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How emerging modes might change (sustainable) mobility patterns

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ABSTRACT

Mobility is currently undergoing a substantial transition, with emerging mobility modes holding the potential to reshape how individuals move within cities. Using a Norway-wide survey, we uncover latent subgroups of mobility patterns by examining current travel behaviors and (anticipated) future preferences across a range of alternatives, encompassing both conventional and emerging modes. The level of behavior-preference dissonance (i.e., non-alignment), various travel needs (e.g., safety, environment, cost), and sociodemographic variables are considered covariates. Results uncover seven distinct mobility classes ranging from current (un)sustainable use (behavior) to (un)sustainable future preferences. There is a noticeable preference for electric vehicles (EVs), while autonomous vehicles are less popular. Policymakers should navigate the transition to EVs with caution, ensuring that the integration of EVs complements rather than displaces active travel. In a class, despite indicating a desire for more (emerging) sustainable options, they paradoxically anticipate making more trips than other groups, potentially offsetting their environmental impact.

1. Introduction

The surge in carbon emissions from daily vehicle transportation has posed unprecedented challenges to cities, emphasizing the urgent need for the development of sustainable transport systems (Xia et al., 2023). In recent years, emerging transport options and technological advancements have opened up new possibilities for reshaping mobility landscapes. However, to design effective and user-centric transport solutions for the future, it is imperative to gain a comprehensive understanding of individuals' daily travel behavior, preferences, and needs.

There has been a notable upsurge in emerging transport innovation, primarily fuelled by technological advancements and an increasing focus on sustainability (Canzler and Knie, 2016). Electric Vehicles (EVs) have emerged as eco-friendly alternatives to fossil-fuel-powered cars, while autonomous vehicles (AVs) are expected to enhance both safety and energy efficiency while driving. The use of micro-mobility solutions, such as e-scooters and e-bikes, has gained prominence as a means of addressing short-distance (first/last mile) travel needs. Moreover, the use of shared mobility services could contribute to the reduction of traffic congestion by discouraging the ownership or use of private automobiles.

The current study aims to uncover different mobility patterns considering current travel behavior and preference transitions by exploring the diverse array of transport options, encompassing both conventional (e.g., fossil-fuel cars, walking, biking) and emerging

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alternatives, such as EVs, mobility services (e.g., carsharing, ridesharing), e-bikes, e-scooters, AVs. Additionally, we examine the role of transport needs, ranging from safety and environment (climate) to novelty, fitness, travel cost, and time considerations on such mobility patterns.

Emerging mobility options and their transformative trends are reshaping travel preferences, demanding integrated research about (i) mobility patterns while considering these options in addition to conventional mobility options, and (ii) how current travel behavior is related to future travel preferences. Despite this, so far, studies have tried to investigate stated preferences (choices) for only a newly added emerging option such as carsharing (e.g., Carrone et al., 2020), ridesharing (e.g., König and Grippenkoven, 2020), AVs (e.g., Stoiber et al., 2019), e-scooters (Esztergár-Kiss et al., 2022), and e-bikes (Jones et al., 2013), in a confined travel choice set, disregarding the preferences for all other emerging travel options. The absence of consideration of other plausible mobility options might lead to misleading travel predictions. We contribute to the literature by revealing distinct mobility patterns by taking a range of mobility options, encompassing both conventional and emerging alternatives into account simultaneously.

2. Literature background and theoretical foundation

Few past studies have explored travel mobility patterns and transitions in travel behavior context to some extent. However, such studies have also typically focused on a limited choice set of basic conventional modes such as cars, bicycles, and public transport (De Vos, 2018; Haustein and Kroesen, 2022; Negm et al., 2024). For instance, Haustein and Kroesen (2022), through a longitudinal survey, examined shifts in various travel modality groups over time. They identified five distinct subgroups of mobility patterns and discovered associations with age, gender, income, and residential location. However, these modality groups were solely based on traditional travel modes like cars (and carsharing), public transport, bicycles, and walking, without considering preferences for emerging mobility options.

Theoretically, it has been also shown that travel behavior and preferences may show some level of dissonance or consonance (De Vos, 2018). In line with the cognitive dissonance theory of Festinger (1957), De Vos (2018) showed that travel preferences and travel behavior may not always match up. On the other hand, in line with the habit concept, past travel habits (behavior) have been also shown as a factor associated with present travel choices for some travelers (Gärling and Axhausen, 2003). Consequently, it can be posited that current travel behavior can be related to future travel decisions and preferences. However, current travel behavior and anticipated future preferences may not align for certain other travelers (De Vos, 2018). Hence, in line with these theories, it is more reasonable to posit that (modality) mobility patterns, especially in the era of mobility transition, can be a function of both current travel behavior and anticipated future travel preferences.

According to Festinger's theory of cognitive dissonance, recent theoretical developments in the travel behavior domain have underscored the significance of dissonant and consonant patterns between attitude and behavior, as well as between preference and behavior (De Vos, 2018; Negm et al., 2024). In this context, consonant travelers are individuals who align their preferred mode with their actual (revealed) travel behavior, indicating consistency between preference and mode use/choice. Conversely, dissonant travelers are those who do not use a mode despite preferring it. In this regard, De Vos (2018) explored whether individuals choose their preferred mode of travel. De Vos's study focused solely on conventional modes, overlooking the role of emerging mobility options. The study revealed that approximately half of the participants opted for a non-preferred travel mode. Notably, dissonance among travelers was most prominent within the public transport user group, while cyclists exhibited the least dissonance.

Therefore, it is also crucial to assess the extent to which different mobility classes can be characterized by the level of dissonance and consonance among travelers. For instance, when aiming for a successful shift from an unsustainable mobility pattern to a sustainable one, the question arises: should the focus be on consonant or dissonant travelers? Which group of travelers is more likely to engage in a sustainable mobility transition? In terms of travel satisfaction, it has been recently shown that consonant travelers are more satisfied with travel experiences than dissonant travelers (Negm et al., 2024), however, less is known about how consonant or dissonant travelers may shift from conventional to emerging mobility options.

In this study, first, we categorize individuals into distinct mobility classes based on their revealed travel behavior (i.e., mode use) and their stated future preferences. This classification allows us to identify various subgroups with unique behavior-preference patterns, offering insights into how current travel behavior correlates with future travel preferences. Examining the link between behavior and future preference while considering both conventional and emerging options simultaneously can provide more comprehensive insights into mobility and modality transitions ((in)consistency between behavior and preferences). This examination can reveal some (potential) shifts from current (un)sustainable mobility patterns to future (un)sustainable mobility patterns. Following this, we examine whether the identified classes demonstrate dissonance or consonance in terms of current travel behavior and future preferences.

Moreover, mobility behavior, encompassing both current travel behavior and future stated preferences, can be explained by travel needs or transport perceptions/aspects. Theoretical evidence indicates that diverse needs play a crucial role in shaping our behavior and preferences (Beirão and Cabral, 2007; Şimşekoğlu et al., 2015). Travel needs, in this context, encompass a broader concept that includes transport priorities, perceptions, and even attitudinal elements (Schröder and Wolf, 2017; Mehdizadeh et al., 2022). The significance assigned to various aspects when choosing a transport mode—such as the need for safety, economic considerations, convenience, environmental friendliness, image, time efficiency, enjoyment, stress reduction, physical activity, and reliability—reflects distinct travel needs (Schröder and Wolf, 2017). Individuals with varying needs are likely to exhibit different behavior-preferences mobility patterns (Schröder and Wolf, 2017). Therefore, our hypothesis suggests that a wide range of travel needs may vary across distinct mobility groups.

Sociodemographic variables have been traditionally shown to be important when it comes to travel behavior and preferences.

Variables such as age, gender, and level of education are shown to be important in travel choices. Therefore, we also consider these variables as covariates in mobility classes which are based on the relationship between travel behavior and preferences.

3. Research focus and model conceptualization

When it comes to (emerging) mobility transition, which mobility shifts and patterns are expected? How can people be grouped based on current travel behavior and their future preferences? How dissonant or consonant are different mobility groups? What travel needs are related to such mobility groups?

To address these questions, we conducted a national survey in Norway. The survey probed participants' current travel behavior for 10 distinct transport options and their stated future preferences for the same 10 modes plus one new option as well as their opinions on the importance of 12 different travel needs when considering their daily mobility behaviors. As illustrated in Fig. 1, to discern underlying mobility patterns in the data and to identify (in)consistency between current travel behavior and future travel preferences, we employ a Latent Class Analysis (LCA). LCA is a robust statistical technique that allows for the identification of latent subgroups based on observed responses, providing a nuanced understanding of how individuals' behavior and preferences interact to shape their mobility patterns. To achieve this, we utilize variables associated with travel behavior and travel preferences as indicators within a latent class model (Vermunt and Magidson, 2004), thereby uncovering the extent of (in)consistencies among travel behavior and future preferences. LCA can reveal the specific groups/combinations that exist and their relative sizes. The green links are used as covariates following the establishment of mobility classes based on the blue links, which encompass both revealed travel behaviors and stated future preferences (this will be discussed in the Method section). Essentially, these covariates provide further insight into the complex relationship between revealed behaviors and projected preferences within the context of mobility classification. The contribution of this study lies in its multidimensional approach to examining daily mobility patterns. By integrating both conventional and emerging transport options, we capture the evolving nature of mobility patterns. In other words, we analyze multiple mobility options, including conventional and emerging options, in order to capture mobility styles rather than examining a single preference for a new, emerging option disregarding the preference for all other (emerging) options.

Moreover, profiling classes across various transport needs and mode-specific dissonance allows us to disentangle the complex

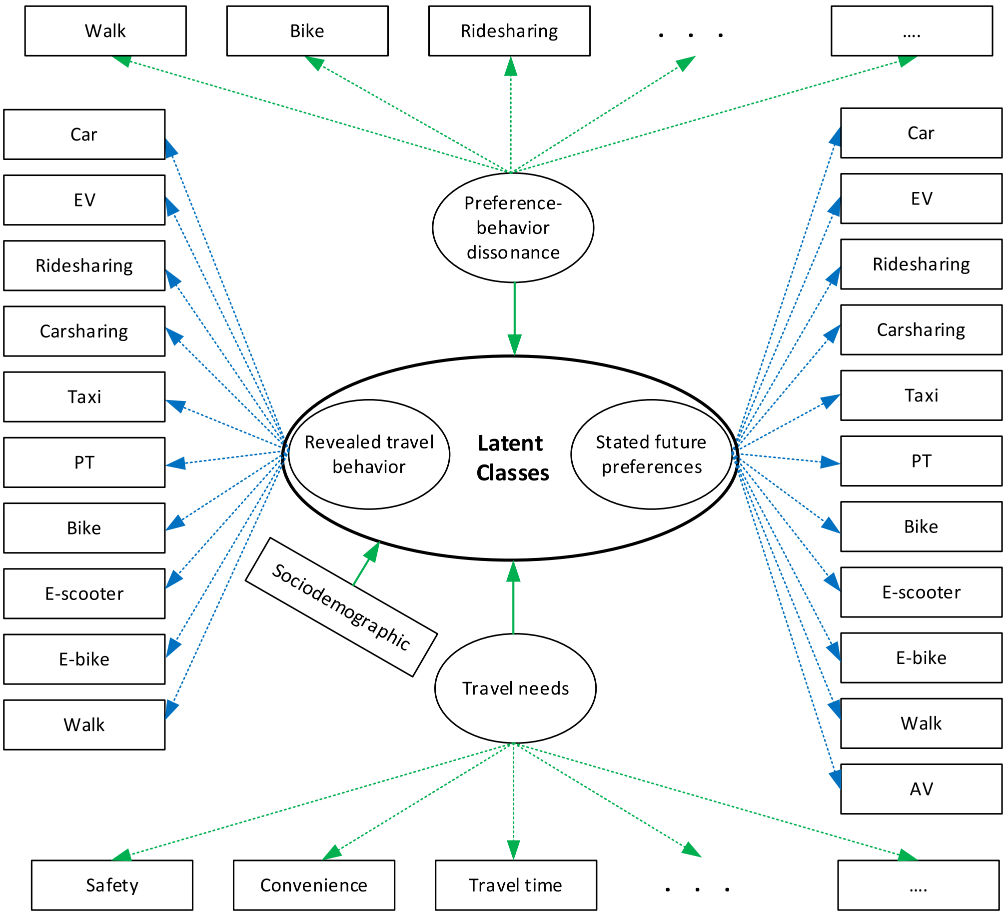

Fig. 1. The conceptual modeling framework.

decision-making processes that underlie individuals' mobility patterns, including the trade-offs they are willing to make between different aspects of mobility. Additionally, more detailed analyses will be conducted to better understand the sources of dissonances between behavior and preferences. Understanding the factors driving daily mobility patterns is important for planners, policymakers, and transportation providers as they seek to design sustainable and inclusive mobility solutions.

In the following sections, we present the methodology used for data collection and analysis, detail the results of the LCA, and discuss the implications of our findings. Moreover, we conclude with key takeaways and propose potential avenues for future research in this dynamic field of study.

4. Method

4.1. The study context: Mobility landscape in Norway

Norway, with a population of 5,391,369 as of January 1, 2021, has one of the lowest population densities in Europe at 17.3 inhabitants per square kilometer, second only to Iceland. Despite its overall low density, over 80 % of Norwegians reside in urban areas, where the density rises dramatically to 1,991 inhabitants per square kilometer as of 2020 (Norwegian Ministry of Transport, 2021).

According to the Norwegian Ministry of Transport (2021), the country boasts 94,700 km of public roads, divided into 10,500 km of national roads, 44,700 km of county roads, and 39,500 km of local roads. According to the Norwegian National Travel Survey 2018/19 (Grue et al., 2021), cars were the predominant mode (53 %) of transport in Norway. 20 % of daily trips were made on foot, 5 % by bike, and 11 % by PT. 57 % of the population reported having very good or good access to PT, with the best access in the largest cities. In 2018/19, 85 % of households had access to a car. Of these households, 43 % had one car, 33 % had two cars, and 9 % had three or more cars, with an average of 1.4 cars per household. EVs were more common in households with two or more cars, among higher income groups, and in large urban areas, particularly Oslo and Bergen. 72 % of the population had access to a bike, with 91 % owning only one type of bike. Traditional bikes were owned by 69 % of the population, while 7 % had e-bikes in 2018/19. Most e-bike owners also possess a traditional bike, a trend similarly seen among city bike users.

According to the Norway National Transport Plan 2022–2033, the government has implemented comprehensive reforms across the transport sector. These reforms aim to enhance efficiency, innovation, and cooperation by facilitating competitive tendering. The plan outlines a total financial framework of approximately NOK 1,200 billion (118 billion euros) for the period from 2022 to 2033, with NOK 1,076 billion sourced from state funds and NOK 123 billion from road tolls (Norwegian Ministry of Transport, 2021). These funds will be allocated to developing and maintaining advanced transport solutions throughout the country. Norway's level of public investment in transport is notably high compared to other nations, with investment levels more than doubling as a proportion of the economy since 2003 (Norwegian Ministry of Transport, 2021). The overarching, long-term policy objective for the transport sector is to establish an efficient, environmentally friendly, and safe transport system by 2050 (Norwegian Ministry of Transport, 2021).

Norway's unique societal and legal landscape makes it an ideal place to study emerging mobility modes, thanks to its tech-savvy culture and significant financial resources (Ryghaug and Skjølsvold, 2019). The country leads globally in EV adoption, driven by supportive government policies, substantial financial incentives, and a cultural embrace of new technologies (Mersky et al., 2016; Skjølsvold and Ryghaug, 2020). Several incentives have boosted EV demand in Norway, including tax exemptions, toll-free roads, reduced ferry fares, access to bus lanes, priority parking with charging facilities, and an extensive network of charging stations (Ryghaug and Skjølsvold, 2019). In 2022, an impressive 79 % of the 174,000 newly registered passenger cars in Norway were electric.[1] The Norwegian Parliament has also established a national objective that all new cars sold by 2025 should be zero-emission.[2] Moreover, the Norwegian National Transport Plan (2018–2029) outlines the potential benefits of integrating AVs, such as helping to achieve climate goals, improving transport safety, and enhancing public health outcomes (Nenseth et al., 2019).

In addition, car sharing has long been a part of Norway's mobility landscape (George and Julsrud, 2018). As of late 2018, the country had 11 car-sharing service providers or platforms, offering more than 7,000 vehicles to more than 200,000 registered members (George and Julsrud, 2018). Despite its long history, car-sharing services are primarily concentrated in the Oslo metropolitan area. The geographical concentration of availability highlights the need to increase accessibility throughout the country.

By 2029, the Norwegian e-bike market is expected to be worth 241.92 million USD, up from 153.83 million USD in 2024.[3] It has been observed that the use of bicycles for daily commutes has increased, with more commuters traveling distances ranging from 5 to 15 km for work, business, and local errands. The shift to cycling is expected to continue over the forecast period. In addition, Norway's emphasis on improving cycling infrastructure, including the expansion of bike lanes, is expected to increase demand for bicycles, especially among commuters traveling distances of 5 to 15 km.

Meanwhile, e-scooters have quickly gained traction in Norway, particularly in Oslo (Fearnley et al., 2020). Introduced by Voi and TIER in May 2019, these commercial e-scooter services were among the earliest in Europe and globally. According to a study in Oslo, most riders use e-scooters for short hops, covering about a kilometer in just a few minutes (Fearnley et al., 2020). While studies in North America often show e-scooters replacing car trips, Oslo had a different pattern, with only 8 % of e-scooter rides substituting car travel (Fearnley et al., 2020). Nonetheless, more than half of e-scooter journeys involved combining them with other travel modes, indicating their role as part of a wider, multimodal network that offers an alternative to owning and using a car. Furthermore, e-

[1] https://www.ssb.no/transport-og-reiseliv/landtransport/statistikk/bilparken/artikler/fire-av-fem-nye-biler-i-2022-var-elbiler.

[2] https://www.regjeringen.no/en/topics/transport-and-communications/veg/faktaartikler-vei-og-ts/norway-is-electric/id2677481/.

[3] https://www.mordorintelligence.com/industry-reports/norway-e-bike-market.

scooters contributed to increased mobility, with 22 % of respondents in Oslo stating they venture out more often, and 11 % mentioning that their last e-scooter ride was purely for fun (Fearnley et al., 2020).

4.2. Data

In December 2023, a nationwide survey was carried out, involving 1,002 Norwegian participants aged 18 and above, who completed a self-administered online questionnaire. The survey employed a randomized selection process facilitated by the "infact" survey panel, ensuring comprehensive representation across various regions, age groups, and gender demographics throughout Norway. Data collection spanned all 11 counties within the nation. Prior to participation, all respondents were explicitly informed about the voluntary nature of the survey and provided assurances regarding the confidentiality of their responses.

The results of the survey reveal that 49 % of the respondents identified themselves as female. Regarding the distribution of age, 10.9 % were in the 18–22 age bracket, 37.1 % fell between 25 and 44, 34.6 % were aged 45–64, and the remaining respondents were over 64 years old. A thorough comparative analysis was conducted between the demographic composition of the survey sample and the latest official population statistics from Norway (Statistics Norway, 2023[4]). Overall, the demographic characteristics of the sample closely mirrored those of the general population, as demonstrated in Table 1.[5] For instance, the proportion of females in the sample aligned with the gender distribution of Norwegians aged 16 and above, which stands at approximately 50 %. Furthermore, the geographic distribution of the respondents was consistent with the population data of Norway.

4.3. Measures

This study employed a variety of instruments to conduct a comprehensive survey of Norwegian transportation policies and advancements in mobility transition. The development and translation of numerous validated English scales into Norwegian were carried out by competent researchers proficient in both Norwegian and English.

Travel behavior was measured by asking how often participants typically use each of the transport modes (i.e., fossil-fuelled car (driver/passenger), electric car (driver/passenger), ridesharing, carsharing, taxi, public transport (bus, train), bike, e-bike, e-scooter, walking) for their daily travel. A six-point scale from (1) almost never; (2) 1 to 5 days per year; (3) 6 to 11 days per year; (4) 1 to 3 days per month; (5) 1 to 3 days per week; to (6) 4 or more days per week was used for evaluations. This item and answer scale has also been used in the Netherlands Mobility Panel studies (Hoogendoorn-Lanser et al., 2015) and in another Norwegian research (Mehdizadeh, 2024).

The level of preference for the use of each of the transport modes plus AVs for future daily travel was evaluated with the same answering scale. Before asking the question, we provided the following explanation: "Imagine yourself six years ahead in time (year 2030) – given that you have access to the transportation means on the list, how often would you anticipate traveling with each mode in 2030? With this question, we want to know more about which types of transportation you prefer to use in the future, so check off how much you would like to use the various means of transportation based on the year 2030.".

As for travel needs, it was asked how important each of the following aspects/needs (i.e., safety, comfort, environment, image, being inexpensive, being stress-free, flexibility, protection from bad weather, timesaving, physical activity, reliability, fun) of transport is when they choose a transport mode. A five-point Likert scale from (1) not at all, to (5) very important was used to measure these items. Based on existing scales (Şimşekoğlu et al., 2015; Schröder and Wolf, 2017; Mehdizadeh et al., 2022), this instrument was developed.

4.4. Modeling

4.4.1. Latent class analysis

Based on observed variables, LCA identifies latent subgroups within a population. As a probabilistic technique, LCA can identify (in)consistencies among variables about mobility patterns. Fig. 1 illustrates the conceptual framework that underpins the model by suggesting that indicators indicating travel behavior and future preferences represent distinct mobility classes. This aspect of the model (measurement model) determines the optimal number of latent classes based on the shared heterogeneity among these indicators (Vermunt and Magidson, 2013). In the model, the indicators for revealed travel behavior and anticipated future preferences are considered class indicators. Therefore, clustering is entirely determined by the shared variance among these indicators. To elucidate the associations between latent class variables and indicators, ordinal regression models were used since indicators were categorized as

[4] https://www.ssb.no/en/.

[5] Regarding educational diversity, it appears that the survey's "panel" may have concentrated mainly on two broad educational categories: individuals with advanced degrees (such as college/university graduates, especially those with Master's degrees or higher) and those with less formal education. This could lead to an overemphasis on highly educated participants, potentially skewing the sample, while neglecting individuals with minimal educational backgrounds, like those who only completed primary school.This potential bias might stem from the fact that individuals with higher education are typically more willing to engage in panel studies compared to other demographic segments (Reinikainen et al., 2018). Consequently, the data could be inclined towards respondents with higher educational achievements, leaving those with primary school qualifications underrepresented. However, our analysis primarily distinguishes between those with higher education (college and university) and those with less education, without delving into more nuanced educational differentiations.

Table 1
Sample profile (N = 1,002).

Attribute	Category	Sample (%)	Population (%)
Age	18–24	10.9	10.58
	25–44	37.1	34.08
	45–64	34.6	32.24
	65 +	17.6	23.09
Gender	Female	49.0	49.63
	Male	50.5	50.38
	Other	0.4	–
	Prefer not to disclose	0.1	–
Education	Primary school	4.8	23.7
	High school	38.4	36.3
	College and university (bachelor)	33.3	25.3
	University (Master and higher)	21.5	11.6
	Other	2	3.2

ordinal.

Next, the classes are profiled on the basis of different covariates: travel needs, the absolute value of the degree of dissonance (dd) between travel behavior and preference (i.e., $|dd|$), and socio-demographic factors. By profiling classes across these covariates, we are able to gain a deeper understanding of (in)consistencies in mobility patterns. To assess the associations of these covariates, we employ the 3-step procedure outlined by Vermunt (2010). Unlike the 1-step approach, where covariates are directly included to predict class membership, this procedure offers a distinct advantage: it ensures that covariates do not influence the measurement aspect of the model. In essence, classification relies solely on the indicators rather than the covariates. The 3-step procedure entails the following steps: first, estimating the model using only the indicators; second, probabilistically assigning subjects to latent classes, thereby generating posterior membership probabilities; and third, estimating the effects of covariates on latent class membership. Notably, these effects are adjusted for classification errors to mitigate bias. This method enables researchers to ascertain the effects and significance of covariates while accounting for measurement errors, without permitting the covariates to influence the classification process based solely on indicators (Vermunt, 2010; Kroesen, 2019).

It is the principal objective of latent class analysis to identify the model that captures most effectively the relationships among the indicators by having the fewest latent classes (Kroesen, 2019). To identify the optimal model, supplementary models were computed, ranging from one to ten latent classes. The Bayesian Information Criterion (BIC) is used to assess and compare models with different numbers of classes (Vermunt and Magidson, 2013). When comparing different solutions, the one with the lowest BIC is preferred (Vermunt and Magidson, 2013). The BIC is a measure that balances parsimony with model fit (Vermunt and Magidson, 2013). Therefore, the BIC is the primary criterion to consider, followed by other factors such as the smallest class size. As shown in Table 2, the solution with 7 classes has the lowest BIC. To ensure this solution does not include a class with a very small size, we assumed that a class with around 80 participants (approximately 8 %) is reliable. In other solutions, the smallest class sizes were much lower (e.g., 2 %).

According to BIC statistics and the smallest class size, the 7-class model emerges as the most optimal model. Given this, the result section provides a comprehensive interpretation of this particular solution using jamovi 2.3.21 (The jamovi project, 2022), an open-source, freely available statistical software.

4.4.1.1. Detailed disaggregated analyses. To explore the underlying mechanisms of dissonance, we also adopted a non-aggregated, individual-based analysis model. To explain potential modal dissonance or shifts, further disaggregated regression analyses were conducted for individuals within each class. Using these analyses, we identify variations in current travel behavior and future travel preferences among individuals.

These regression models aimed to explain changes in mode use (the original value of the degree of dissonance for each mode; dd) based on changes in other modes' use (i.e., dd of other modes), changes in overall mobility rates, sociodemographic characteristics, and travel needs. The degree of dissonance (dd) for each mode per individual is calculated as the difference between future stated travel preferences and revealed travel behavior (dd = future stated travel preference – revealed travel behavior). This metric can range from -5 to $+5$ for each travel mode.

A negative regression weight between two dd suggests a substitution relationship between the two modes, indicating that an increase in one mode corresponds to a decrease in the other. Conversely, a positive regression weight indicates a complementary relationship, where the use of one mode increases alongside the other. Additionally, if increased overall mobility (trip-making) has a positive regression weight, it indicates that the rise in mobility rate explains the positive (or negative) dissonance of a particular mode. A dummy variable was created for this purpose to capture the increase in overall mobility rates, with 1 indicating that individuals anticipate increasing their overall mobility and 0 otherwise. Essentially, this variable represents the difference between future overall mobility rates (the sum of trips made by all modes in the future) and current overall mobility rates.

In the models, 11 dependent variables were included: degrees of dissonance for fossil-fuelled cars, EV, ridesharing, carsharing, taxis, PT, bicycles, e-bikes, e-scooters, and walking, as well as anticipated future AV use. These analyses help clarify how dissonance manifests among individuals, indicating whether it suggests a shift to other modes or an anticipated increase in mobility.

Since the LCA optimal solution identifies seven classes, the total number of models is 77 (11*7). All regression models were tested using SPSS. To keep the results tables concise, only standardized coefficients are presented along with their significance at 10 %, 5 %,

Table 2
Determination of number of latent classes.

Class	AIC	BIC	Log-likelihood	Smallest class size
1	55927	56109	−27859	Accepted*
2	52207	52573	−25892	Accepted
3	50980	51529	−25173	Accepted
4	50499	51232	−24826	Accepted
5	49937	50854	−24439	Rejected
6	49694	50795	−24212	Rejected
7	**49461**	**50746**	**−23990**	**Accepted**
8	49360	50829	−23833	Rejected
9	49182	50835	−23638	Rejected
10	49259	51095	−23570	Rejected

Accepted: the smallest class size is ≥ 8%.

and 1 %, as well as R-square and model significance for F change. Accordingly, a few important findings from these analyses will be discussed for each class to ensure the brevity of the results discussion.

5. Results

5.1. Travel behavior-preference dissonance

Fig. 2A illustrates the average current travel behavior (mode use) alongside future travel preferences per mode for the whole sample. Fig. 2.b displays the level of dissonance (dd), representing the difference between current behavior and future stated preferences, per mode. These descriptive findings suggest that, in general, individuals intend to use each presented mode more in the future compared to the present, except for fossil-fuel cars. The most significant dissonance is observed for EVs, indicating a potential shift from conventional cars to EVs. Additionally, it appears that people anticipate making more trips in the future compared to the current situation. To put it another way, the sum of the positive differences (dissonance) is much greater than the sum of the negative differences for cars. For nine modes, participants anticipate making 3.26 (on the six-point scale) more trips in the future than they do now, while the opposite is true only for fossil-fuel cars; participants anticipate making 0.69 fewer trips in their cars.

5.2. Latent class analysis results

Table 3 provides a comprehensive overview of class profiles, showcasing evaluations of both current travel behavior and future travel preferences. Meanwhile, Table 4 offers a detailed exploration of the classes, including analyses of travel dissonance (|dd|), travel needs, and sociodemographic factors. Overall, these tables offer highly interpretable insights into the various classes under study. Additionally, we conducted more detailed disaggregated regression analyses to better understand the variations in dissonance (dd) across different classes. The results of these analyses are included in the supplementary material file, presented in seven tables (Table A1 to Table A7), with each table containing 11 models[6] corresponding to a specific class. Notably, the models for Class 3, which show interesting transition patterns, are also shown in Table 5. Below, we provide an interpretation of the LCA and the further regression results.

Class 1 – *Multimodal current users and multimodal future preferences*. This group constitutes 8 % of the population, engaging in a variety of mobility options ranging from conventional to emerging ones. Notably, their trip-making rates surpass those of other subgroups. Upon closer examination of their current behavior and future stated preferences, it becomes evident that these individuals aim to maintain their current level of multimodality in the future, alongside sustaining their high trip-making rates. Interestingly, this group tends to prefer additional modes such as bikes, e-bikes, and e-scooters, alongside their existing choices. Overall, it appears that these travelers are receptive to emerging options, positioning them as early adopters of AVs. Interestingly, the most dissonant travelers are part of this group. In other words, as we found earlier, dissonant travelers are those who intend to use more sustainable mobility options compared to the current situations in these data. So, in this context, dissonant travelers are sustainability-oriented and willing to use more sustainable options (Fig. 3a). However, a closer look at trip-making rates reveals that these dissonant travelers are more likely to make more trips compared to the current situation. This may imply that these people may offset their increased trips in the future by choosing more sustainable options, showcasing a potential negative spill-over effect. In terms of travel needs, this group places great importance on the environment, image, time-saving, physical activities, and fun when making mode choices (Fig. 3b). This group is significantly skewed towards men, individuals aged 35–44, and highly educated people.

Further detailed analysis (Table A.1) indicates that people in this category are not necessarily replacing traditional cars with some emerging modes, such as EVs. In the future, they might own both electric and non-electric cars and use them interchangeably. It appears that various emerging modes complement each other. For instance, those who plan to use carsharing more frequently also intend to use more EVs. Similarly, an increase in ridesharing use is positively correlated with greater e-scooter use. Additionally, the

[6] Only the statistically significant models were interpreted.

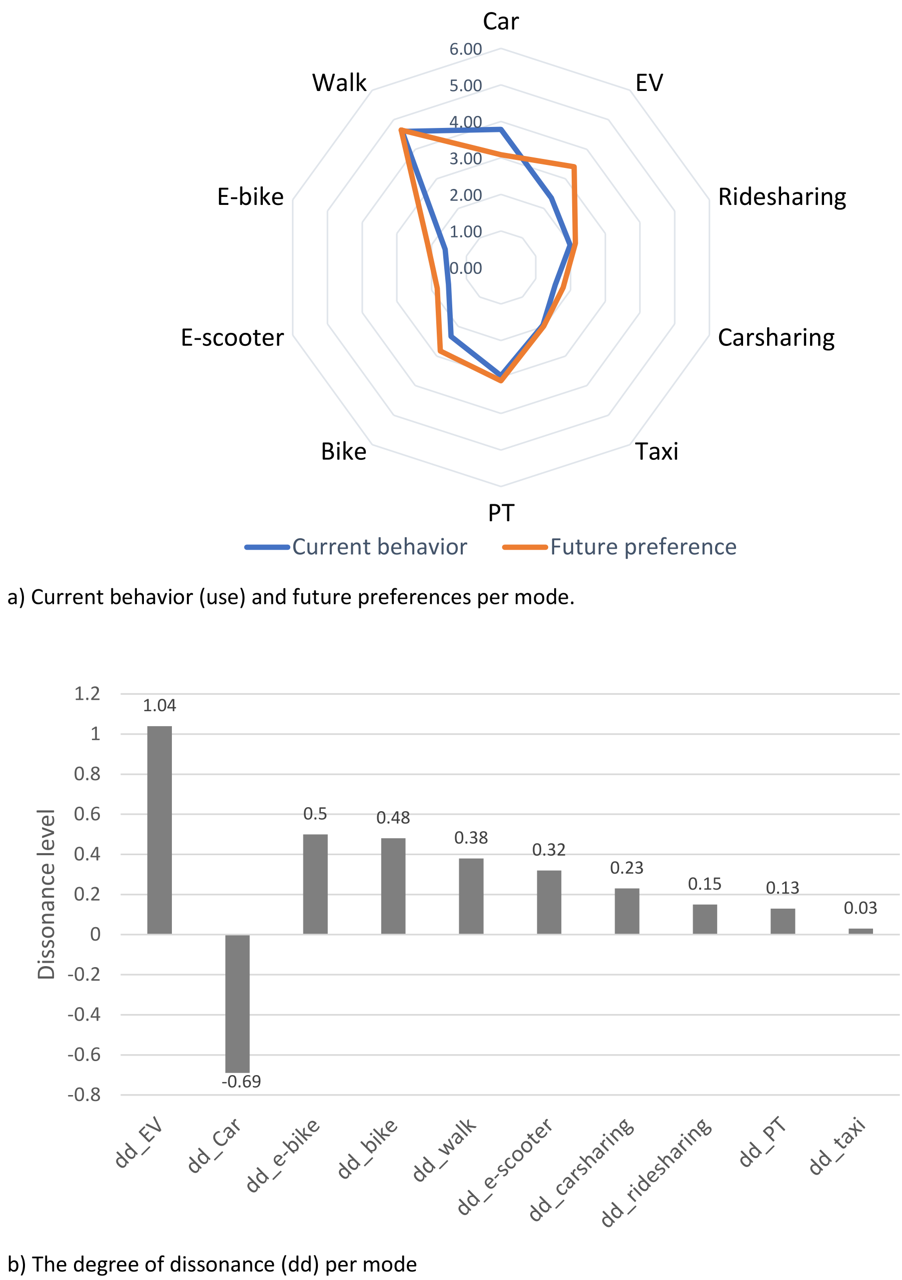

Fig. 2. The degree of dissonance between travel behavior and future preferences.

expected rise in e-bike use and walking rates seems to be driven by an overall increase in future mobility. Furthermore, individuals who prioritize stress-free travel are more likely to adopt EV use in the future, explaining the positive shift towards EVs compared to the present.

Class 2—*Walkers and occasional users of ridesharing, taxis, and e-bikes, with a preference for EVs and occasional utilization of sharing services, PT, e-bikes, and e-scooters*. This group constitutes 8 % of the population. Members of this class are the second ones who make the most trips. Despite not being current car users, they are contemplating the adoption of EVs in the future. Showing a commitment to sustainable choices, they are predominantly users and supporters of sustainable transportation options, making them somewhat multimodal sustainable travelers. They are also relatively dissonant and belong to the groups that prioritize different travel needs to a lesser extent. This category is predominantly composed of men and individuals at the young age bracket (25–34) with college and bachelor university degrees.

Further detailed models (Table A.2) indicate that the anticipated increase in EV use in the future is likely due to higher overall mobility rates. E-biking and e-scooting complement each other within this group. Additionally, there may be a shift from car use to

Table 3
Latent classes profiles.

Indicator	**Class**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
	Class size (%)	8 %	8.2 %	14 %	21.1 %	15.6 %	15.1 %	19 %
	Mobility* (trip-making): behavior	4.32	3.15	2.54	2.54	2.12	2.15	1.84
	Mobility: future preference	4.56	3.38	3.06	2.85	2.24	2.24	1.94
Car (behavior)	Almost never	3.3 %	8.5 %	24.1 %	**46.1 %**	14.2 %	**53.8 %**	29.3 %
	1 to 5 days per year	3.3 %	**24.4 %**	2.9 %	1.0 %	9.9 %	1.9 %	0.0 %
	6 to 11 days per year	1.6 %	22.0 %	3.6 %	2.9 %	0.0 %	3.2 %	1.5 %
	1 to 3 days per month	26.2 %	18.3 %	13.9 %	8.3 %	4.3 %	7.7 %	4.0 %
	1 to 3 days per week	26.2 %	15.9 %	20.4 %	28.2 %	27.8 %	21.2 %	15.2 %
	4 or more days per week	**39.3 %**	11.0 %	**35.0 %**	13.6 %	**43.8 %**	12.2 %	**50.0 %**
EV (behavior)	Almost never	13.1 %	9.8 %	**73.0 %**	**62.1 %**	**64.8 %**	**82.1 %**	**82.3 %**
	1 to 5 days per year	6.6 %	24.4 %	2.9 %	1.0 %	8.6 %	1.3 %	0.5 %
	6 to 11 days per year	0.0 %	**26.8 %**	2.2 %	1.9 %	1.9 %	1.3 %	0.0 %
	1 to 3 days per month	13.1 %	18.3 %	1.5 %	3.9 %	1.9 %	1.3 %	0.5 %
	1 to 3 days per week	18.0 %	14.6 %	5.1 %	13.6 %	4.3 %	7.7 %	5.1 %
	4 or more days per week	**49.2 %**	6.1 %	15.3 %	17.5 %	18.5 %	6.4 %	11.6 %
Ridesharing (behavior)	Almost never	9.8 %	17.1 %	**40.9 %**	**59.7 %**	**48.8 %**	**76.3 %**	**86.9 %**
	1 to 5 days per year	4.9 %	20.7 %	25.5 %	8.7 %	33.3 %	9.6 %	6.6 %
	6 to 11 days per year	4.9 %	23.2 %	27.0 %	5.3 %	11.7 %	1.9 %	1.0 %
	1 to 3 days per month	26.2 %	**28.0 %**	5.1 %	14.1 %	6.2 %	8.3 %	4.5 %
	1 to 3 days per week	**26.2 %**	9.8 %	1.5 %	10.2 %	0.0 %	2.6 %	0.0 %
	4 or more days per week	27.9 %	1.2 %	0.0 %	1.9 %	0.0 %	1.3 %	1.0 %
Carsharing (behavior)	Almost never	16.4 %	12.2 %	**81.8 %**	**90.8 %**	**90.1 %**	**99.4 %**	**96.0 %**
	1 to 5 days per year	4.9 %	18.3 %	6.6 %	2.4 %	6.8 %	0.0 %	0.5 %
	6 to 11 days per year	4.9 %	**30.5 %**	3.6 %	1.0 %	1.2 %	0.0 %	0.0 %
	1 to 3 days per month	23.0 %	17.1 %	5.1 %	0.0 %	0.0 %	0.6 %	1.5 %
	1 to 3 days per week	19.7 %	15.9 %	0.7 %	4.4 %	0.0 %	0.0 %	0.0 %
	4 or more days per week	**31.1 %**	6.1 %	2.2 %	1.5 %	1.9 %	0.0 %	2.0 %
Taxi (behavior)	Almost never	4.9 %	6.1 %	32.1 %	50.0 %	42.0 %	**49.4 %**	**84.3 %**
	1 to 5 days per year	14.8 %	28.0 %	**46.7 %**	**39.3 %**	**47.5 %**	24.4 %	8.1 %
	6 to 11 days per year	8.2 %	24.4 %	18.2 %	6.8 %	7.4 %	12.8 %	4.0 %
	1 to 3 days per month	**27.9 %**	**29.3 %**	2.9 %	1.5 %	3.1 %	10.9 %	1.5 %
	1 to 3 days per week	27.9 %	9.8 %	0.0 %	1.0 %	0.0 %	1.9 %	1.0 %
	4 or more days per week	16.4 %	2.4 %	0.0 %	1.5 %	0.0 %	0.6 %	1.0 %
Public transport (PT) (behavior)	Almost never	0.0 %	3.7 %	9.5 %	14.1 %	26.5 %	1.3 %	**86.4 %**
	1 to 5 days per year	0.0 %	15.9 %	**29.9 %**	20.4 %	**51.9 %**	1.9 %	10.1 %
	6 to 11 days per year	14.8 %	**40.2 %**	19.0 %	**27.7 %**	16.0 %	**40.4 %**	2.5 %
	1 to 3 days per month	**55.7 %**	26.8 %	21.2 %	21.4 %	5.6 %	27.6 %	0.5 %
	1 to 3 days per week	19.7 %	9.8 %	13.1 %	14.1 %	0.0 %	19.2 %	0.5 %
	4 or more days per week	9.8 %	3.7 %	7.3 %	2.4 %	0.0 %	9.6 %	0.0 %
Bike (behavior)	Almost never	9.8 %	17.1 %	14.6 %	**31.1 %**	**69.1 %**	**78.2 %**	**75.3 %**
	1 to 5 days per year	1.6 %	13.4 %	21.9 %	10.7 %	19.1 %	9.6 %	4.5 %
	6 to 11 days per year	6.6 %	**39.0 %**	**27.7 %**	13.6 %	10.5 %	3.8 %	7.6 %
	1 to 3 days per month	**37.7 %**	15.9 %	27.0 %	11.2 %	1.2 %	5.1 %	7.6 %
	1 to 3 days per week	29.5 %	12.2 %	8.8 %	21.4 %	0.0 %	3.2 %	4.0 %
	4 or more days per week	14.8 %	2.4 %	0.0 %	12.1 %	0.0 %	0.0 %	1.0 %
E-scooter (behavior)	Almost never	9.8 %	13.4 %	**76.6 %**	**86.4 %**	**88.9 %**	**97.4 %**	**95.5 %**
	1 to 5 days per year	16.4 %	**40.2 %**	14.6 %	6.8 %	8.0 %	1.3 %	2.5 %
	6 to 11 days per year	8.2 %	31.7 %	7.3 %	4.4 %	3.1 %	0.6 %	2.0 %
	1 to 3 days per month	18.0 %	12.2 %	1.5 %	1.5 %	0.0 %	0.0 %	0.0 %
	1 to 3 days per week	**32.8 %**	2.4 %	0.0 %	1.0 %	0.0 %	0.6 %	0.0 %
	4 or more days per week	14.8 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
E-bike (behavior)	Almost never	11.5 %	15.9 %	**71.5 %**	**79.1 %**	**88.9 %**	**97.4 %**	**89.4 %**
	1 to 5 days per year	6.6 %	**30.5 %**	15.3 %	7.8 %	7.4 %	1.9 %	4.5 %
	6 to 11 days per year	9.8 %	29.3 %	10.9 %	8.7 %	2.5 %	0.6 %	4.5 %
	1 to 3 days per month	24.6 %	20.7 %	0.0 %	1.5 %	0.0 %	0.0 %	0.0 %
	1 to 3 days per week	**36.1 %**	2.4 %	2.2 %	1.9 %	0.0 %	0.0 %	0.5 %
	4 or more days per week	11.5 %	1.2 %	0.0 %	1.0 %	1.2 %	0.0 %	1.0 %
Walk (behavior)	Almost never	4.9 %	12.2 %	3.6 %	0.0 %	13.0 %	7.7 %	**32.3 %**
	1 to 5 days per year	6.6 %	13.4 %	2.9 %	0.0 %	8.6 %	0.6 %	6.6 %
	6 to 11 days per year	6.6 %	7.3 %	4.4 %	1.9 %	12.3 %	1.3 %	5.1 %
	1 to 3 days per month	24.6 %	20.7 %	10.9 %	1.9 %	23.5 %	9.6 %	13.1 %
	1 to 3 days per week	14.8 %	18.3 %	35.8 %	14.6 %	15.4 %	28.8 %	20.2 %
	4 or more days per week	**42.6 %**	**28.0 %**	**42.3 %**	**81.6 %**	**27.2 %**	**51.9 %**	22.7 %
Car (future preference)	Almost never	9.8 %	6.1 %	**40.9 %**	**68.9 %**	24.1 %	**62.2 %**	**42.9 %**
	1 to 5 days per year	6.6 %	20.7 %	9.5 %	1.9 %	9.9 %	1.9 %	0.0 %
	6 to 11 days per year	8.2 %	24.4 %	5.8 %	3.4 %	2.5 %	5.1 %	1.0 %
	1 to 3 days per month	24.6 %	**28.0 %**	16.8 %	5.8 %	6.2 %	5.8 %	1.5 %

(*continued on next page*)

Table 3 (*continued*)

Indicator	**Class**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
	Class size (%)	8 %	8.2 %	14 %	21.1 %	15.6 %	15.1 %	19 %
	Mobility* (trip-making): behavior	4.32	3.15	2.54	2.54	2.12	2.15	1.84
	Mobility: future preference	4.56	3.38	3.06	2.85	2.24	2.24	1.94
	1 to 3 days per week	**27.9 %**	18.3 %	21.2 %	10.2 %	**29.6 %**	14.1 %	17.7 %
	4 or more days per week	23.0 %	2.4 %	5.8 %	9.7 %	27.8 %	10.9 %	36.9 %
EV (future preference)	Almost never	8.2 %	3.7 %	16.8 %	30.6 %	**48.8 %**	**67.9 %**	**57.1 %**
	1 to 5 days per year	1.6 %	20.7 %	3.6 %	0.0 %	7.4 %	2.6 %	0.0 %
	6 to 11 days per year	1.6 %	23.2 %	10.9 %	0.5 %	2.5 %	0.6 %	2.0 %
	1 to 3 days per month	9.8 %	**32.9 %**	11.7 %	8.3 %	3.1 %	6.4 %	2.0 %
	1 to 3 days per week	31.1 %	19.5 %	26.3 %	29.6 %	10.5 %	11.5 %	8.1 %
	4 or more days per week	**47.5 %**	0.0 %	**30.7 %**	**31.1 %**	27.8 %	10.9 %	30.8 %
Ridesharing (future preference)	Almost never	6.6 %	7.3 %	**34.3 %**	**56.3 %**	**48.8 %**	**80.1 %**	**90.9 %**
	1 to 5 days per year	4.9 %	22.0 %	16.1 %	7.8 %	28.4 %	5.8 %	3.5 %
	6 to 11 days per year	3.3 %	24.4 %	31.4 %	3.4 %	12.3 %	3.2 %	1.0 %
	1 to 3 days per month	13.1 %	**35.4 %**	8.8 %	15.5 %	8.0 %	5.1 %	2.5 %
	1 to 3 days per week	34.4 %	8.5 %	9.5 %	13.1 %	2.5 %	4.5 %	1.0 %
	4 or more days per week	**37.7 %**	2.4 %	0.0 %	3.9 %	0.0 %	1.3 %	1.0 %
Carsharing (future preference)	Almost never	6.6 %	4.9 %	**57.7 %**	**73.8 %**	**83.3 %**	**94.2 %**	**96.5 %**
	1 to 5 days per year	3.3 %	12.2 %	17.5 %	8.3 %	8.0 %	0.6 %	0.0 %
	6 to 11 days per year	3.3 %	**34.1 %**	13.9 %	4.9 %	2.5 %	0.0 %	1.0 %
	1 to 3 days per month	16.4 %	30.5 %	7.3 %	4.9 %	3.1 %	4.5 %	1.0 %
	1 to 3 days per week	32.8 %	18.3 %	3.6 %	6.8 %	1.9 %	0.0 %	0.0 %
	4 or more days per week	**37.7 %**	0.0 %	0.0 %	1.5 %	1.2 %	0.6 %	1.5 %
Taxi (future preference)	Almost never	11.5 %	4.9 %	**48.9 %**	**56.8 %**	37.7 %	**46.8 %**	**83.3 %**
	1 to 5 days per year	9.8 %	15.9 %	28.5 %	34.0 %	**48.1 %**	23.1 %	7.6 %
	6 to 11 days per year	8.2 %	29.3 %	16.8 %	4.9 %	8.6 %	14.1 %	4.0 %
	1 to 3 days per month	13.1 %	**35.4 %**	5.1 %	1.5 %	3.7 %	12.2 %	4.0 %
	1 to 3 days per week	**36.1 %**	8.5 %	0.7 %	1.5 %	1.9 %	3.2 %	0.0 %
	4 or more days per week	21.3 %	6.1 %	0.0 %	1.5 %	0.0 %	0.6 %	1.0 %
Public transport (PT) (future preference)	Almost never	1.6 %	1.2 %	2.9 %	11.7 %	19.1 %	0.0 %	**88.4 %**
	1 to 5 days per year	3.3 %	12.2 %	20.4 %	15.0 %	**53.1 %**	0.0 %	9.1 %
	6 to 11 days per year	11.5 %	**42.7 %**	**28.5 %**	**32.0 %**	21.6 %	**38.5 %**	1.5 %
	1 to 3 days per month	**41.0 %**	31.7 %	21.9 %	18.9 %	5.6 %	28.8 %	0.0 %
	1 to 3 days per week	26.2 %	9.8 %	20.4 %	17.5 %	0.0 %	17.9 %	0.5 %
	4 or more days per week	16.4 %	2.4 %	5.8 %	4.9 %	0.6 %	14.7 %	0.5 %
Bike (future preference)	Almost never	3.3 %	8.5 %	0.0 %	22.8 %	**59.3 %**	**72.4 %**	**72.7 %**
	1 to 5 days per year	1.6 %	13.4 %	7.3 %	6.8 %	19.8 %	10.3 %	2.0 %
	6 to 11 days per year	6.6 %	25.6 %	**30.7 %**	7.8 %	14.2 %	2.6 %	4.0 %
	1 to 3 days per month	16.4 %	**29.3 %**	24.1 %	17.0 %	3.7 %	6.4 %	9.6 %
	1 to 3 days per week	**41.0 %**	15.9 %	34.3 %	19.4 %	3.1 %	7.1 %	7.1 %
	4 or more days per week	31.1 %	7.3 %	3.6 %	**26.2 %**	0.0 %	1.3 %	4.5 %
E-scooter (future preference)	Almost never	4.9 %	4.9 %	**47.4 %**	**69.4 %**	**85.2 %**	**96.8 %**	**89.4 %**
	1 to 5 days per year	1.6 %	20.7 %	13.9 %	7.8 %	10.5 %	0.6 %	4.5 %
	6 to 11 days per year	21.3 %	**37.8 %**	22.6 %	13.6 %	4.3 %	2.6 %	4.5 %
	1 to 3 days per month	18.0 %	31.7 %	14.6 %	3.4 %	0.0 %	0.0 %	1.5 %
	1 to 3 days per week	**39.3 %**	3.7 %	1.5 %	3.9 %	0.0 %	0.0 %	0.0 %
	4 or more days per week	14.8 %	1.2 %	0.0 %	1.9 %	0.0 %	0.0 %	0.0 %
E-bike (future preference)	Almost never	3.3 %	0.0 %	18.2 %	**49.5 %**	**79.6 %**	**94.2 %**	**79.3 %**
	1 to 5 days per year	8.2 %	17.1 %	**27.0 %**	12.6 %	13.0 %	5.8 %	7.1 %
	6 to 11 days per year	11.5 %	**43.9 %**	26.3 %	28.2 %	5.6 %	0.0 %	10.6 %
	1 to 3 days per month	14.8 %	35.4 %	20.4 %	1.9 %	1.2 %	0.0 %	1.0 %
	1 to 3 days per week	**45.9 %**	3.7 %	8.0 %	2.9 %	0.6 %	0.0 %	0.5 %
	4 or more days per week	16.4 %	0.0 %	0.0 %	4.9 %	0.0 %	0.0 %	1.5 %
Walk (future preference)	Almost never	6.6 %	3.7 %	2.2 %	0.0 %	8.6 %	8.3 %	**34.3 %**
	1 to 5 days per year	0.0 %	18.3 %	0.0 %	0.0 %	13.0 %	0.0 %	5.1 %
	6 to 11 days per year	4.9 %	28.0 %	0.0 %	0.5 %	13.0 %	1.9 %	4.0 %
	1 to 3 days per month	27.9 %	**28.0 %**	10.2 %	0.0 %	21.0 %	3.8 %	14.1 %
	1 to 3 days per week	19.7 %	12.2 %	**44.5 %**	9.7 %	17.3 %	35.3 %	18.7 %
	4 or more days per week	**41.0 %**	9.8 %	43.1 %	**89.8 %**	**27.2 %**	**50.6 %**	23.7 %
AV (future preference)	Almost never	1.6 %	6.1 %	**51.1 %**	**68.4 %**	**74.1 %**	**81.4 %**	**88.4 %**
	1 to 5 days per year	6.6 %	25.6 %	13.1 %	4.9 %	5.6 %	0.0 %	0.0 %
	6 to 11 days per year	3.3 %	**30.5 %**	9.5 %	2.9 %	3.1 %	2.6 %	1.5 %
	1 to 3 days per month	19.7 %	22.0 %	7.3 %	2.9 %	2.5 %	6.4 %	1.0 %
	1 to 3 days per week	29.5 %	9.8 %	10.9 %	10.7 %	4.9 %	6.4 %	2.0 %
	4 or more days per week	**39.3 %**	6.1 %	8.0 %	10.2 %	9.9 %	3.2 %	7.1 %

* Average of trip-making across all modes. The original scale was from (1) Almost never to (6) 4 or more days per week.

Table 4
Covariates distributions across classes.

	Class	1	2	3	4	5	6	7
Covariate	**Class size (%)**	8 %	8.2 %	14 %	21.1 %	15.6 %	15.1 %	19 %
|dd_Car|	Mean	**1.39**	1.34	1.53	1.47	0.99	0.87	0.99
|dd_EV|	Mean	1.25	1.32	**2.22**	1.69	1.18	0.76	1.25
|dd_ridesharing|	Mean	**1.18**	1.12	0.80	0.69	0.54	0.34	0.25
|dd_carsharing|	Mean	**1.36**	1.21	0.80	0.53	0.38	0.19	0.20
|dd_taxi|	Mean	**1.30**	1.17	0.53	0.40	0.36	0.41	0.24
|dd_PT|	Mean	**0.90**	0.77	0.71	0.72	0.53	0.35	0.33
|dd_bike|	Mean	1.20	1.18	**1.23**	1.08	0.51	0.47	0.50
|dd_e-scooter|	Mean	**1.13**	1.01	1.02	0.58	0.26	0.08	0.19
|dd_e-bike|	Mean	1.30	1.05	**1.53**	0.90	0.35	0.07	0.40
|dd_walk|	Mean	0.77	**1.50**	0.57	0.21	0.66	0.35	0.69
|dd_overall|	Mean	**1.18**	1.17	1.09	0.83	0.58	0.39	0.50
Safety	Mean	4.33	3.68	4.45	**4.48**	4.40	4.33	4.22
Comfort	Mean	4.26	3.62	4.04	4.18	**4.33**	4.24	4.20
Environment	Mean	**4.02**	3.48	3.79	3.79	3.22	3.47	2.90
Image	Mean	**3.67**	3.55	2.47	2.43	2.51	2.35	2.33
Inexpensive	Mean	4.25	3.88	4.42	**4.48**	4.27	4.26	3.95
Stress-free	Mean	4.05	3.49	4.10	3.98	**4.09**	4.01	3.90
Flexibility	Mean	4.16	3.67	4.36	**4.51**	4.35	4.33	4.22
Weather	Mean	4.11	3.44	4.14	4.09	**4.23**	4.22	4.22
Timesaving	Mean	**4.33**	3.61	4.24	4.24	4.29	4.13	4.06
Physical activity	Mean	**4.15**	3.43	3.64	3.87	3.16	3.45	2.88
Reliability	Mean	4.10	3.61	4.52	4.56	4.44	**4.49**	4.24
Fun	Mean	**3.85**	3.67	3.39	3.38	3.48	3.13	3.29
Gender	Man	**73.8 %**	**61.0 %**	48.2 %	46.1 %	45.1 %	47.4 %	**52.0 %**
	Woman	26.2 %	39.0 %	**51.1 %**	**53.9 %**	**54.9 %**	**50.6 %**	47.5 %
	Other	0.0 %	0.0 %	0.7 %	0.0 %	0.0 %	1.3 %	0.5 %
	Prefer not to disclose	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.6 %	0.0 %
Age	18–24	27.9 %	34.1 %	8.8 %	11.7 %	7.4 %	3.8 %	5.1 %
	25–34	21.3 %	**36.6 %**	**24.1 %**	14.1 %	13.6 %	12.8 %	9.6 %
	35–44	**44.3 %**	22.0 %	21.2 %	16.5 %	21.6 %	15.4 %	19.2 %
	45–54	4.9 %	4.9 %	19.7 %	**23.8 %**	21.0 %	21.2 %	**24.2 %**
	55–64	1.6 %	1.2 %	14.6 %	15.0 %	14.2 %	21.2 %	19.7 %
	65+	0.0 %	1.2 %	11.7 %	18.9 %	**22.2 %**	**25.6 %**	22.2 %
Education	Primary school	1.6 %	3.7 %	2.2 %	6.3 %	3.1 %	3.8 %	8.6 %
	High school	31.1 %	32.9 %	**35.8 %**	**40.3 %**	37.0 %	**35.3 %**	**46.5 %**
	College or university (bachelor)	24.6 %	**37.8 %**	28.5 %	32.5 %	**42.0 %**	34.6 %	30.3 %
	University (Master and higher)	**42.6 %**	25.6 %	32.1 %	18.4 %	16.0 %	23.1 %	12.1 %
	Other	0.0 %	0.0 %	1.5 %	2.4 %	1.9 %	3.2 %	2.5 %

walking among this group. However, the significant increase in walking is largely due to higher overall mobility rates rather than shifts from other travel modes. Although women in this group are more likely to use e-scooters more frequently in the future, they are less likely to opt for e-bikes.

Class 3—*Current car users and walkers with a preference for EVs, PT, biking, and walking in future trips*. Comprising 14 % of the population, this group exhibits a potential shift from fossil fuel-based cars to EVs. Their future mobility preferences extend to PT, biking, and walking. Notably, they do not express interest in AVs. Their trip-making rate is lower than classes 1 and 2, but higher than the other groups. When it comes to EVs, biking, and e-biking, they are the most dissonant travelers. Interestingly, this dissonance level for these modes leans towards favoring sustainable modalities in the future. Even though they moderately emphasize certain travel needs, their reported needs are not among the strongest across different classes. There is no noticeable gender gap in this group. It is slightly skewed towards young people and individuals with lower education levels.

As reported in Table 5, further analysis reveals that a plausible shift from car use to EV use may occur among people in this group. Specifically, the high level of positive dissonance towards EVs is significantly explained by a reduction in car use ($b = -0.414$) at a 1 % significance level, rather than by changes in overall mobility (trip-making) rates. On the other hand, the increased rate of walking dissonance is better explained by an increase in overall mobility rates rather than a shift from another travel mode. Similarly, the high levels of biking and e-biking dissonance are significantly attributed to an overall increase in mobility among participants in this group. E-scooting and AV use appear to complement each other. Regarding demographic variables, older people in this group are more inclined to use EVs and public transport in the future, while highly educated people are less likely to use e-scooters.

Class 4—*Current active transport users (walking and biking) with a preference for the same active modes plus EVs*. This class encompasses 21 % of the population, showcasing a higher rate of active mode use compared to other groups. Interestingly, they express a desire to continue this active mobility in the future but are also inclined towards adopting EVs for future trips. It appears that the introduction of EVs may influence these active travelers, who are currently not car-dependent, to consider EVs as part of their future transport choices. This could potentially lead to a shift where current non-car users may opt for EVs, impacting traffic patterns and potentially posing a challenge to sustainability goals. Policymakers should carefully examine the role of EVs in travel behavior transition, recognizing their

Table 5
Standardized coefficients from disaggregated regression models: potential modal shifts by dissonance level, mobility changes, sociodemographics, and travel needs for *Class 3*.

	Y (Dependent variable)										
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
X (predictor)	dd_Car	dd_EV	dd_ridesharing	dd_carsharing	dd_taxi	dd_PT	dd_bike	dd_e-scooter	dd_e-bike	dd_walk	AV
dd_Car	—	−0.414***	−0.222**	−0.170*	−0.049	−0.187*	0.066	−0.165*	−0.014	−0.098	0.130
dd_EV	−0.443***	—	−0.055	0.081	−0.059	−0.298**	−0.002	−0.002	0.046	−0.070	0.180
dd_ridesharing	−0.208**	−0.049	—	−0.038	−0.002	0.171*	0.029	0.116	0.063	−0.165*	0.097
dd_carsharing	−0.153*	0.067	−0.036	—	−0.182*	0.017	0.100	0.010	0.020	−0.096	0.060
dd_taxi	−0.039	−0.044	−0.001	−0.163*	—	−0.020	0.080	−0.043	−0.085	0.034	0.108
dd_PT	−0.169	−0.252**	0.166*	0.017	−0.023	—	−0.068	0.039	−0.014	0.094	0.063
dd_bike	0.059*	−0.002	0.028	0.101	0.090	−0.068	—	−0.016	0.146	−0.002	0.023
dd_e-scooter	−0.153*	−0.001	0.115	0.010	−0.050	0.039	−0.017	—	0.138	0.122	0.166
dd_e-bike	−0.013	0.040	0.063	0.021	−0.099	−0.014	0.152	0.140	—	−0.042	0.125
dd_walk	−0.089	−0.059	−0.161*	−0.098	0.039	0.095	−0.002	0.120	−0.041	—	0.084
AV	0.130	0.168*	0.103	0.067	0.135	0.069	0.025	0.179*	0.133	0.092	—
Increased overall mobility	0.177*	0.167	0.306**	0.201*	0.177	0.185*	0.292**	0.159	0.264**	0.277**	−0.098
Age	0.117	0.278**	−0.137	−0.080	0.148	0.206*	−0.016	0.045	0.062	0.141	−0.282
Being female	0.115	0.118	−0.007	0.043	0.012	0.075	0.147	0.008	0.088	0.252**	−0.086
Highly educated	−0.068	0.100	0.041	−0.158	−0.098	0.031	0.002	−0.206**	−0.029	0.099	0.314
Safety	−0.070	0.069	−0.009	−0.256**	0.009	0.147	0.082	0.046	−0.017	0.012	−0.014
Comfort	0.022	−0.095	−0.089	0.423***	0.300**	−0.039	−0.077	−0.042	0.160	0.075	−0.157
Environment	−0.050	0.010	−0.046	−0.026	−0.103	0.061	0.060	−0.095	0.067	−0.019	0.192
Image	0.097	−0.066	0.006	0.193*	0.101	−0.077	−0.080	−0.030	0.083	0.051	−0.049
Inexpensive	−0.074	−0.024	−0.017	0.099	−0.033	−0.050	−0.198*	−0.127	0.093	0.098	0.043
Stress-free	0.035	0.137	−0.052	−0.089	−0.090	0.202*	0.209*	0.128	0.080	−0.016	−0.106
Flexibility	0.002	−0.194*	0.063	0.224**	0.106	−0.094	−0.029	0.005	−0.029	0.191*	0.108
Weather	0.023	0.079	0.034	−0.147	−0.124	0.118	−0.021	0.013	−0.111	−0.081	0.154
Timesaving	0.009	0.048	−0.114	−0.046	0.043	−0.124	−0.050	0.009	−0.033	0.025	0.114
Physical activity	0.106	0.160*	−0.034	0.103	0.147	0.127	−0.056	0.095	−0.051	−0.034	−0.129
Reliability	−0.029	0.060	0.048	−0.160	−0.077	−0.050	0.156	0.059	0.040	−0.039	−0.089
Fun	0.029	0.034	0.098	−0.094	0.100	0.088	0.144	0.004	−0.152	−0.102	0.249
Model fit											
Sig. F Change	0<.001	0<.001	0.006	0.025	n.s	0.017	0.019	0.009	0.006	0.015	0<.001
R Square	0.36	0.40	0.32	0.29	0.20	0.30	0.29	0.31	0.32	0.30	0.36

Note
(i) * Significant at 10%, ** significant at 5%, *** significant at 1%. n.s: non-significant.
(ii) dd (the original value of the degree of dissonance per mode per individual) = (Future stated travel preference) – (Revealed travel behavior). The degree of dissonance for each mode per individual can range from −5 to +5.
(iii) Increased overall mobility: A dummy variable indicates whether the overall mobility rate across all modes for an individual is expected to increase in the future compared to the present.

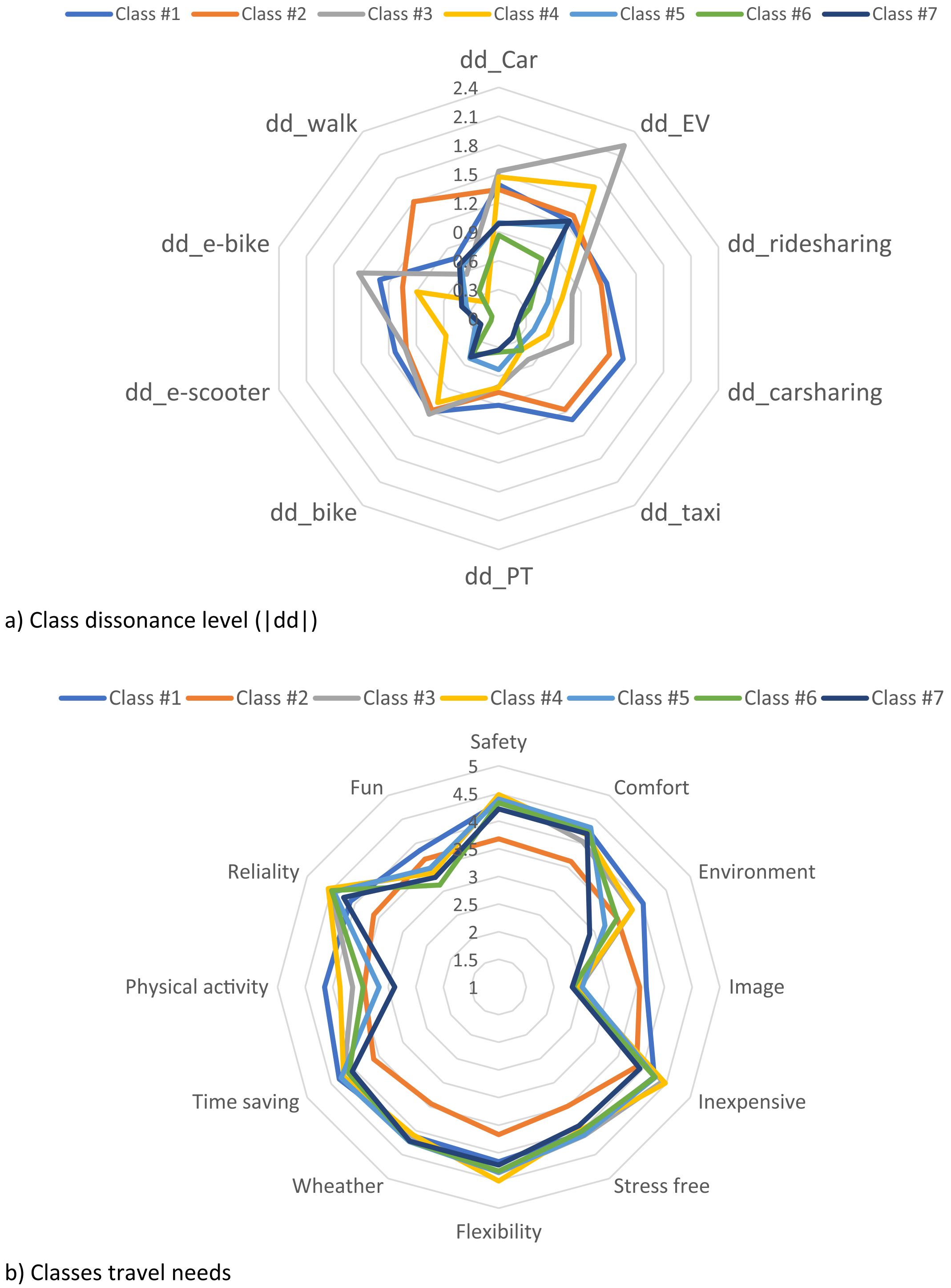

Fig. 3. Latent class profiles across travel dissonance and travel needs.

potential influence on current non-car users and the implications for overall sustainability objectives. Despite EVs being categorized as clean or green modes, the motivation behind encouraging individuals already content with active travel options to also adopt EVs warrants thoughtful consideration. This group's trip-making rate is somewhat moderate, falling between low and high. Their dissonance levels are average across classes. They prioritize safety, cost, and flexibility significantly when choosing a travel mode. This group is slightly skewed towards women, individuals aged between 45 and 54, and those with lower levels of education.

A further disaggregated investigation (Table A.4) shows that the preference for EV use in the future is driven by both a shift from car use and an increase in overall mobility rates. However, the impact of the modal shift (b = -0.457) is approximately twice as large as the changes in mobility rates (b = 0.234). On the other hand, the high positive dissonance towards biking is mainly explained by an increase in overall mobility rates. People in this group prefer to walk in the future at the same rate as they do in the present, with walking dissonance not being influenced by modal shifts or changes in mobility rates. Overall, different emerging modes tend to complement each other among people in this class.

Class 5—*Car users and walkers maintaining a preference for cars and walking in the future*. Constituting 15.6 % of the population, this class engages in relatively fewer trips compared to certain groups (classes 1–4). Demonstrating a steadfast preference, members of this class are not open to other modes, sticking to the traditional combination of cars and walking for their current and future trips. Individuals in this group are among the consonant travelers. In terms of travel needs, they prioritize comfort, stress-free experiences, and weather protection when choosing a mode. This group is predominantly composed of women, older individuals (65+), and those with an average level of education.

A further analysis (Table A.5) indicates that while some car users may switch to EVs, other shifts in car use are unlikely. People in this group show resistance to adopting AVs and e-scooters. Additionally, e-bikes and ridesharing might replace walking to some extent in the future for this group.

Class 6—*Current walkers occasionally using PT and preferring the same modes for future trips*. This group comprises 15.1 % of the population and tends to make fewer trips compared to the average population. They are the most consonant travelers across all classes. Reliability is of utmost importance to this group when choosing a travel mode, compared to others. There are no significant gender differences, and the majority of individuals are older with lower levels of education.

Even though there is a general trend in this group favoring PT and walking, a closer look shows that some individuals might switch from traditional cars to EVs (Table A.6). However, EV and car use are partly due to an overall increase in mobility rates. Similarly, the positive dissonance of walking and PT use is linked to higher mobility rates rather than a specific shift in travel modes. It is likely that ridesharing services, e-scooters, and e-bikes are competing with PT use among people in this group. Additionally, despite a preference for PT, many do not view it as a time-saving option.

Class 7—*Current car users unlikely to prefer any other modes for the future, potentially undertaking the fewest trips*. Constituting 19 % of the population, this class maintains a steadfast preference for car use and is unlikely to explore different modes for their future trips. They undertake fewer trips compared to other classes, with relatively lower importance placed on their travel needs compared to other groups. Nevertheless, they are consonant travelers and fall within the middle-age range, typically with lower levels of education.

A closer look at the individual level (Table A.7) reveals that some car users are likely replacing their trips with EVs. Additionally, many emerging modes are competing with each other within this group. Overall, people in this group do not see significant shifts from car use to sustainable alternatives. Any positive dissonance in mode use is primarily due to increased overall mobility rates.

6. Conclusion and discussion

The findings from the study reveal several intriguing patterns and insights regarding travel behavior, preferences, and potential transitions in mobility. These insights offer implications for policy and practice aimed at promoting sustainability, managing dissonance, and understanding shifting travel patterns. A latent class analysis was employed to reveal distinct subgroups of people in terms of current travel behavior and future preference considering their cognitive dissonance, travel needs, and sociodemographic variables. Additional analyses were also carried out to understand how dissonance appears in different individuals. Here are some key findings and transformative trends identified.

6.1. Emergence of multimodal sustainable travelers

Classes 1 and 2 represent individuals who exhibit a propensity towards multimodal travel and sustainable transport options. These groups, though relatively small in proportion (together 16 % of the population), are characterized by their openness to various modes, including emerging ones like e-scooters, carsharing, ridesharing, and EVs. It appears that the high preferences for various emerging alternatives in the future are partly due to increased overall mobility rates, even though there might be some shift from cars to EVs within these two groups. Policy interventions could focus on supporting and incentivizing the adoption of sustainable modes among these early adopters. According to the Norway National Transport Plan 2022–2033 and the government's mobility transition pathways, people in these two groups could be targeted by policies such as financial incentives for EVs and e-bikes (Norwegian Ministry of Transport, 2021). In class 1, despite being dissonant travelers, indicating a desire for more sustainable options, they paradoxically anticipate making more trips in the future than other groups, potentially offsetting their environmental impact. This suggests a complex relationship between sustainability aspirations and actual travel behavior, where increased mobility may come at the expense of environmental goals.

6.2. Potential shift towards EVs

Overall, there is a notable trend towards EVs among the emerging mobility options, with approximately 43 % of the population expressing willingness to incorporate EVs into their daily mobility in the future. Particularly, classes 3 and 4 demonstrate a growing interest in EVs as a potential alternative to fossil fuel-based cars. This shift towards EVs, particularly among individuals who (solely) currently use active transport modes like walking and biking, presents both opportunities and challenges for policymakers. Strategies to encourage EV adoption should be accompanied by efforts to maintain active travel behaviors to ensure overall sustainability objectives are met. Policymakers need to carefully navigate this transition, ensuring that the introduction of EVs complements rather than displaces active transport modes. Government incentives could be more effectively managed by focusing on people in these groups, particularly those in Class 3, who are mostly 25–34 years old. The high future preference for EVs in this age group may be due to changes in their life stage.

6.3. Gender and age disparities in travel preferences

The study highlights gender and age disparities in travel preferences. For instance, Class 4, which consists of active transport users leaning towards EVs, is skewed towards women and individuals aged 45 to 54. Men exhibit a higher degree of multimodality and dissonance compared to women. The data indicate that they are more likely to increase their overall mobility rates, and some might also shift from cars to EVs. Nonetheless, dissonant travelers are typically younger and demonstrate a propensity for utilizing a diverse range of sustainable transport options which might indicate a change of life stage. Understanding these demographic variations can inform targeted interventions to address specific needs and preferences within different population segments. For example, this could mean offering young people on the verge of establishing a family incentive for mobility without owning a combustion engine car. Additionally, policies could focus on providing financial incentives for EVs and e-bikes to those in their mid-20 s to early 30 s or developing more robust public transport services tailored to the commuting patterns of younger professionals.

6.4. Importance of reliability and safety in mode choice

Class 6, predominantly composed of older individuals with lower levels of education, emphasizes reliability and safety in mode choice. Despite making fewer trips compared to the average population, they exhibit high consonance in travel behavior. This suggests a preference for familiar and reliable modes, highlighting the importance of providing dependable transport options, particularly for older demographics. Efforts can be directed towards enhancing the reliability of alternative options to combustion engine cars. This may include improving the frequency and punctuality of public transport services, ensuring reliable EV charging infrastructure, and providing user-friendly interfaces for ride-sharing and micro-mobility services.

6.5. Managing dissonance and consonance

Based on the results provided, the distinction between dissonant and consonant travelers offers valuable insights into the dynamics of travel behavior and preferences.

Dissonant travelers are characterized by their preference to shift towards more sustainable mobility options compared to their current behaviors. They are often associated with a desire to adopt emerging modes such as EVs, e-bikes, or ridesharing services, alongside active travel modes like walking or biking. Interestingly, dissonant travelers tend to make more trips compared to consonant travelers. This suggests a potential trade-off between increased mobility demand and sustainability goals. Despite their sustainability orientation, the higher trip-making rates among dissonant travelers may offset the environmental benefits associated with mode shift, highlighting the importance of balancing mobility rates with sustainability objectives.

Consonant travelers (around 50 % of the population), on the other hand, exhibit a preference for maintaining their current travel behaviors without significant shifts towards more sustainable options. They may prioritize familiar and reliable modes such as private car use or walking for their current and future trips. While consonant travelers may contribute less to environmental impacts compared to dissonant travelers, their reluctance to embrace sustainable modes (or to be multimodal) presents challenges for achieving sustainability goals.

In various groups, those with higher levels of consonance (e.g., classes 5 and 7) tend to show less preferences for (sustainable) emerging travel modes and are less likely to switch to emerging options. These travelers, characterized by their consistency, appear trustworthy, making them a steady target for policy interventions. However, their resistance to change suggests that policies aiming to alter their behavior may face challenges. To encourage consonant travelers to maintain walking while shifting away from car use, strategies could focus on making the car less reliable. This could involve implementing measures such as restricted parking, congestion charging schemes, or even reducing road capacity for cars to prioritize other modes and make them more reliable. These efforts align with initiatives like the "byvekstavtale[7]" (urban growth agreement), where the central government incentivizes city growth without a corresponding increase in private car use. Cities implement this by prioritizing public transport, biking, and walking over cars.

Conversely, dissonant travelers in groups like 1, 2, and 3 may benefit from policies promoting modal shifts, as they express intentions to use a variety of emerging travel modes in the future. However, a closer examination of these dissonance patterns reveals that a significant portion of such dissonances stems from an increase in overall mobility rates rather than a substantial shift from cars to EVs and other emerging modes. This finding, combined with the age profiles of these classes, might suggest that dissonant travelers are active and likely in stages of their lives where mobility needs are high and change rapidly. While they represent a target group for emerging services, incentives should be designed to encourage sustainable choices while limiting overall mobility growth. For example, incentivizing trips up to a certain limit or tying incentives to specific sustainability criteria could help achieve this balance. Simultaneously, pull policies such as maintaining current EV incentives, particularly for people in class 3, providing public financial

[7] https://www.regjeringen.no/no/tema/transport-og-kommunikasjon/kollektivtransport/byvekstavtalerogtilskudd/id2571977/.

support for the purchase of e-bikes, and facilitating increased use of electric micro-mobility options could help replace some car trips with more sustainable alternatives.

6.6. *Managing trip-making rates: A paradoxical policy*

The trade-off between mobility (trip-making) and modality behavior may affect the carbon footprint of travel per km per transport mode. Every transport mode (even the sustainable alternatives) contributes to the emissions of carbon dioxide per person per kilometer. As reported by Ritchie and Roser (2023), fossil-fuel-powered cars, EVs, buses, trains, and active transport (walking or biking) can emit 170 g, 47 g, 79 g, 35 g, 16–50 g of carbon dioxide per person per km, respectively (Ritchie and Roser, 2023).

Promoting sustainable and emerging travel modes, a key policy, might unintentionally increase overall travel and carbon footprints. We find that people who use or are willing to use more sustainable and emerging travel modes are more likely to make more trips than those who are using unsustainable modes. Counterintuitively, we find that individuals identifying as "sustainable travelers" might end up making more trips compared to their "unsustainable counterparts" who may decrease their overall travel. This paradoxical scenario may result in an overall increase in CO_2 emissions from the "sustainable" group. This implies that emerging modes may have some negative spillover effects on sustainability. Therefore, policymakers should also carefully consider mobility restrictions policies (e.g., restricted parking, congestion charging schemes) in addition to encouraging people to take sustainable options.

6.7. *Less preference for AVs compared to the other emerging options*

Among different emerging options, only 8 % of the population prefers to incorporate AVs into their daily mobility in the future. There might be barriers or concerns among the public regarding AV adoption and integration into daily travel routines. These barriers could include issues related to safety, trust in technology, regulatory concerns, or concerns about the impact on traditional modes.

To sum up, this study unveils patterns and insights into travel behavior, preferences, and future mobility trends. The emergence of multimodal sustainable travelers underscores the importance of supporting early adopters of sustainable transport options. However, the paradoxical relationship between increased mobility and sustainability aspirations among certain groups highlights the need for careful balance and targeted interventions. Moreover, the potential shift towards EVs presents both opportunities and challenges, particularly in maintaining active travel behaviors alongside EV adoption. Gender and age disparities in travel preferences underscore the importance of tailored interventions to address diverse needs within different demographic segments.

The strong preference for car use among certain groups highlights the need for innovative strategies beyond the adoption of emerging options such as EVs, AVs, or mobility services. It suggests that simply introducing new technologies or services may not be sufficient to encourage current car users to switch to sustainable options. As policymakers navigate these complexities, they could also consider the broader implications of promoting sustainable and emerging travel modes. Ensuring that efforts to encourage mode shift are coupled with measures to mitigate potential negative spillover effects on sustainability is essential for long-term success. In essence, this study emphasizes the need for a holistic and adaptive approach to transportation policy and practice.

6.8. *Limitations*

While the study provided insights into travel behavior and preferences, it is important to acknowledge its limitations. Primarily, the study's reliance on a cross-sectional design limits its ability to capture longitudinal changes in travel behavior accurately. By nature, cross-sectional studies offer a snapshot of data at a specific point in time, which may not fully capture the dynamic nature of travel patterns over time. Additionally, the reliance on self-reported travel behavior and anticipated future preferences introduces potential biases. Individuals may misreport their travel behavior or future preferences, leading to discrepancies between stated preferences and revealed behavior. Therefore, some parts of dissonance might be attributed to this bias. Moving forward, future research in travel behavior could consider longitudinal designs, such as mobility panel surveys, to track changes in behavior over time accurately. By incorporating emerging mobility modes into these surveys, researchers can better capture the real shifts in travel preferences and behaviors. This approach would enable policymakers and practitioners to make informed decisions based on up-to-date and comprehensive data, ultimately leading to more effective transportation interventions and policies.

CRediT authorship contribution statement

Milad Mehdizadeh: Idea, Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Modeling, Formal analysis, Data curation, Conceptualization. **Christian A. Klöckner:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104340.

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