renovation	(Chen et al. 2017)	MISQ(E)	Design	survey, interviews	proprietary
	Driving business transformation toward sustainability: exploring the impact of supporting IS on the performance contribution of eco-innovations	(Hanelt et al. 2017)	ISJ	Behavioral	survey, interviews	proprietary
	Using a Digital Services Capability Model to Assess Readiness for the Digital Consumer	(Wulf et al. 2017)	MISQ(E)	Design	survey, interviews	proprietary
RO6	Algorithmic management of work on online labor platforms: when matching meets control	(Möhlmann et al. 2021)	MISQ	Behavioral	survey, interviews	proprietary
RO7	Examining the Heterogeneous Impact of Ride-Hailing Services on Public Transit Use	(Babar and Burtch 2020)	ISR	Economics of IS	econometrics (DiD)	public
	Mitigating Traffic Congestion: The Role of Intelligent Transportation Systems	(Cheng et al. 2020)	ISR	Economics of IS	econometrics (DiD)	public
	Show Me the Way to Go Home: An Empirical Investigation of Ride-Sharing and Alcohol Related Motor Vehicle Fatalities.	(Greenwood and Wattal 2017)	MISQ	Economics of IS	econometrics (DiD)	public

Table 6: **IS8 Papers with core SSM contributions**

RO	Title	Authors	Outlet	IS Tradition	Method	Data
	Platform Competition in the Sharing Economy: Understanding How Ride-Hailing Services Influence New Car Purchases	(Guo et al. 2019)	JMIS	Economics of IS	econometrics (DiD)	proprietary
	Innovation and Policy Support for Two-Sided Market Platforms: Can Government Policy Makers and Executives Optimize Both Societal Value and Profits?	(Jung et al. 2019)	ISR	Economics of IS	equilibrium modeling	synthetic