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Exploring the factors influencing the use of public transport by commuters living in networks of small cities and towns

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ABSTRACT

The use of public transport is directly associated with a reduced environmental impact for satisfying daily mobility needs. Current research has focused on identifying the factors affecting the use of public transport, elements such as age, car ownership, travel distance, or parking availability having been associated with a direct impact on an individual's transport mode choice. However, most of these studies focused on the travel behaviour of individuals living in large cities, where the population density is high, and public transport is usually more developed than in small cities and towns. The present study provides additional insights into the impact of eleven different factors on the use of public transport by employees living and working in networks of small cities and towns in Northern Europe. The study uses ordered logistic regression to analyse the data collected in 2019 through a regional travel survey conducted in Agder, Norway. The results reveal that the choice of public transport as a daily commute mode is significantly affected by car ownership, distance to work, parking availability, and ticket prices. Additionally, the results indicate that the odds of employees using public transport increase when the respondents do not have persons in care. On the other hand, factors such as low bus frequency and long walking distances to the home bus stop show a negative impact on the use of public transport. Based on these results, regional and local policy actions are proposed.

1. Introduction

The factors that influence humans in their daily mobility behaviour, and consequently their decisions regarding the travel mode choice for reaching habitual destinations, have been closely researched for more than six decades (Reeder, 1956). Such studies have explored factors that were already in focus more than a century ago (Watkins, 1911). This research direction, generated initially by the challenges of automobiles and rush-hour traffic, has more recently become critical in the light of sustainable development strategies that agree on the use of public transport (PT) as the best motorized urban mobility choice. Defined by the Home: Oxford English Dictionary. (2022) as "transport available for public use; a transport system (of buses, trains, etc.) that runs on fixed routes at set times and may be used by anyone with a valid ticket or pass", the PT available to the inhabitants of a town, city or even a region can vary in its diversity. Densely populated areas tend to have a more diverse PT offer, which may include rail and bus-based services, and sometimes even access to newer mobility concepts such as shared city bikes or scooters. At the opposite spectrum, lower density areas, such as small cities, towns, or suburbs, often have a limited PT offer that may consist of a single type of vehicles, such as buses, providing the PT services. But who are the users of PT, what factors influence their choice of PT for daily commute purposes, and is the travel behaviour triggered by these factors similar in cities of different sizes?

Determined mainly by the mobility needs of employees, children, and students, daily commuting patterns have diverse modal splits, depending on the urban area studied (Pucher, 1988). In most cases, these choices reflect the quality of the PT service provided, the accessibility of people to the PT service, and the competitiveness of the PT service with other transport modes. However, they also reflect the optimization between the urban form in which the PT service operates, and the quality of the service provided in relation to the needs of the inhabitants (Pucher, 1988).

While the traffic generated by children and students is largely absorbed by more sustainable transport modes (walking, cycling, PT, or car passenger), the issues concerning the daily commute of employees continues to be unanswered, especially in areas with large modal shares in favour of private cars, such as low-density urban areas or networks of

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small cities and towns (Næss et al., 1995; Wiersma et al., 2016). The employees were selected as a focus group for our research due to the combination of three elements: a) daily mobility demand generated by employment; b) higher access to cars compared to youth and children (legal driver licence age, larger income), retired (health aspects, time availability), or unemployed individuals (income aspects); c) time constraints (work schedule, often dependent individuals such as children in the household) and value of travel time. This combination makes employees one of the population groups with the highest demands in what concerns the daily mobility provision, but also one of the most car dependent groups when the PT provision does not satisfy these demands.

In Agder, Norway, a county that is an example of a network of small cities and towns, the car dominates the modal split, with a share of approximately 70 percent.[1] PT in Agder, composed in its vast majority of bus-based services offered by the regional public transport authority (PTA), is used for approximately five percent of passenger trips. What influences the mode choice of employees in Agder when it comes to them using the bus-based PT available to them for their daily commute? Moreover, is their behaviour in line with that of other people around the world?

Public transport use has been associated by numerous studies with high frequency of PT provision (Brechan, 2017; Nielsen and Lange, 2007), high accessibility (Ding et al., 2017; Saghapour et al., 2016), low car ownership (Chakrabarti and Joh, 2019; Md Oakil et al., 2016), affordable ticket prices (Paulley et al., 2006), and even younger age groups (O'Fallon et al., 2004). It should be noted that the vast majority of travel behaviour studies that focus on daily commuting have targeted large cities and metropolises around the world as their case studies (Chng et al., 2016; Saghapour et al., 2016; Yu et al., 2019), and it is rare for a study to single out the entire employed population of a region and explore its travel behaviour in relation to PT usage (Chng et al., 2016).

We expect that an investigation of PT usage by employees living and working in a region where the predominating urban forms are small cities and towns would contribute to the growing body of research that explores the decarbonization of passenger transport in sparsely populated areas. At the same time, it would help urban planners, policy makers, and PT providers to better understand their potential market and devise targeted interventions that could bring a market share increase for PT usage in these regions.

The present study employs an ordered logistic regression model to investigate the level of influence of eleven individual factors on the travel mode choice of employees in Agder, Norway, with specific focus on PT use. The factors selected for the analysis have been previously identified in research as being influential (or determinants) on the mode choice for daily commute habits. Logistic regression is a commonly used analysis for the prediction of travel mode choice (Collins and Chambers, 2005; Ha et al., 2020). Nevertheless, the application of an ordered logistic regression model to a quantitative data set collected in a network of small cities and towns with the purpose of identifying the most influential factors for the PT use of employees has not yet been attempted. For that purpose, we employ the data from the travel habits survey conducted in the frame of the OPTCORA project in 2019. Based on the results of our analysis, we propose a series of urban planning, transport planning and policy interventions that show potential in terms of increasing PT use for the daily commute of employees in Agder.

The remainder of this paper is structured into five sections. Section 2 presents the literature review and Section 3 discusses the data collection and methodology. The results of the study are presented in Section 4 and the conclusions of the main findings, together with ideas for further research, are covered in Section 5.

[1] For the case of Agder, the modal share for car and PT use is approximated from travel habit reports for the two main urban regions: Kristiansand and Arendal (Haugsbø et al., 2015a, 2015b).

2. Literature review

Methods for increasing the use of PT have been researched in diverse contexts around the globe, with no standardized solution being achieved. In 2002, Lanzendorf introduced the concept of "mobility style" to explain the correlation of an individual's travel mode choice "with several other factors, such as personal and household characteristics, availability of transport modes, and urban form elements (e.g., residential neighbourhood, garden ownership, and dwelling type)" (p. 163). In 2013, Vij et al. took the concept further and introduced a new construct: "'modality styles', or behavioural predispositions, characterized by a certain travel mode or set of travel modes that an individual habitually uses" (p. 164).

In both cases, the concepts have been addressed by analysing psychological factors (personal values and beliefs, feelings of safety or comfort, etc.) through the application of econometrics analyses (latent class choice, continuous logit mixture models, and combinations of logit models and regression analysis). This shows the importance of applying statistical analyses to data reflecting the travel behaviour of individuals in a specific region in order to achieve a first level of understanding of their behaviour patterns. The results can then be further correlated with geographical and socio-economic factors and developed with qualitative data inputs into more holistic travel behaviour models (Christiansen et al., 2017; El-Geneidy et al., 2014).

2.1. Travel mode choice and main factors of influence

In a 2014 study, Nordfjærn et al. (2014) evaluated the role of deliberate planning, car habit and resistance to change in PT mode use in the six largest urban areas in Norway. They employed a combined model that included both the theory of planned behaviour and a habit-based model. Their results showed that strong subjective norms of PT use are in fact the most important predictor of intentions. They also concluded that "favourable attitudes towards PT mode use were weakly related to intentions, when car habit and resistance to change were accounted for in the model" (Nordfjærn et al., 2014, p. 90). The authors further noted that "car habit is not the sole factor related to intentions of using public transportation and that social cognition and social influence are instrumental in promoting use of such transportation", pointing out that PT use "seems to partly reflect a planned and deliberate psychological process" (Nordfjærn et al., 2014, p. 90).

The results of several other research projects have shown that previous behaviour acts as a strong regressor on future behaviour (Gärling and Axhausen, 2003; Verplanken et al., 1997). In most cases, the habitual travel behaviour of an individual can easily be identified from travel survey responses based on the frequency of their use of a specific transport mode in connection to regular trips (e.g., daily commute). In our research we analyse the data collected from employees in a travel survey to determine how a set of eleven individual factors can affect the travel behaviour of employed individuals in regard to their daily work commute. The eleven factors were selected as being representative for: PT accessibility as defined by Litman (2008) (distance to bus stop, frequency, travel time by PT, distance to work, importance of bus prices), car use habits (car ownership, finding parking), and socio-economic variables with increased potential for affecting travel behaviour (age, gender, education level, persons in care). In the following subsections we review the results of other studies that have highlighted the impact of these eleven factors on urban travel behaviour. The results are meant to help urban and transport planners understand the habits of the population in relation to PT use. This could support the design of impactful changes for the system and potentially an increased modal shift of employees from personal cars to PT.

2.1.1. Distance to work and accessibility by PT for daily commuting purposes

A large share of the home-to-work trips are outside walking distance boundaries, especially in areas with low density habitation, generating a need for motorized travel in relation to daily commuting (Ding et al., 2017). Studies have found that the increase in **distance** between home and the job location is positively correlated with an increase in PT use if a reliable service is available and accessible (Chng et al., 2016), especially if the car ownership rate is low (Hagenauer and Helbich, 2017; Scheiner, 2010; Yu et al., 2019). Furthermore, Balcombe et al. (2004) found a "strong overall relationship between [PT] demand, expressed in trip rated, and settlement size" (p. 10) for PT use. Their data, collected in the UK between 1997 and 1999, show that 19 percent of the inhabitants of small urban areas use PT once a week or more, whereas in large, highly densified urban areas such as Greater London, 45 percent of the population uses PT with the same frequency. Small urban areas are defined by the OECD as having between 50 000 and 200 000 inhabitants (OECD, 2020). The authors also discussed the complex relationship between land use and PT demand, showcasing the importance of urban density, employment location, urban form, and other such aspects in facilitating PT use.

In Norway, approximately 65 percent of people live in small cities and towns with populations of under 200,000 inhabitants (SSB, 2020). The most recent national travel survey data shows that Norwegians travel an average of 47.2 km per day, with an average trip length of 14.5 km (Hjorthol et al., 2014), a distance consistent with the typical urban landscape of the country. This, combined with a limited provision of high frequency PT and a high car ownership rate, explains why PT use outside the largest Norwegian cities remains unpopular, with the car being preferred as a daily transport mode choice for approximately 88 percent of all Norwegians (Statista, 2020).

The distance between home and work, and the location of the two in relation to each other play an important part in determining the level of accessibility by PT between that an employee benefits from. Litman (2008) defines PT accessibility as "the quality of transit serving a particular location and the ease with which people can access that service". According to Saghapour et al., the accessibility by PT is defined by factors "generally categorized into three groups: access to PT stops, duration of journeys by PT modes and access to destinations by PT modes" (2016, p.1786). The four factors that will be further discussed, access to PT stops, pricing of PT trips, travel time by PT, and the service frequency, fit with both definitions. The last two factors are definitory for the quality of a PT service (Balcombe et al., 2004), while the first two relate more to the accessibility to the PT service.

The **accessibility of individuals to a PT stop** can be characterized by the physical distance to the stop, the ease of access to the stop (ramps, elevators etc.), and the infrastructure available at the stop (shelter, bike or car parking etc.). In our study we only focus on the physical distance to the stop, putting a special emphasis on pedestrian access. Diverse recommendations exist for the maximum walking distance to a PT stop, but the 400 m radius distance appears in diverse regulations and indicators sets for sustainable transport, such as the ones of the Confederation for British Road Passenger transport (Balcombe et al., 2004), the "Liveable neighbourhoods policy" of the Western Australian Planning Commission (Department of Planning, Lands and Heritage, 2020), or WBCSD mobility (2015) "Sustainable Mobility Indicators – SMP2.0".

Daniels and Mulley (2013) studied the factors that influence the walking distance to PT and found that walking trips to train stations are significantly longer than those to bus stations and that the length of the trip to be taken by PT also has a directly proportional influence on the distance travelled to the PT stop. Their findings were generally consistent with the 400 m distance between households and stations and highlighted the "well-known difficulties in measuring pedestrian accessibility to public transport", as the use of a radial catchment does not mean that the real walking distance to the stop a maximum of 400 m. El-Geneidy et al. (2014) found that the walking distance to bus-based public transport service is around 524 m for home-based trip origins and that "walking distances vary based on route and trip qualities (such as type of transit service, transfers and wait time), as well as personal, household, and neighbourhood characteristics.".

Some urban sustainability monitoring indicator sets, such as the "ISO 37120:2018 Sustainable cities and communities – Indicators for city services and quality of life", place strong emphasis on the distance to the PT stop, combined with the frequency of the available transport there. The indicator for this aspect is the "Percentage of population living within 0.5 km of public transit running at least every 20 min during peak periods" (International Organization for Standardization, 2018, p. 70). Given that ISO 37120:2018 is the only international standard for sustainable urban development, this specific indicator for transport sustainability conveys the importance of proximity to PT and service quality provided to the population in relation to sustainable mobility.

Service frequency and **pricing** are explored as factors of influence in relation to the increase of ridership by a large number of studies, with conclusions that, in most cases, an increase in frequency up to a certain point is correlated with a patronage increase, while an increase in pricing tends to have the opposite effect on the PT patronage (Balcombe et al., 2004; Ha et al., 2020; Paulley et al., 2006).

According to Litman, PT dependent riders, who usually represent a small percent of the total population but the bulk of the PT users, "are generally less price sensitive than choice or discretionary riders (people who have the option of using an automobile for that trip)" (2004, p.4). He also pointed out that there is a stronger negative impact of fare increases than the positive impact of a similar amount of fare decreases when it comes to ridership. Beirão and Sarsfield Cabral (2007) further clarify the individual perception regarding the cost per travel, noting that car users tend to only consider the fuel costs for their trip, ignoring all other costs associated with owning a car.

Pricing variation does not have an identical effect in all PT networks. Litman (2004) found that city size has a strong influence on price elasticity, with large cities having lower price elasticities than lower-density areas, such as suburbs or smaller cities. Exploring the impact of price reduction and frequency increase on PT ridership in the Norwegian context, which is largely dominated by small cities and towns, Brechan (2017) presented results from 24 experimental case studies. Nine of the cases studied covered frequency increase, with three cases being set in the region of Agder, while the other 15 cases (three of which were also set in Agder) focused on price reduction. The results show that both price reductions and frequency increase have a visible increase impact on PT ridership, with increased frequency outperforming pricing schemes. Both schemes showed positive results for increasing PT use in all of the case studies located in Agder.

With regard to optimal frequency for Norwegian cities, Nielsen and Lange (2007) suggested "6 –12 departures per hour at working daytime as a suitable frequency level to aim at for middle sized cities" (p. 15). This frequency falls into the "forget the timetable" category, where users do not need to plan their trips when going to a PT stop.

The travel time (TT) by PT **or accessibility by PT** is usually assessed in comparison with the travel time by other means (modal accessibility gap), mainly personal car in the case of longer distances. The TT showcases the competitiveness of the PT service with other transport modes (Ha et al., 2020) and is an integral part of the level of accessibility by PT that a person benefits from (Guan et al., 2020). Collins and Chambers (2005) revealed that a TT by PT 1.25 times as long or longer than by car is a critical figure, with users showing significantly less preference for using PT once that limit had been reached. It is important to note Ha et al. (2020), who indicated that "commuters select their modes by valuing the travel time difference in both absolute[2] and

[2] Travel time gap, calculated as the absolute difference in time spent for travelling the same route at the exact same time by two different modes (in this case PT and car).

relative[3] aspect". Nevertheless, few studies have focused on low-density areas, such as networks of small cities and towns, and their modal accessibility gap values.

The study by Kawabata (2009) showcased the difference in modal accessibility to one's job, comparing data for cars and public transport commuting in the Boston and San Francisco Bay areas. They found that car users have a much higher job accessibility factor for a 30-minute threshold than PT ones, with the disparity value in favour of cars being 0.750 in Boston and 0.775 in San Francisco (Kawabata, 2009). Their results contrast with the case of Hong Kong in 1996, presented by Kwok and Yeh (2004), where the disparity value was −0.853, which put the PT at an advantage in that case. More recent studies by Guan et al. (2020) for Shanghai and Ha et al. (2020) for Seoul analysed real travel data and showcased how the disparity level can actually vary from being in favour of the car to being in favour of PT during the same day, depending on the transport mode chosen. They both compare PT data with taxi data, concluding that, depending on the PT mode (rail, bus), PT may have a shorter TT during rush hour compared to the car, but that this situation reverses outside of rush hours.

Thus, it is clear that aspects such as urban land use and city size, which influence the distance to work and availability of proximity services for individuals, the level of accessibility to PT (both physical and monetary), and the service quality and speed of the PT network, all play important roles in determining the level of location-based accessibility by PT for an individual user.

2.1.2. Car ownership and parking provision

Car ownership is seen as a highly influential factor for the use of PT. Research from around the world has proven that a high household car ownership rate is generally associated with a reduced usage of PT and active transport modes (Balcombe et al., 2004; Chng et al., 2016; Paulley et al., 2006). Car ownership levels are often seen as being correlated to other factors, such as parenthood (Chakrabarti and Joh, 2019) or the price elasticity of demand, due to the existing option of taking the car instead of PT if the price becomes too expensive (Paulley et al., 2006).

Car ownership and car use can be influenced by a number of factors, one of which is the **parking provision**. It is hard to use a car if you have nowhere to park it, or if parking is difficult to find. In their guide on PT demand, Balcombe et al. (2004), discussed the inverse relation between population density and car use, arguing that a combination of lower income and lower car ownership, combined with "a scarcity of parking provision" (p. 24), could explain the higher use of sustainable transport modes in densely populated urban areas. McCahill et al. (2016) found that an "increase in parking provision from 0.1 to 0.5 parking space per person was associated with an increase in automobile mode share of roughly 30 percentage points" (p. 159). Christiansen et al. (2017) suggested that "limited access to parking is the single most effective way of reducing car use on work trips" (p. 198). Both Christiansen et al. (2017) and O'Fallon et al. (2004) offered proof that workplace parking fees can work in favour of a mode shift from car towards PT. On the other hand, Christiansen et al. (2017) argued that these measures are most effective in compact cities. It would be interesting to explore how parking scarcity influences the mode choice of daily commuters living in low density areas.

2.1.3. Age, gender, education and parenthood

Several studies have demonstrated that demographic factors are crucial in analysing and predicting the use of PT and that this mode choice is more popular for certain demographic groups, with young people (under 25) and elderly tending to be more PT-oriented (Coogan et al., 2018; Ding et al., 2017; Ha et al., 2020; Litman, 2004; O'Fallon et al., 2004). The age groups in between seem to be more car-dependent (Ding et al., 2017), but historical data show that the 25–34 age group is using PT more than it did in 1990 (Coogan et al., 2018). Nevertheless, if the income of the household allows it and the urban landscape encourages car-oriented behaviour to the detriment of PT, this group can be driven towards habitual car use (Ding et al., 2017). Another reason for this behaviour could be the shift from childless lifestyles towards parenthood, which has been proven to be generally associated with an increased rate of car ownership (Md Oakil et al., 2016; O'Fallon et al., 2004) and a more car-oriented lifestyle in everyday trips (Chakrabarti and Joh, 2019; Ha et al., 2020).

When discussing PT use from the perspective of gender as a factor of influence, we observe that results from studies in multiple cities found that women tend to use PT more than men, while men tend to drive more than women do (Buehler, 2011; Ng and Acker, 2018). At the same time, the education level is found to have a direct relationship with the use of PT, individuals with post-secondary or higher education studies using PT in a higher proportion than the ones with certificate levels (Rachele et al., 2015).

2.2. Travel mode choice modelling and logistic regression

Logistic regression is one of the most popular methods employed in transport studies, specifically in the analysis of travel mode choice and the travel behaviour of individuals. Several types of logistic regression analysis can be employed for this purpose and are usually applied on data sourced from surveys and travel diaries (Chng et al., 2016; Ha et al., 2020).

In the literature review covered in Section 2.1 (Table 1) logistic regression was chosen as the method of data analysis in 10 out of the 27 references. The most popular logistic regression type observed in our literature review is the binomial or binary logistic regression, which six studies employed in their methodology (Chakrabarti and Joh, 2019; Christiansen et al., 2017; Collins and Chambers, 2005; Ha et al., 2020; Lanzendorf, 2002; Md Oakil et al., 2016). This is also the least complex logistic regression approach, as it only models a binary dependent variable. Other logistic regression models used in the studies cited in the previous Section 2.1 are: multinomial logistic regression (Chng et al., 2016; O'Fallon et al., 2004), mixed logit models (Vij et al., 2013), and ordered logistic regression (Saghapour et al., 2016).

In our study we have decided to employ an ordered logistic regression model to analyse travel behaviour data sourced from a regional travel survey in exploring the correlations between PT use (as dependent variable) and eleven different social-economic, PT accessibility, and quality of PT factors (as independent variables) that previous research has proven to be influential on the use of PT. This regression model allows for the dependent variable to have more than two possible values, which is the case for our data set.

Saghapour et al. (2016) employed ordered logistic regression for exploring the correlations between PT trips and socio-economic characteristics and built environment factors by using a combination of travel survey data and data about the built environment and PT network collected from other sources. This model was also used by other researchers to model the desire for using PT based on stated preference survey data (de Vos et al., 2020) or the relationship between mode choice and commuting stress based on data sourced from a large-scale travel survey (Legrain et al., 2015).

2.3. Contribution of present research to the current state of the art

Based on the analysis of previous research, we observed that factors that influence the quality of the PT offer (frequency, transit time), accessibility to the PT, and also socio-economic factors such as the presence of children in the household or the availability of a car for daily use are direct determinants of mode choice for travellers. The literature review suggests that travellers not only choose the most convenient

[3] Travel time ratio, calculated as the ratio between travel time by PT and travel time by another transport mode (in this case car) for travelling the same route at the exact same time.

Table 1
Summary of literature review.

No	Author(s)	Topic and area for data sourcing	Main method	Relevance
1	Lanzendorf (2002)	Utility of mobility styles to analyze travel behavior (Cologne, Germany)	binomial logistic regression	General view* Method**
2	Vij et al. (2013)	Understand modality and their influence on mode choice (Karlsruhe, Germany)	Mixed logit	General view Method
3	Nordfjærn et al. (2014)	Role of Theory of Planned Behavior, car habit, and resistance to change in PT use (Norway)	Structural Equation Modelling	General view Method
4	Saghapour et al. (2016)	Research context for PT accessibility and modelling PT trips (Melbourne, Australia)	Ordered logit regression	Factors*** Method
5	Ding et al. (2017)	Effect of built environment on travel mode choice (Baltimore, USA)	Structural equation model	Factors
6	Balcombe et al. (2004)	Factors influencing the demand for PT and quantitative indicators for them (mainly UK)	Diverse	Factors
7	Chng et al. (2016)	Relationships between commute mode, PT connectivity, and wellbeing (London, UK)	Multivariate logistic regression	Factors Method
8	Scheiner (2010)	Interrelations between trip distances and mode choice to determine stability of travel behavior (Germany)	Cross-sectional spatial comparisons	Factors
9	Yu et al. (2019)	Effect of built environment on transit travel in urban villages (Shenzhen, China)	Structural equations modelling	Factors
10	Hagenauer and Helbich (2017)	Predictive performance of machine learning classifiers for mode choice (Netherlands)	7 machine learning classifiers	Factors
11	Daniels and Mulley (2013)	Influences on walking distance to access public transport (Sydney, Australia)	ARCGIS	Factors
12	El-Geneidy et al. (2014)	Define service areas around transit stations foot access (Montreal, Canada)	Multi-level regression	Factors
13	Ha et al. (2020)	Impact of travel time, cost, and transit burdens on mode choice (Seoul, Korea)	Binomial logistic regression	Factors Method
14	Collins and Chambers (2005)	Importance and relationship of psychological and situational factors in predicting mode choice (Melbourne, Australia)	Logistic regression	Factors Method
15	Kawabata (2009)	Accessibility disparity between commuting by car and PT (Boston & San Francisco, USA)	Cross-sectional measures of disparity	Factors
16	Kwok and Yeh (2004)	Propose modal accessibility gap index based on accessibility and GIS (Hong Kong, China)	ArcView 3.2. Hansen's gravity measure	Factors
17	Guan et al. (2020)	Modal accessibility gap index, based on travel routes and points of interest (Shanghai, China)	Isochron accessibility Contrast model	Factors
18	Paulley et al. (2006)	Guidance manual on factors (fares, income, etc.) affecting PT demand (diverse)	Meta-analysis	Factors
19	Litman (2004)	Review of price elasticities and cross elasticities for use in PT planning (diverse)	Literature review	Factors
20	Brechan (2017)	Random effects meta-analysis of price reduction and service frequency (Norway)	Meta-analysis Homogeneity test	Factors
21	Nielsen and Lange (2007)	Design of PT service concepts and networks in urban and rural districts (Norway)	Diverse	Factors
22	Chakrabarti & Joh (2019)	Compare travel behavior of adults in households with and without young children (California, USA)	Ordinary Least Squares and Binary logistic regression	Factors Method
23	McCahill et al. (2016)	Can increases in parking availability cause increase in car use? (Nine cities, USA)	Bradford Hill criteria	Factors
24	Christiansen et al. (2017)	Impact of parking availability on car use in different urban contexts (Norway)	Binary logistic regression	Factors Method
25	O'Fallon et al. (2004)	Effect of policy measures on decision to drive in morning peak period (New Zealand)	Multinomial logit and nested logit models	Factors Method
26	Coogan et al. (2018)	Effect of changes in demographics, traveler preferences and markets on PT ridership (diverse)	Diverse	Factors
27	Md Oakil et al. (2016)	Impact of parenthood on car ownership (Netherlands)	Logistic regression	Factors Method

(limited walking, high frequency) and competitive (optimal value of travel time and related costs) offer for their trips, but also that they are influenced in this decision by the structure of their household (presence of children).

Even though the literature body concerning travel behaviour in relation to PT use is extensive, we observe limitations in treating cases that deal with small urban forms, low-density areas, and networks of small cities and towns. In general, this type of analysis is made for large cities and metropolises (Guan et al., 2020; Ha et al., 2020). Therefore, in our study we chose to focus on the travel behaviour and identification of determinant factors for the use of PT of employees in the region of Agder, Norway. The region consists of a network of small cities and towns where the population has an increased need for motorized transport for daily commuting and also a high car dependency based on the statistical data presenting the modal split. For this purpose, we selected a set of eleven different factors that have a proven influence on the use of PT to be analysed in relation to the use of PT.

The factors selected are key ones in reflecting the location-based accessibility by PT to work of the employees who completed the survey. Five of the selected factors, *distance to work, walking distance to home bus stop, travel time by PT, frequency of PT at home bus stop, and PT ticket price,* are covering the three aspects of PT accessibility, as defined by Saghapour et al. (2016). The socio-economic characteristics, which several researchers described as influential in the travel mode choice of an individual (Coogan et al., 2018; Ha et al., 2020; Md Oakil et al., 2016; O'Fallon et al., 2004) are covered by four specific variables in our research: *age, gender, education level, and persons in care*. We also included two variables that reflect the impact of car access and the built environment on the travel mode choice of employees in Agder: *car ownership* and *ease of finding parking at work*.

All the factors have been selected after reviewing previous literature in the field and concluding that they have strong potential to be direct determinants of the daily transport mode choice of employees. Therefore, we decided to test the following hypothesis: the selected eleven factors affect the mode choice of employees living and working in the region of Agder, Norway. To prove this hypothesis, a statistical analysis model, namely ordered logistic regression, was applied to the data collected in a regional travel survey conducted in 2019 in the Agder region.

3. Study design

This section presents the geographical area covered by the study, together with the data set used and the methodological approach employed for the data analysis. The ordered logistic regression model specifications are further presented in relation to the selected variables.

3.1. Study area

Typical Norwegian geography is represented by regions where the dominating urban settlements are small cities and towns, mainly coastal, with one city of small or medium size being the "regional centre". The region of Agder, located in South-Eastern Norway, is a perfect example of this, having a territory of 16,434 km^2 and a population of approximately 307,000 inhabitants (Citypopulation, 2020). With access to the North Sea, approximately 80 percent of the population of Agder is concentrated on the coastal area in small cities and towns.

The three largest municipalities in Agder are, as of the third quarter of 2021, Kristiansand (113 448 inhabitants, area of 644.16 km^2), Arendal (45 474 inhabitants, area of 270 km^2, situated 64 km north-east of Kristiansand), and Grimstad (24 000 inhabitants, area of 303.6 km^2, situated 47 km north-east of Kristiansand). The region, represented by low population densities and benefiting from easy access to motorized vehicles and free parking offered by employers, has a modal split in favour of PT lower than the national average of 10.8 percent (Statista, 2020): the split is nine percent in Kristiansand (Haugsbø et al., 2015a) and four percent or below in the other municipalities (Haugsbø et al., 2015b).

Agder has a sole regional PT provider which offers bus-based services: Agder Kollektivtrafikk (AKT). The local PT infrastructure is mainly concentrated on the municipality of Kristiansand, the rest of the municipalities having little to no local transport lines. At the regional level, PT is ensured predominantly through regional bus lines (marked in red on the map in Fig. 1) that connect the main municipalities. A limited train connection exists, but the line does not directly connect the coastal municipalities (marked in dotted line on the map in Fig. 1). The rest of the regional PT network is composed of local routes (light blue continuous line on map) connecting small municipalities and villages. The local routes have low average speeds, and the majority are located inland, where the population densities are low. Therefore, as far as the PT use and PT mode choice is concerned in our study, these should always be interpreted as the use of bus-based services when mentioned in relation to Agder.

The PT fares in Agder are zone based, with one zone corresponding to one municipality. Table 2 gives an overview of the fares for adult single tickets and monthly passes charged by AKT in January 2022 (prices in euros are estimative, calculated with a rate of 10 NOK (Norwegian Kroner) per 1 EUR (Euro)). As an example, a single ticket between Arendal and Kristiansand (four zones) costs 130 NOK (approx. 13 EUR) if bought before boarding the bus, for a distance of 64.4 km and a travel time of 90 min with the regular bus connection, or 62 min with the direct bus route that has four departures a day during rush hours. Estimated driving time for the same distance is approximately 60 min, and the costs are 259.5 NOK, according to public reimbursement policies in Norway which include car wear. When only gas and toll prices are considered, a price of approximately 100 NOK is achieved for the same distance (76.6 NOK – conservative estimate of 17 NOK per litre for fuel

Fig. 1. Regional public transport network of Agder, Norway. Image courtesy of AKT.

Table 2
Overview of typical bus fares for adult passengers in Agder (January 2022).*

No. of zones	Adult single ticket bought in advance	Adult single ticket bought on board	Adult weekly ticket	Young adult (20–29) monthly ticket	Adult (30–66) monthly ticket
1	33 NOK (3.3 EUR)	55 NOK	272 NOK	535 NOK	815 NOK
2	46 NOK (4.6 EUR)	77 NOK	329 NOK		975 NOK
3	92 NOK (9.2 EUR)	153 NOK	462 NOK		1375 NOK
4	130 NOK (13 EUR)	217 NOK			
5	162 NOK (16.2 EUR)	270 NOK			
All zones (6 +)	197 (19.7 EUR)	328 NOK			
Kristiansand area*	–	–	–	410 NOK	615 NOK

*Source of data: https://www.akt.no/betal-reisen/billettpriser/enkeltbilletter-barn-voksen-og-honnor/.

and seven litres per 100 Km fuel consumption; 24 NOK rush hour toll price). As users generally consider the fuel and possibly toll and parking costs alone when comparing costs between driving and using PT (Beirão and Sarsfield Cabral, 2007), the single trip fares do not present a visible advantage over driving, especially when the frequency provision is also considered.

The region of Agder is representative through its geography not only for Norway, but for all other coastal Nordic regions; countries like Sweden, Denmark, and Finland have the same typology of coastal urban settlements. With an expected rise of 22 percent in population and a passenger traffic increase of one percent by 2040 (Madslien et al., 2014), the county of Agder is now focusing on promoting more sustainable mobility solutions in order to mitigate passenger-transport-related emissions.

3.2. Survey and data collection

The present study used data collected in the frame of the Optimization of the Public Transport in the Coastal Region of Agder (OPTCORA) project. OPTCORA studies the optimization of PT from the perspective of the needs of employees in Agder, Norway (employees that were 20–66 years old at the moment of data collection in 2019). The primary aim of OPTCORA is to examine the daily commute habits of employees that live in the coastal area of Agder, specifically in the following municipalities – Kristiansand, Lillesand, Grimstad and Arendal – and to assess the potential of mode choice change in favour of PT for car users. For that, it is necessary to understand what motivates the current users of PT in their mode choice and explore the possibilities of extending this motivation to a part of the car-users group.

In this paper, we present findings from the OPTCORA travel habits survey data collected between June and September 2019. The bilingual survey (Norwegian and English), which was completely anonymous according to the standards of NSD (Norwegian Centre for Research Data), was distributed by to public and private employers with a workforce of>100 persons located in the Agder municipalities of Arendal, Grimstad, Lillesand, and Kristiansand. No incentive was offered to the companies or respondents. A total of 2,026 responses were collected from employees at 29 different companies. After identifying and removing partial or inadmissible cases, a total of N = 1 849 responses were retained as usable.

The survey consisted of 36 questions, which varied from multiple-choice questions (closed-end) and matrix questions to Likert-scale questions and open-ended questions. The first section of the survey aimed to establish a profile of the respondents, the second and third sections looked at the travel habits of the respondents, and the last concluded the survey and allowed for any other comments not covered in the questionnaire. The respondents were asked general questions about their satisfaction, daily commute habits, and regular travel mode choice. The main focus of the survey was to understand the travel habits of employees in Agder and their satisfaction with the PT services currently offered to them.

In the space of the present research, we have included 10 of the questions that presented the most relevance to our analysis based on the literature review and the setting of the analysis. Table 3 presents the questions considered, their abbreviation (which will be used further to present the results of the study), the type of variable the question represents, and the possible answers that the respondents could choose from when filling in the questionnaire.

3.3. Modelling technique

3.3.1. Ordered logit model

In some studies, the dependent variable has more than two categories, and these categories can be ordered in a reasonable or logical way. In such situations, the researchers are interested in predicting the ordinal outcome, their main challenge being the achievement of this with a regression model. In the existing literature, certain techniques are recommended to apply linear regression to the data when the dependent variable is ordinal. For instance, one suggestion is to code the midpoints of all categories. In these cases, the main hurdle is how to determine a reasonable number of the highest category. In addition, the dependent variable still possesses the characteristics of a non-normal and noncontinuous variable that violates the criteria for applying a linear regression model (Hoffmann, 2016). Another technique suggested in the literature is to transform categorical variables into interval scales, a process known as optimal scaling (Casacci and Pareto, 2015).

An alternative solution that is frequently adopted by researchers in the social and behavioural sciences is to consider an ordinal variable as a continuous variable. The main criterion for this approach is that the ordinal variable must have seven or more categories. However, some researchers recommend that even five categories are sufficient to treat it as a continuous variable. However, this technique has two limitations. Firstly, if the ordinal variables' categories do not follow an approximately normal distribution, estimates are likely to be biased. Secondly, it is challenging to make a strong assumption about the distance between two groups of the ordinal variable. Because of these limitations, it is recommended not to apply the traditional ordinary least squares (OLS) regression model (Long, 1997; McCullagh, 1980; Winship and Mare, 1984). Therefore, most researchers prefer to apply the methods explicitly developed for ordinal dependent variables, such as the ordered logistic regression technique (Fullerton, 2009; Hoffmann, 2016; Qiao, 2015; Saghapour et al., 2016). The error term in ordered logistic regression is assumed to follow a logistic distribution. Probabilities are used to define the cut-points of the distribution; that is, the points at which different groups are differentiated (Hoffmann, 2016).

3.3.2. Variable selection

The present study applies ordered logistic regression on a selected set of variables to examine the impact of independent variables on an individual's travel mode choice, more specifically the use of PT. The independent variables can be classified as objective factors (having persons in care, distance to work, walking distance to home bus stop, ease of finding parking at work, car ownership, frequency of PT at home bus stop, travel time by bus, age, gender, education level) and subjective ones (bus price critical for using bus). The dependent variable in the model is the use of the bus (the only PT mode available in Agder, which is the case study for our research) as a travel mode choice. The survey asked respondents about their frequency of using the bus for their trips to work (on a five-point Likert scale). The ordinal responses (ranging

Table 3
Detailed description of variables used in the study.

Question	Abbreviation	Choice of answers	Variable type
How do you use different means of transport to and from work? category: Bus	Bususe	Never Rarely Occasionally Often Every day	Dependent
Do you have persons in your care?	Care	Yes No Sometimes (Shared custody)	Independent
Are the bus prices crucial for your choice of means of transport to and from the workplace?	Busprice	Yes No Don't know	Independent
What is the distance between your place of residence and your workplace?	Distwork	Under 5 Km 5–10 Km 11–20 km 21–45 km Over 45 km	Independent
How long does it take for you to walk from home to the nearest bus stop?	Distancebus	0–5 min 5–10 min >10 min Don't know	Independent
How easy is it to find a parking spot at work?	Findingparking	Easy Depends on time Hard Don't know	Independent
Does your household have cars available for use?	Carownership	No car 1 car 2 cars 3 cars or more	Independent
How frequent is the bus connection between your home and your place of work at the time of your commute?	Frequency	Every 10 min or more often Every 15–20 min Every 30 min One bus an hour Irregular service Don't know	Independent
How long does it take you to travel to work if you use public transport?	Timebus	<15 min 15–30 min 30–45 min 45–60 min More than one hour Don't know	Independent
Age	Age	Under 20 20–30 31–40 41–50 51–60 61–66 67 and over	Independent
Gender	Gender	Female Male Other I prefer not to say	Independent
Level of studies	Education	Higher education-long (>4 years in higher education) Higher education-short (up to 4 years in higher education) Upper secondary education Lower secondary education I prefer not to say	Independent

from never to every day) provided the premises of applying an ordered logit modelling technique.

3.4. Limitations

The present study has several limitations that have to be mentioned. First and foremost, the study only considers the daily work-trip related travel habits of employees living and working in Agder, where the PT provision is predominantly bus-based. Therefore, when the aspect of occupation is considered, our data is not representative for other population groups (students, retired individuals, etc.). The data collection method does not differentiate between job types (e.g., white collar, blue collar).

The sampling procedure was limited to electronic surveys distributed to the employees by the companies who responded to the invitation to participate in the study. Only companies with>100 employees, located in municipalities serviced by bus Line 100 in Agder (Kristiansand, Lillesand, Grimstad, Arendal), were invited to participate, due to the focus of the OPTCORA project. As a result of the sampling procedure, some groups in the employed population may have been underrepresented, such as persons not so comfortable with technology, entrepreneurs, employees of smaller enterprises, etc. We have also observed that persons with a higher education were strongly overrepresented in the sample (79.45 percent of respondents had higher education studies), compared to the demographic data available (on average, 35 percent of the population in the four municipalities has higher education studies). This type of limitation has also been encountered by Roche-Cerasi et al. (2013), who performed a similar data collection in Oslo, Norway.

Another limitation in regard to the survey is that some of the questions used to collect the data could be open to interpretation as to their formulation (in regard to the question text or option answers). For example, the question related to *Bususe*, which presents a five points Likert scale answer option (Table 3), may leave too much room for personal interpretation to the respondent. Therefore, the answers for the middle range options (Rarely, Occasionally, Often) are not to be interpreted by the analysis as exact, given the subjectivity aspect. For future surveys, a more specific range for the scale is recommended, possibly stating frequencies of use such as "Less than once a week", "Less than once a month" etc.

The question related to the *Busprice* also presents a point of interpretation, its formulation not informing about the respondent's perception of the bus prices (expensive or not), but more about the relation to bus prices in general when choosing a transport mode to work. We also need to mention the question relating to persons in care (*Care*). This question could have had response options that differentiated between children (and their ages), and health impaired adults. As the question stands now, the results are conclusive but not detailed enough regarding the type of person in care, their age, level of dependence to care, etc.

In our analysis we use four sociodemographic variables: age, gender, education, and household structure. The survey data collected only targeted employees, therefore using the employment status would have been redundant. Data about marital status, ethnicity, migration background, religious affiliation and income were not collected. The income related data was not collected due to GDPR.

Considerations voiced by the data protection responsible at AKT, while the rest were not seen as critical in assessing the travel habits of employees in Agder.

4. Results and discussion

In this section we present the results of the ordered logistic regression analysis on the dataset introduced earlier. We begin with the summary statistics for the categorical variables, then introduce the correlation coefficients between the variables, in parallel to the odds ratio results, and finally present the estimated coefficients for the ordered logistic

Table 4
Summary statistics for categorical variables.

Variables	Categories	Label	Frequency	Percentage
Bususe	1	Never	1234	66.74
	2	Rarely	227	12.28
	3	Sometimes	148	8.00
	4	Often	103	5.57
	5	Every day	137	7.41
Care (persons in care)	1	Yes	895	48.40
	2	Sometimes	43	2.33
	3	No	911	49.27
Busprice (critical for use)	1	Yes	541	29.26
	2	No	1132	61.22
	3	Don't know	176	9.52
Distwork	1	<5 Km	556	30.07
	2	5–10 Km	485	26.23
	3	11–20 km	376	20.34
	4	21–45 km	292	15.79
	5	Over 45 km	140	7.57
Distancebus (home stop, walking)	1	<5 min	932	50.41
	2	5–10 min	510	27.58
	3	>10 min	354	19.15
	4	Don't know	53	2.87
Findingparking (at work)	1	Easy	1040	56.25
	2	Depends on time	586	31.69
	3	Hard	92	4.98
	4	Don't know	131	7.08
Carownership	0	No car	117	6.33
	1	1 car	823	44.51
	2	2 cars	777	42.02
	3	3 cars or more	132	7.14
Frequency (bus at home stop)	1	10 min or less	113	6.11
	2	15–20 min	326	17.63
	3	30 min	506	27.37
	4	60 min	277	14.98
	5	Irregular service	187	10.11
	6	Don't know	440	23.80
Timebus (travel time home to work)	1	<15 min	234	12.66
	2	15–30 min	441	23.85
	3	30–45 min	316	17.09
	4	45–60 min	252	13.63
	5	>60 min	266	14.39
	6	Don't know	340	18.39
Age	1	<20	7	0.38
	2	20–30	156	8.44
	3	31–40	383	20.71
	4	41–50	549	29.69
	5	51–60	532	28.77
	6	61–66	202	10.92
	7	>66	20	1.08
Gender	1	Female	1070	57.87
	2	Male	766	41.43
	3	Other	1	0.05
	4	I prefer not to say	12	0.65
Education	1	Higher education-long	949	51.33
	2	Higher education-short	520	28.12
	3	Upper secondary	333	18.01
	4	Lower secondary	20	1.08
	5	I prefer not to say	27	1.46

regression model.

Summary statistics for all the variables are presented in Table 4. As complementary data to the summary statistics, it should be mentioned that the respondents have the following distribution according to the stated home municipality: 34 percent Kristiansand, 29.5 percent Arendal, 21.1 percent Grimstad, 3.7 percent Lillesand, and 11.7 percent from other municipalities in Agder. The respondents work in the following municipalities: 36.5 percent Kristiansand, 30.6 percent Arendal, 29.2 percent Grimstad, 3.2 percent Lillesand, 0.5 percent other municipalities.

The summary statistics show that approximately 67 percent of the respondents never use the bus for their regular daily commute, while 7.41 percent use it every day. For the variable *Care*, results indicate that about half of respondents do not have any person in their care. When asked about the role of the *Busprice* in relation to their transport mode choice, the highest percentage (61.22 percent) expressed that the bus price is not crucial for their transport mode choice for their work commute. The majority of respondents (close to 70 percent) travel 5 km or more to reach their workplace. At the same time, 50 percent walk less than five minutes to reach the bus stop from their home. The highest percentage (56.25 percent) reported that they can find parking at work easily. The vast majority of respondents (86.53 percent) stated that they own one or more cars in their household.

Only a small percentage of the respondents (6.11 percent) mention that they have access to the bus with a higher frequency (10 min or less). Similarly, a small percentage (12.66 percent) express that it takes<15 min to reach their workplace from home by bus.

About 9 percent of the respondents are younger than 31 years old, and 20 percent are older than 60. We can observe that almost 58 percent of the respondents are female, and most of the respondents (79.45 percent) have completed higher education studies.

The results presented in Table 5 show that none of the independent variables has a strong and significant correlation with other independent variables. To check multicollinearity, we have calculated the variance inflation factor (VIF). The results presented in Table 6 show that the VIF value for all variables is<4. Thus, the results confirm that the problem of multicollinearity does not exist in the case of the variables selected for analysis in our study. We have included all eleven independent variables in the analysis.

The results of the estimated model are presented in Table 7. The likelihood ratio Chi-Square test value is 814.25 with a p-value 0.0000. These results confirm that the model is statistically significant. We have computed both the ordered logg-odds coefficient and the proportional odd ratio for the ordered logit model. The proportional odd ratio explains the odds of the high category of dependent variable compared to the rest of the categories for a one-unit change in the independent variable, assuming the rest of the independent variables are held constant in the model. This shows that for a one-unit increase in the category "No person in care" the odds of being in the high category of *Bususe* versus the combined rest of the categories are 1.29 times higher, given the other independent variables are kept constant in the model. In the

Table 5
Values of correlation coefficients among variables.

	Care	Busprice	Distwork	Distance bus	Find parking	Car ownership	Frequency	Timebus	Age	Gender	Education
Care	1.0000										
Busprice	−0.0119	1.00									
Distwork	−0.0624***	−0.0614***	1.0000								
Distancebus	0.0235	0.0582**	0.2292***	1.0000							
Findparking	0.0942***	−0.0436*	−0.0924***	−0.0425*	1.0000						
Carownership	−0.2521***	0.0780***	0.2626***	0.1164***	−0.2482***	1.0000					
Frequency	−0.0132	0.1850***	0.0820***	0.2243***	−0.1084***	0.2001***	1.0000				
Timebus	−0.0832***	0.1343***	0.3730***	0.3038***	−0.1036***	0.2162***	0.4565***	1.0000			
Age	0.2497***	0.1344***	0.0160	0.1054***	−0.0001	0.0998***	0.0450*	0.0156	1.0000		
Gender	−0.0081	−0.0296	0.0069	−0.0255	0.0701***	−0.0839***	−0.0452*	−0.0645***	0.0131	1.0000	
Education	0.0646***	0.0218	0.0484**	0.0243	−0.1258***	0.0676***	0.1059***	0.1113***	0.0449*	−0.0020	1.0000

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

Table 6
Estimated variance inflation factor (VIF).

Variable	VIF	1/VIF
Timebus	1.55	0.6449
Frequency	1.35	0.7410
Distwork	1.28	0.7792
Carownership	1.28	0.7821
Care	1.18	0.8469
Distancebus	1.15	0.8694
Age	1.13	0.8855
Findparking	1.09	0.9182
Busprice	1.07	0.9314
Education	1.04	0.9624
Gender	1.02	0.9832

following paragraphs we will only discuss the interpretation of the ordered logg-odds to avoid redundancy.

The results show that, for four variables – *Busprice, Distwork, Findingparking,* and *Carownership* – all categories significantly impact the dependent variable *Bususe*. Two categories of the variable *Busprice* – “No” and “Don’t know” – have a negative and significant impact on the dependent variable. This means that if the subjects were in the “No” and “Don’t know” categories, their ordered log-odds of being in a higher category of the dependent variable would decrease by 0.93 and 0.64, respectively. In other words, the subjects who consider that the bus price is not crucial in choosing their daily transport mode would have less probability of taking the bus. This result reveals the possibility to influence the behaviour of the segment of population for which the bus price is crucial into using PT more through monetary incentives; this is partly aligned with the findings of Brechan (2017), where fare reductions proved effective in the case studies located in Agder. It also partly confirms the finding of Litman (2004), who observed that lower density areas, such as Agder, have higher price elasticities and therefore a stronger negative impact on PT usage generated by price increase. Our data set does not contain detailed enough information to calculate an average price elasticity for Agder; therefore, we lack insight into the level of impact fare variations would have on PT use in the region imilarly, all categories of the variable *Carownership* have a negative and significant impact on *Bususe,* indicating that when the respondents own cars, their ordered log-odds of being in a higher category of the dependent variable would decrease by 1.4 (for one car), 2.31 (for two cars), and 2.63 (for 3 and more cars). This finding is consistent with other literature treating the subject covered in Section 2 of this paper, where easy access to a car in the household is strongly associated with a decline in PT usage, specifically in low-density areas such as small cities and towns. The present survey did not collect data about the ease of access to the cars in the household, therefore we cannot establish that particular threshold of influence.

All categories of the *Distwork* variable have a positive and significant impact on the dependent variable. This result demonstrates that with the increase in work distance, the ordered log-odds of being in a higher category of the dependent variable would increase by 1.01 (for 5–10 Km), 1.42 (for 11–20 km), 1.92 (for 21–45 km), and 2.11 (for Over 45 km). Thus, the subjects who need to travel a greater distance to reach their workplace would have a higher probability of taking the bus. These results confirm the findings of Chng et al. (2016), who found that PT use significantly increased for greater commute distances, but also with the findings of Hagenauer and Helbich (2017) who showed that trip distance is the most important variable for determining the usage of any travel mode. Similarly, all categories of the variable *Findingparking* have a positive and significant impact on the dependent variable. This result indicates that when the subjects found it hard to find parking, the ordered log-odds of being in a higher category of the dependent variable would increase, which is consistent with all literature covering this specific causality relation that we presented in the literature review (Section 2).

Table 7
Estimated coefficients for ordered logistic regression.[a]

Variable	Category	Label	Coefficient	Standard error	Odds ratio
Care	2	Sometimes	−0.2506	0.4160	0.7784
	3	No	0.2581*	0.1405	1.2945*
Busprice	2	No	−0.9256***	0.1179	0.3963***
	3	Don't know	−0.6352***	0.2176	0.5298***
Distwork	2	5–10 Km	1.0074***	0.1741	2.7383***
	3	11–20 km	1.4204***	0.2051	4.1386***
	4	21–45 km	1.9245***	0.2419	6.8519***
	5	Over 45 km	2.1064***	0.3050	8.2183***
Distancebus	2	5–10 min	−0.2754**	0.1298	0.7592**
	3	>10 min	−0.3606**	0.1674	0.6973**
	4	Don't know	−0.3304	0.6579	0.7186
Findingparking	2	Depends on time	0.2267*	0.1246	1.2544*
	3	Hard	0.5456**	0.2290	1.7256*
	4	Don't know	1.0038***	0.2182	2.7287***
Carownership	1	1 car	−1.3962***	0.2377	0.2475***
	2	2 cars	−2.3147***	0.2595	0.0988***
	3	3 cars or more	−2.6286***	0.3561	0.0722***
Frequency	2	15–20 min	0.0655	0.2269	1.0677
	3	30 min	−0.3675	0.2264	0.6924
	4	60 min	−0.7926***	0.2528	0.4527***
	5	Irregular service	−1.2045***	0.2980	0.2998***
	6	Don't know	−2.1115***	0.3024	0.1211***
Timebus	2	15–30 min	0.9926***	0.2157	2.6983***
	3	30–45 min	0.4528*	0.2475	1.5727*
	4	45–60 min	0.4115	0.2691	1.5091
	5	>60 min	−0.3854	0.3144	0.6801
	6	Don't know	−1.4376***	0.3734	0.2375***
Age	2	21–30	−1.2982	0.8007	0.2730
	3	31–40	−1.4101*	0.7994	0.2441*
	4	41–50	−1.3587*	0.7966	0.2570*
	5	51–60	−1.2909	0.7899	0.2750
	6	61–66	−1.4026*	0.8023	0.2460*
	7	>66	−1.5956	0.9739	0.2028
Gender	2	Male	0.0463	0.1113	1.0474
	3	Other	1.1723	1.4814	3.2294
	4	Prefer not to say	0.6364	0.5950	1.8897
Education	2	Higher education (short)	−0.1905	0.1327	0.8265
	3	Upper secondary	−0.3068*	0.1619	0.7358*
	4	Lower secondary	−0.2342	0.6162	0.7912
	5	Prefer not to say	−0.1658	0.5261	0.8476

Log Likelihood = -1589.7675.
[a] Number of observations = 1849. LR Chi2 (27) = 814.25. Prob > Chi2 = 0.0000. Pseudo R2 = 0.2033.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

The results of the model show that four variables – *Busprice*, *Distwork*, *Findingparking*, and *Carownership* – have statistically significant results for all of their categories. The graphical presentation of the results (Fig. 2) gives an overview of which category under each variable has the strongest impact on bus use. For instance, for the variable *Busprice* the category "No" has a stronger negative impact compared to "Don't know". For the variable *Distwork* the category "Over 45 km" has the highest positive impact compared to the other three categories. The "Don't know" category of the variable *Findingparking* has a strong positive impact compared to "Depends on time", and "Hard". Finally, for the variable *Carownership*, the category "3 cars or more" has the highest negative impact compared to the rest of the categories.

On the other hand, the factor *Distwork,* shows a different behaviour to that registered by other researchers. An example of that is the longitudinal study of Scheiner (2010), who explored the interrelations between travel mode choice and trip distance using data collected in Germany between 1976 and 2002. The data analysis performed by Scheiner showed that PT use increases constantly for trips up to 10 km but remains constant or even decreases once that distance mark is exceeded, both for car owners and for people with no cars in the

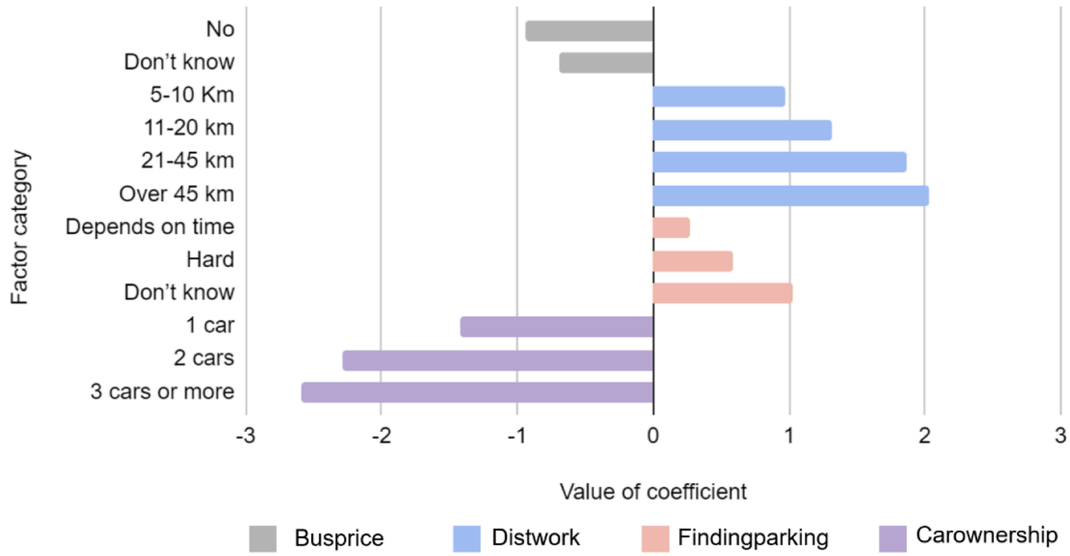

Fig. 2. Influence of categories for factors Busprice, Distwork, Findingparking and Carownership on Bususe.

household. The limited information provided by our dataset does not allow for a clear conclusion as to what reasons determine this particular behaviour in the case of employees in Agder. An assumption could be that the nature of a region's geography and the quality of the PT service provided may influence the mode choice relation to travel distance.

Only one category of the variable *Care*, specifically the "No person in care" category, has a significant impact on *Bususe.* As expected, the impact is positive, indicating that the use of PT shows to be more popular for respondents with no persons in care (generally meaning no children in care). Given that families with children tend to be more car-dependent (Md Oakil et al., 2016; O'Fallon et al., 2004), our finding confirms the negative relation between PT use and having children in care (if we assume that in most of the cases the persons in care are children) highlighted in previous research (Chakrabarti and Joh, 2019; Ha et al., 2020) for the case of small cities and towns, which have not been explored in detail so far. We do observe a need to differentiate the *Care* variable into categories covering different ages for the children and other types of persons in care (disabled persons, elderly, etc.).

The results also show that three out of the five categories of the variable *Frequency,* except the second and third categories ("15–20 min" and "30 min") have a negative and significant impact on *Bususe.* As expected, when the subjects' accessibility to PT is reduced due to a limited PT provision, which requires more planning for taking a trip and severely limits the flexibility of the user, then their ordered log-odds of being in a higher category of the dependent variable would decrease. In this particular case, a frequency with an interval higher than 30 min brings a clear negative impact to the choice of PT for the daily commute of employees. Again, these results are consistent with the findings of travel behaviour research around the world, presented in Section 2, and also with the Spatial Network Analysis for Multimodal Urban Transport Systems (SNAMUTS) accessibility tool standard, which requires "a service frequency of 20 min (or better) during the weekday inter-peak period" (Curtis and Scheurer, 2017, p.96). The results also directly confirm the results of Brechan (2017), who tested the impact of frequency increase in 12 different Norwegian pilot projects, three of which are based in Agder, and found that PT usage was positively influenced by higher PT frequencies.

The second and third categories of the variable *Distancebus* have a negative and significant impact. This illustrates that, as expected, when respondents cover a longer distance from home to the bus stop, their probability of taking the bus is reduced. For the variable *Timebus,* which evaluates the influence of the commute time by bus on the choice of PT for the daily commute, we obtained mixed results. For instance, when the subjects are in the second and third categories, where their travel time to work by PT is of maximum one hour, their ordered log-odds of being in a higher category of the dependent variable would increase by 0.99 and 0.45, respectively. However, when the subjects are in the sixth category, where they do not know the travel time of the bus from home to work, the results show a negative and significant impact on *Bususe*. This suggests that the lack of awareness about the actual travel time by PT to work may be strongly correlated with reduced potential for behaviour change in favour of PT. The results for the second, third, and fourth categories explain the gradual decrease in the values of the coefficients reflecting a gradual decline in the probability of using the bus, due to the negative impact of very long commute times on PT use, as confirmed by previous research (Balcombe et al., 2004; Ha et al., 2020; Kawabata, 2009).

For the variable *Age,* only the third, fourth, and sixth categories have a negative and significant impact on *Bususe,* which decreases from the third to the fourth category and then increases again for the sixth category. This indicates that, the youngest age group (category one, used as the base category) is using PT considerably more than employees above the age of 30. This result confirms the findings of both (Coogan et al., 2018) and Litman (2004), who both state that younger people tend to use transit more than older ones. The age group 31 to 40 (category 3) has the least probability of using the bus compared to the youngest group, behaviour that can be explained by the fact that this is the group which tends to have small children. Nevertheless, the ordered log-odds for the age group above 60 (category 6) are comparable to the third category (-1.40 compared to −1.41). This finding contradicts the results of Litman (2004), who stated that elderly people (age group not stated by Litman) tend to be more transit dependent. It should be noted that the target group of our research are employed adults, which may affect the results regarding the younger and elderly age groups due to not considering students and retired individuals.

The results for the *Gender* variable are inconclusive. They confirm the results of Roche-Cerasi et al. (2013), who found no significant association between the transport mode use and the gender of the respondents for Oslo residents. When the *Education* variable is considered, we observe only one category (category three, *Upper secondary* studies completed by the respondents) with a statistically significant negative impact on the *Bususe* (-0.31). This suggests that respondents that have completed an intermediate level of education are more car dependent than respondents with long higher education studies, partly confirming the findings of (Rachele et al., 2015). The reasons behind these results could be diverse, such as type of job performed (white collar, blue collar), flexibility of the schedule, personal need for status associated with car etc. As the survey data does not give details on these accounts, a clear conclusion can not be drawn on these results.

5. Conclusions, policy recommendations, and future research

Our study offers additional insight into the level of influence of eleven individual factors on the travel mode choice of employees living and working in networks of small cities and towns. The research uses the region of Agder in Norway as a case study, profiting from its representativity as a coastal network of small cities and towns typical for Northern Europe. We consider the contribution of our research to be primarily in the area of travel behaviour analysis from the perspective of the relation between PT usage and age, gender, education level, accessibility, time, parking provision, car ownership, household componence, and costs, based on precise and quantifiable data, in the context of networks of small cities and towns. Secondly, we contribute to the current body of research through the choice of the data sample that singles out the employed adult population in the aforementioned urban typology.

5.1. Conclusions

Through the analysis of employees' travel data, by applying an ordered logistic regression model, we confirm the initial hypothesis that the eleven selected factors we analysed are indeed valid in terms of influencing the PT mode choice in the context of networks of small cities and towns, with the exception of one factor, the gender of the respondents. Nevertheless, delving into more detail for each of the factors signals some discrepancies between the case of small cities and towns and their larger counterparts. Our results clearly confirm the findings of previous research concerning the impact of car ownership, parking availability, and the PT fare on the use of PT for daily work commute. Therefore, we conclude that these three factors can be considered generally valid, independent of the urban size, but that the actual value of their impact may vary depending on context.

On the other hand, a factor for which all categories proved to be statistically significant and to have an increasing positive impact on the use of PT, *Distwork*, shows a different behaviour to that registered by other researchers (Scheiner, 2010). Therefore, we recommend that more research be performed on the relation between the distance to work and the transport mode choice with particular focus on the influence of the built environment on this relation.

Complementing the previous findings of Brechan (2017), our results show that ticket costs and an increase in frequency for the PT provision have the capacity to influence modal choice for the inhabitants of Agder. Based on our results, we can conclude that the minimum frequency interval for positively influencing employees in using PT is 15–20 min, a larger time interval presenting a negative impact. Nevertheless, there is a need for further insight, both into more detailed time intervals and their impact and also for exploring the price elasticities registered in the region and the relation between ticket fares and modal shift.

Personal circumstances, such as family context and specifically the presence of persons in care in the household (typically small children for employees aged under 45), have a significant impact on the commute mode choice in our case. Nevertheless, more details should be gather further concerning how parents with children of different ages behave. Overall, we observe that PT use is more popular for people living within comfortable walking distance (five minutes or less) to PT stops with good frequency (20 min or less), having no persons in care, with limited access to cars and for which parking at work is not readily available. Our conclusion is that individuals who do not have persons in care, live within the catchment area of a high frequency PT stop, and yet do not use PT, present a higher potential for shifting their transport mode.

The two variables in our analysis that were found to behave somewhat differently in our case study than in other studies reviewed are the *Age* and the *Gender* of the respondents. In our case, the youngest age group (category one, age under 20) confirms the findings of Litman (2004) and (Coogan et al., 2018) having a visible higher PT use than any other age group, but the results for the second youngest group (21–30) are inconclusive. At the same time, the results for the oldest group considered (age over 60), contradict the findings of Litman (2004), their use of PT being similar to respondents aged 31 to 40. Since older respondents tend not to have children in care, we can only conclude that there is a need for further investigation in this matter to be able to determine what are the reasons for older employees to have such a strong car-habit in their daily commute behaviour. At the same time, results for the *Gender* variable show inconclusive results in our analysis, contrary to the findings of Buehler (2011) and Ng and Acker (2018), who found that women tend to use PT more and drive less than men.

In the case of five of the eleven factors, a common answer category was "Don't know". For the factor *Busprice* it is hard to interpret whether the respondents choosing this option had a common travel behavior. At the same time, for the *Findingparking* factor, this answer points in the direction of respondents who do not use a car and therefore are not aware whether it is difficult or not to find a parking place in the employer's parking. For the remaining three factors, *Distancebus*, *Frequency,* and *Timebus*, which are all related to knowledge of using the public transport, this answer points in the direction of the respondent not using the bus in any circumstance. The results in Table 7 support this assumption, with statistically significant negative impact registered for these answer categories of the factors *Frequency* and *Timebus*. We could even venture to conclude that the respondents in these categories are car captives, a conclusion that supports de Oña's (2020) claim that "involvement with public transport would be the factor contributing the most to behavioural intentions or loyalty, followed by service quality perceptions and satisfaction" (p. 311).

5.2. Policy recommendations

Following the conclusions presented in the previous Section 5.1, the first policy recommendation proposed relates to the development of campaigns and incentives targeted specifically at user groups with proven potential for mode change from private cars towards PT. We believe it is crucial that urban planners and PT providers consider this aspect when devising strategies for the decarbonization of passenger transport, as user group targeted policies may bring quicker results. In the case of Agder, to increase the modal shift of employees from cars to PT, we recommend a dedicated focus on individuals who do not have persons in care (more specifically children), who live within the catchment area of a high-frequency PT stop (<30 min between departures), and who do not currently use PT.

Even though car ownership is one of the factors with the highest influence on PT use, measures to reduce the number of cars per household in small cities and towns are hard to apply, especially at a local or regional level. At the same time, the aspect of pressing towards a reduced car ownership, while the accessibility level provided by the PT network is low when the frequency aspect is considered (only 23.7 percent of the respondents have a frequency of PT of 20 min or less at their home PT stop, despite 50.4 percent of them living within 5 min walk to a PT stop), triggers ethical questions related to freedom of movement and limiting the access to job markets for people in lower income groups. Nevertheless, it could be interesting to explore more policy shifts in limiting free parking availability for workplaces with good PT connection, or even the introduction of tiered parking permits with cost tiers based on the home-to-work accessibility factor for employees. A similar discussion can be suggested for the distance-to-work factor.

Overall, the results of our study provide policy makers and PT providers in Agder, and in regions that share strong similarities with Agder from an urban context and cultural perspective, with potential leverage points that could be employed to trigger an increase in travel behaviour shift towards PT. Based on the results, we can suggest regional and local policy actions that combine increasing the accessibility of inhabitants to high-frequency PT routes (minimum 20-minute intervals), limiting parking provision at the workplace, and providing affordable ticket fares specifically targeted at employees based on existing models such as the Hjem-Jobb-Hjem in Stavanger (HjemJobbHjem, 2020). These may prove to be successful in increasing the market share of PT for the employees user group.

5.3. Further research

To finalize our study, we would like to underline the need for further research to further develop the findings of our study, but also to overcome the limitations identified in Section 3.4. The representativity of our data set is limited, being sourced in the coastal area of a northern European country that benefits from the services of a unique PT provider for the entire region. Therefore, the results are hard to generalize for regions with different geographical, cultural, social, and PT service situations. At the same time, our study provides only a cross-sectional picture of the travel behaviour data, without the possibility to follow the temporal evolution of the respondents' behaviour. It would be ideal if this could be achieved, so we recommend that a similar analysis be applied on data extracted from national travel surveys in order to provide a glimpse into the temporal evolution of employees' travel behaviour in a specific region.

Another aspect that is not covered by our research is the impact of attitudes and beliefs on travel behaviour in relation to the factors we analysed. The available data set did not cover such aspects, so this is another topic that we recommend for further research. Furthermore, when considering the data related to cars and the car use, it would be interesting to explore the car accessibility level of the individuals in relation to their home location (central, suburb, rural). Such information would help in clarifying the impact of density and car accessibility on the travel behaviour of persons living in small cities and towns and allow for a better comparison with other urban areas.

Our results showed a statistical difference in behaviour for persons with upper secondary education. As in our data employees with higher education studies are overrepresented, we recommend more focus on collecting data that is more evenly spread among the different education level groups. This would allow for a more correct picture of the behaviour to be drawn. It would also be beneficial to gather more insights into the type of job the respondents have and analyse the data in relation to level of education. This will allow for a better understanding of the car use in relation to a possible car dependency imposed by the job type. Further studies could be useful to explore the reasons why older employee groups (age above 60) are still car captive in their daily travels, unlike similar age groups in other locations.

It could be worthwhile for future studies to explore the impact value ranges for these specific factors in relation to different urban typologies and define a set of standardized indicators for them. This may help urban planners and PT providers assess the potential of improving the PT modal share in their urban context based on the values of a limited set of proven influential factors.

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Appendix A. Supplementary data

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