Identifying key determinants of long-distance rail travel: A review with meta-analysis

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SHORT SUMMARY

This study aims to provide a review of factors influencing long-distance travel by rail and aims to identify key research gaps, challenges, and needs. We specifically focus on long-distance trips between 100 and 1500 km made by both conventional and high-speed rail. For this, we first propose a conceptual model that allows for categorizing the wide range of factors discussed. Next, by reviewing 67 studies, we identify determinants in four directions: journey, spatial, socio-demographic, and socio-psychological characteristics. To support the review, a meta-analysis is conducted on travel fares and travel duration. Own-price elasticities range between -0.32 and -0.50 whereas own-time elasticities range between -0.34 and -1.53. Finally, we offer a research agenda that highlights current gaps and discusses potential future directions that allow for advancing our understanding of how and which determinants influence long-distance travel choices so that effective policies can be designed.

Keywords: High-speed rail, long-distance travel, meta-analysis, systematic review, travel behavior.

1. INTRODUCTION

Long-distance trips substantially differ from daily travel, predominantly in terms of frequency and distance. In Great Britain, domestic long-distance trips over 50 miles represent only 2.3% of all trips but account for 30.2% of total distance travelled (Rohr et al., 2013). Similar patterns are observed elsewhere: trips over 80 km account for 40% total distance in France (Nicolas & David, 2009), while trips exceeding 100 km represent 45% of distance travelled in Germany (Frick & Grimm, 2014).

Demand for long-distance travel is expected to increase further (Shepherd et al., 2019; Van Goeverden et al., 2016), particularly by air, posing significant environmental challenges. In this regard, long-distance passenger travel accounts for almost 50% of the transport-related emissions (Van Goeverden et al., 2016). One direction to mitigate the environmental impacts of passenger

transport are technological innovations, yet some scholars caution that these innovations alone may not be sufficient to achieve the climate targets (Gössling & Dolnicar, 2022). Therefore, managing demand through behavioral shifts towards more sustainable modes represent a complementary strategy. Rail offers a competitive and sustainable alternative to long-distance car travel and short-haul flights, especially for distances up to 1500 km. Nonetheless, modal shifts to conventional and high-speed rail for long-distance travel depend on various factors that differ from local and regional travel.

Previous reviews have examined rail travel behavior and its determinants, but these typically concentrate on local or regional contexts, single decisions, isolated determinants, or alternative modes. More specifically, passenger transport studies in general tend to focus on car and coach travel, whereas studies specifically on rail travel concentrate around local and regional public transport. Consequently, a comprehensive synthesis of determinants influencing long-distance rail travel choices is lacking. This limits our understanding of how journey, spatial, and individual factors determine the way people travel to destinations far away. Addressing this gap is essential for designing sound policies that effectively promote behavioral shifts in long-distance travel.

The goal of this study is to identify factors associated with long-distance rail travel and to synthesize key research gaps and challenges in the current body of literature, by (1) offering a conceptual framework, (2) conducting a systematic review, (3) performing meta-analyses on key journey characteristics, and (4) providing a research agenda. This research agenda consists of research gaps and challenges, and potential directions for future research to overcome these challenges, resulting from discrepancies between the review findings and conceptual framework. We specifically focus on trips between 100 and 1500 km undertaken by conventional and high-speed rail for both business and personal journeys. Here, personal journeys include holidays, leisure trips, and visits to friends and relatives, consistent with Eurostat (2026).

2. CONCEPTUAL MODEL

In this section we offer a conceptual framework. This framework is particularly useful for categorizing the determinants of long-distance rail travel choices discussed in the review. Following De Witte et al. (2013), we distinguish three major directions of determinants, namely: journey characteristics (e.g. fares, travel time, punctuality), spatial characteristics (e.g. accessibility of city center), and individual characteristics. The individual dimension consists of socio-demographic (e.g. age, income) and socio-psychological factors (e.g. attitudes, norms). Besides individually influencing travel choices, an interplay between determinants may also exist. Altogether, these different types of characteristics and their interrelations influence the choices that individuals make with respect to long-distance travel. Here, we not only focus solely on mode choice but other travel choices such as destination and route choices, conditioned on the use of rail options, are included as well. The policy context, which consists of governance and decision-making processes, articulates how transport policies may influence long-distance travel choices through its determinants. Finally, feedback loops may also exist, which depict the reinforcing effect of current on future long-distance travel choices through journey, spatial, and individual determinants.

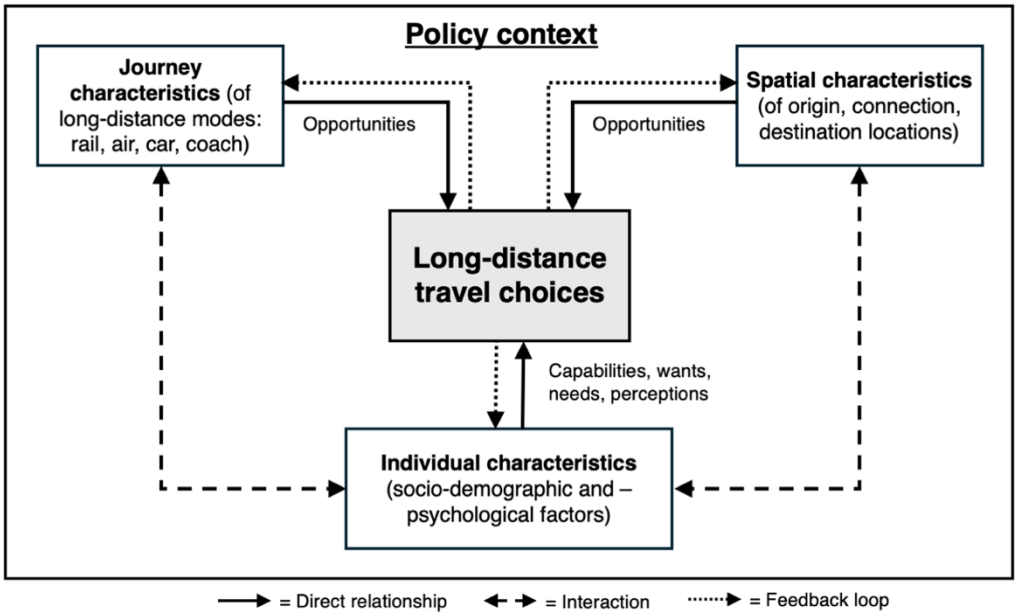


Figure 1: A conceptual framework for categorizing rail travel determinants.

3. METHODOLOGY

Systematic review

We systematically identified and reviewed studies examining the determinants of long-distance rail travel using the following search string:

("international" OR "vacation" OR "holiday" OR "long-distance" OR "long distance" OR "inter-continental" OR "cross-border") AND ("transport*" OR "trip*" OR "travel*") AND ("rail" OR "public transport" OR "train") AND ("choice*" OR "preference*" OR "behav*" OR "willingness to pay") AND NOT urban AND NOT freight AND NOT daily.

Limiting our search to English journal articles only, searches in Scopus and Web of Science returned 637 records. No date restrictions and snowballing techniques were applied. After removing 185 duplicates, 452 studies remained for title, abstract, and keyword screening. Of these, 138 studies were retained for full-text assessment, of which 67 were ultimately selected for inclusion in the review. In the end, we systematically compare the review findings with the conceptual model. In doing so, we offer a research agenda in which (1) key research challenges are identified based on this confrontation and (2) potential directions to overcome these challenges are articulated.

Meta-analyses

This systematic review was complemented with a meta-analysis to quantify the magnitude of key journey characteristics on long-distance rail travel. To ensure comparability, we confined the meta-analysis to studies estimating the effects of travel fares and time on mode choice using discrete choice modelling approaches. Since coefficients (taste parameters) are not directly comparable across studies, we used own-price and -time elasticities as effect sizes. A total of 22 own-

price and 20 own-time elasticities were reported in 8 studies. For another 12 studies that did not report elasticities themselves, we estimate elasticities using reported taste coefficients. This yielded an additional 35 own-price and 27 own-time elasticities. While individual-level elasticities are preferred (Train, 2009), this requires access to original data. Consequently, we relied upon aggregate elasticity approximations (Train, 2009). The estimated own-price elasticities were harmonized to EUR and converted to 2024 price levels to ensure consistency.

Subgroup analyses were conducted to examine differences between reported and estimated elasticities, by estimating four separate models: (i) reported own-price elasticities, (ii) estimated own-price elasticities, (iii) reported own-time elasticities, and (iv) estimated own-time elasticities. For these models, we relied upon sample size weighting, which has become a common practice in meta-analysis when standard errors are lacking (see Bergstrom & Taylor, 2006). Fixed-effects models were estimated for all subgroups in R using the *meta* package developed by Schwarzer (2007).

4. RESULTS AND DISCUSSION

Key findings

Our review of 67 studies on conventional and high-speed rail travel choices yields the following insights:

Journey characteristics are primary determinants of rail use and play a prominent role in research on long-distance rail travel. Travel fares and travel time consistently exhibit a negative impact on rail demand. The meta-analysis yields significant own-price elasticities ranging between -0.5 and -0.32 (see Figure A.1 and A.2), indicating an inelastic response: a 10% fare increase reduces rail use by about 5-9%. Own-time elasticities range from -0.34 to -1.53 (see Figure A.3 and A.4), showing greater heterogeneity across research designs, especially in stated preference studies. Beyond fares and in-vehicle time, schedule-related factors such as access and egress times, waiting, transfers, and deviations from timetables strongly influence mode choice. Transfer and waiting times generally exert a stronger negative effect than in-vehicle time, highlighting the prominent role of out-of-vehicle time. Finally, service frequency appears relatively less important, as travelers often plan journeys around specific departure and arrival times rather than around the number of daily services.

Research on *socio-demographic characteristics* suggests that specific segments are attracted to long-distance rail travel. Women are generally more likely to choose rail travel. Adults between 30 and 65 years are found to travel less by rail. Individuals with a higher education or income level tend to engage in long-distance travel more often, while effects on rail travel are less clear. In general, evidence suggests that rail use peaks among middle-income groups. Lower-income groups as well as students are more likely to choose coach travel. The likelihood of choosing car travel increases significantly for people with a driving license; remarkably, this does not translate into less rail travel among these individuals. Car ownership is more influential.

Socio-psychological characteristics matter but remain underexplored. Perceived comfort, security, and privacy are decisive factors for rail use, particularly for business journeys and night-train services. Conversely, booking complexity reduces rail demand. Socio-psychological factors such as habits, familiarity, norms, and environmental concerns also influence mode choice for long-distance travel. For example, passengers familiar with (night) trains or sensitive to transport-related environmental impacts are more likely to choose rail over alternative modes.

Research on the effect of *spatial characteristics* is limited and often relates to destination rather than mode choice. Barriers to travelling by rail arise when travelers reside far from stations or when destinations lack direct rail access. Evidence also suggests that rail use is higher for single-destination compared to multi-destination trips.

Research agenda

In this section, a research agenda is offered with key research challenges and future directions. We propose directions which contribute to designing effective transport policies, by specifically focusing on current research gaps in relation to the link between long-distance travel choices and its determinants. Building on the conceptual model (see Fig. 1), this section formulates research gaps across four categories of determinants.

Journey characteristics

Existing research on long-distance rail travel has focused predominantly on journey characteristics, particularly fares and travel time. As a result, the meta-analysis synthesized elasticities only for these two. Therefore, a promising research direction is to analyze the impact of time-related factors such as arrival, waiting time, and transfer time, and schedule deviations. Additional work is needed to clarify the role of frequency too, as existing findings are mixed: some studies report small but significant effects, while others find no significant influence at all.

Besides own-elasticities, future research could also examine cross-elasticities to better understand behavioral shifts across modes. Cross-elasticities capture how air, car, and coach demand changes in response to rail fare reductions or service improvements, and vice versa. Analyzing changes in journey characteristics for competing modes would shed light on the extent to which travelers shift to rail when, for example, airfares or car fuel/charging prices increase. Ultimately, complementing own- with cross-elasticities allows for a more holistic perspective on behavioral shifts across long-distance travel modes and strengthens the evaluation of policy designs.

Some journey characteristics, and especially transfer times, may exhibit non-linear effects. Since the current meta-analysis assumes linear responses a future direction is to analyze the extent to which certain ranges of transfer times discourage individuals from choosing rail over other modes. Important research questions include: Do transfer times exhibit a non-linear influence on rail use? What thresholds exist for transfer times among travelers? And how does rail demand change when said times align more closely with travel preferences? This also raises a methodological consideration. Discrete choice models used for travel choices assume compensatory behavior, where negative utility from one attribute can be offset by positive utility from another. However, attributes such as transfer time may be semi- or non-compensatory (see Swait, 2001): they must be sufficiently long to ensure feasibility but are perceived negatively beyond certain thresholds. Future work should explore approaches that better capture such patterns.

Socio-demographic characteristics

Research on socio-demographic factors has primarily focused on income as a source of heterogeneity in level-of-service sensitivity. However, differences in income levels are not the only source, as outlined in this review. Future research should examine differences in sensitivities across additional socio-demographic characteristics (such as age, education, and vehicle ownership). Latent class choice modelling is particularly well suited for this task, as it can identify groups of travelers with distinct sensitivities based on combinations of observed characteristics. Expanding the use of such methods would support the design of tailored transport policies that reflect the diversity of traveler needs and choices.

Socio-psychological characteristics

Socio-psychological factors remain relatively understudied. Recent work indicates that omitting subjective constructs can lead to over- or underestimation of demand elasticities, with substantial effect on policy effectiveness (Muñoz et al., 2026). There is therefore a growing need for research that jointly examines the influence of journey, spatial, and individual characteristics on long-distance travel choices.

Past studies that incorporate socio-psychological characteristics have focused primarily on attitudes; however, the role of norms have received limited attention despite evidence that normative constructs can have substantial effects on travel choices. A potential avenue for future research would be to examine how transport policies interact with such mechanisms. Policies may have a signaling effect that encourages socially desirable behavior (Constantino et al., 2021). Conversely, crowding-out effects may occur if governmental incentives weaken intrinsic motivations (Nyborg & Rege, 2003). Identifying when policies strengthen rather than weaken norm-based behavior is crucial for assessing policies' long-term effects.

Habits represent another underexplored determinant. A related challenge is how, once a desired behavior is established after intervening, this behavior becomes habitual and acts as a determinant for future choices. The influence of social networks and travel socialization processes remains limitedly studied too. Here, travel socialization refers to interaction with family members and friends that shape individuals' travel behavior (Baslington, 2008). In addition, these networks can normalize certain behavior. Future research could investigate how travel socialization processes and different types of social networks shape long-distance travel behavior, particularly in response to policy interventions.

Spatial characteristics

Spatial characteristics constitute another determinant of rail travel choices, particularly the size of the destination city and the accessibility of its center. However, a persistent challenge is understanding how mode, destination, and route choices interact. Only limited research has examined these interdependencies. For example, Grigolon et al. (2012) used 'portfolio' choice experiments to analyze interactions between destination and accommodation choices but did not include mode choice. Future research should test whether destination and mode choices are jointly determined and explore the implications for modelling long-distance trips.

A related and final challenge concerns the common assumption that destination choice precedes mode choice. For long-distance trips, this assumption may not hold. Travelers may first be drawn to a particular mode or route and only thereafter select a suitable destination. Testing alternative decision structures for different traveler groups, such as those proposed by Ishaq et al. (2023), could yield insights into how travel decisions are made. Such findings may encourage revising current modelling practices and could lead to substantially different policy evaluations.

5. CONCLUSIONS

Demand for long-distance travel has steadily been growing over the past decades. One pathway for reducing the associated environmental impacts lies in promoting behavioral shifts to more sustainable modes. Developing sound policies that encourage rail travel requires an understanding of the factors influencing rail travel behavior. Therefore, this review aimed to provide a review of determinants and critically evaluate the research body associated with it. A key issue in the current literature is that individual, spatial, and journey determinants are limitedly explored

concurrently, which limits our understanding of the relative importance of different factors. Moreover, whether certain journey characteristics exhibit a non-linear influence on rail use, such as transfer times, remains to be analyzed. Additionally, social influences on long-distance travel behavior have received only limited attention, despite growing evidence that such factors can substantially affect demand elasticities and, as a result, the design of transport policies. A final challenge concerns the sequence of travel choices. While the overview of travel choice determinants can already assist policymakers in developing policies that encourage rail travel, another research direction relates to revealing heterogeneity and semi- or non-compensatory decision making undertaken by traveler segments which would allow to design tailored policies.

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APPENDIX

Study	Country	Mode	Design	Model	Target group	Purpose	Elasticity	N	95%-CI	Weight
Bursa (2024)	EU	CR	RP	MNL	Tourists	Leisure	-0.45	807	-0.45 [-0.52; -0.38]	0.1%
Hensher (1998)	AU	CR	SP	NL	General	General	-0.01	1426	-0.01 [-0.07; 0.04]	0.1%
Hensher (1998)	AU	CR	SP	NL	General	General	-0.33	1426	-0.33 [-0.38; -0.28]	0.1%
Jung & Yoo (2014)	KR	HSR	SP	NL	General	Non-business	-1.15	3834	-1.15 [-1.18; -1.12]	0.4%
Jung & Yoo (2014)	KR	HSR	SP	NL	General	Business	-1.07	3834	-1.07 [-1.10; -1.04]	0.4%
Kristoffersson & Liu (2024)	EU	CR	RP	NL	General	Non-business	-0.48	324	-0.48 [-0.59; -0.37]	0.0%
Kristoffersson & Liu (2024)	EU	CR	RP	NL	General	Business	-0.47	717	-0.47 [-0.55; -0.40]	0.1%
Kristoffersson et al. (2025)	EU	CR	RP	NL	General	Non-business	-0.56	5270	-0.56 [-0.59; -0.53]	0.5%
Kristoffersson et al. (2025)	EU	CR	RP	NL	General	Business	-0.12	764	-0.12 [-0.19; -0.04]	0.1%
Rich & Mabit (2012)	EU	CR	RP	NL	Dist < 600 km	Short stay	-1.00	111867	-1.00 [-1.01; -0.99]	10.7%
Rich & Mabit (2012)	EU	CR	RP	NL	Dist > 600 km	Short stay	-0.62	111867	-0.62 [-0.63; -0.62]	10.7%
Rich & Mabit (2012)	EU	CR	RP	NL	Dist < 600 km	Leisure	-0.46	111867	-0.46 [-0.46; -0.45]	10.7%
Rich & Mabit (2012)	EU	CR	RP	NL	Dist > 600 km	Leisure	-0.29	111867	-0.29 [-0.29; -0.28]	10.7%
Rich & Mabit (2012)	EU	CR	RP	NL	Dist < 600 km	Business	-0.51	111867	-0.51 [-0.52; -0.51]	10.7%
Rich & Mabit (2012)	EU	CR	RP	NL	Dist > 600 km	Business	-0.31	111867	-0.31 [-0.31; -0.30]	10.7%
Rohr et al. (2013)	UK	CR	RP	NL	General	Commute	-0.36	116039	-0.36 [-0.36; -0.35]	11.1%
Rohr et al. (2013)	UK	CR	RP	NL	General	Business	-0.27	116039	-0.27 [-0.28; -0.27]	11.1%
Rohr et al. (2013)	UK	CR	RP	NL	General	VFR	-0.61	116039	-0.61 [-0.61; -0.60]	11.1%
Zhou et al. (2024)	CH	HSR	SP	LC Class 1	Students	Leisure	-0.28	999	-0.28 [-0.34; -0.22]	0.1%
Zhou et al. (2024)	CH	HSR	SP	LC Class 2	Students	Leisure	-1.56	999	-1.56 [-1.62; -1.50]	0.1%
Zhou et al. (2024)	CH	CR	SP	LC Class 1	Students	Leisure	-0.51	999	-0.51 [-0.57; -0.44]	0.1%
Zhou et al. (2024)	CH	CR	SP	LC Class 2	Students	Leisure	-0.81	999	-0.81 [-0.88; -0.75]	0.1%
Common effect model									**-0.50 [-0.50; -0.49]**	**100.0%**
Prediction interval									**[-1.33; 0.22]**	

Heterogeneity: I^2 = 100.0%, τ^2 = 0.1326, p = 0

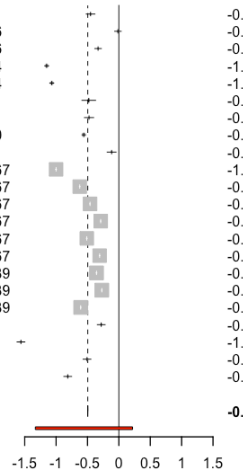


Figure A.1: Meta-analysis for reported own-price elasticities.

Study	Country	Mode	Design	Model	Target group	Purpose	Elasticity	N	95%-CI	Weight
Abouelela et al. (2022)	EU	HSR	SP	MNL	General	General	-2.36	786	-2.36 [-2.43; -2.30]	1.9%
Bursa (2024)	EU	CR	RP	MNL	Tourists	Leisure	-0.73	807	-0.73 [-0.80; -0.66]	1.9%
Cats et al. (2022)	EU	CR	SP	MNL	Academics	Business	-0.11	104	-0.11 [-0.30; 0.08]	0.2%
Curtale et al. (2023)	EU	Night train	SP	MXL	General	Leisure	-0.46	1571	-0.46 [-0.51; -0.42]	3.7%
Curtale et al. (2023)	EU	Night train	SP	MXL ext.	General	Leisure	-0.23	1571	-0.23 [-0.28; -0.18]	3.7%
Curtale et al. (2023)	EU	Night train	SP	HC	General	Leisure	-0.23	1571	-0.23 [-0.28; -0.18]	3.7%
Heufke Kantelaar et al. (2022)	EU	Night train	SP	MXL	General	General	-0.28	804	-0.28 [-0.35; -0.21]	1.9%
Huan et al. (2023)	CH	HSR	SP	NL	Beijing travellers	General	-0.16	2444	-0.16 [-0.20; -0.12]	5.8%
Huan et al. (2023)	CH	CR	SP	NL	Beijing travellers	General	-0.07	2444	-0.07 [-0.11; -0.03]	5.8%
Huan et al. (2023)	CH	HSR	SP	NL	Shijiazhuang travellers	General	-0.17	1631	-0.17 [-0.22; -0.12]	3.9%
Huan et al. (2023)	CH	CR	SP	NL	Shijiazhuang travellers	General	-0.07	1631	-0.07 [-0.12; -0.02]	3.9%
Isler et al. (2024)	BR	CR	SP	MNL	General	Business	-0.68	143	-0.68 [-0.84; -0.51]	0.3%
Isler et al. (2024)	BR	CR	SP	MXL	General	Business	-0.98	143	-0.98 [-1.14; -0.81]	0.3%
Isler et al. (2024)	BR	CR	SP	MNL	General	Non-business	-1.43	143	-1.43 [-1.60; -1.27]	0.3%
Isler et al. (2024)	BR	CR	SP	MXL	General	Non-business	-1.53	143	-1.53 [-1.69; -1.36]	0.3%
Isler et al. (2024)	BR	HSR	SP	MNL	General	Business	-0.48	143	-0.48 [-0.65; -0.32]	0.3%
Isler et al. (2024)	BR	HSR	SP	MXL	General	Business	-0.36	143	-0.36 [-0.52; -0.20]	0.3%
Isler et al. (2024)	BR	HSR	SP	MNL	General	Non-business	-0.37	143	-0.37 [-0.54; -0.21]	0.3%
Isler et al. (2024)	BR	HSR	SP	MXL	General	Non-business	-0.39	143	-0.39 [-0.55; -0.22]	0.3%
Karlinova & Krcal (2022)	EU	CR	SP	MXL	General	General	-0.30	232	-0.30 [-0.43; -0.17]	0.6%
Karlinova & Krcal (2022)	EU	CR	SP	MXL	General	General	-0.32	232	-0.32 [-0.45; -0.20]	0.6%
Lin et al. (2018)	CH	HSR	SP	MXL	General	Leisure	-0.18	1815	-0.18 [-0.23; -0.14]	4.3%
Lin et al. (2018)	CH	CR	SP	MXL	General	Leisure	-0.16	1815	-0.16 [-0.21; -0.12]	4.3%
Pan et al. (2023)	CH	HSR	SP	MNL	Tourists	Leisure	-0.03	787	-0.03 [-0.10; 0.04]	1.9%
Pan et al. (2023)	CH	HSR	SP	MXL	Tourists	Leisure	-0.23	787	-0.23 [-0.30; -0.16]	1.9%
Raux et al. (2021)	EU	CR	SP	MNL	General	Leisure	-3.72	326	-3.72 [-3.83; -3.61]	0.8%
Raux et al. (2021)	EU	CR	SP	MXL	General	Leisure	-5.68	326	-5.68 [-5.79; -5.57]	0.8%
Raux et al. (2021)	EU	CR	SP	LC Class 1	General	Leisure	-3.86	326	-3.86 [-3.97; -3.75]	0.8%
Raux et al. (2021)	EU	CR	SP	LC Class 2	General	Leisure	-6.87	326	-6.87 [-6.98; -6.76]	0.8%
Yao et al. (2013)	CH	HSR	SP	NL	Low income PT users	General	-0.00	3078	-0.00 [-0.04; 0.03]	7.3%
Yao et al. (2013)	CH	HSR	SP	NL	Medium income PT users	General	-0.00	3078	-0.00 [-0.04; 0.03]	7.3%
Yao et al. (2013)	CH	HSR	SP	NL	High income PT users	General	-0.00	3078	-0.00 [-0.04; 0.03]	7.3%
Yao et al. (2013)	CH	CR	SP	NL	Low income PT users	General	-0.00	3078	-0.00 [-0.04; 0.03]	7.3%
Yao et al. (2013)	CH	CR	SP	NL	Medium income PT users	General	-0.00	3078	-0.00 [-0.04; 0.03]	7.3%
Yao et al. (2013)	CH	CR	SP	NL	High income PT users	General	-0.01	3078	-0.01 [-0.04; 0.03]	7.3%
Common effect model									**-0.32 [-0.33; -0.32]**	**100.0%**
Prediction interval									**[-4.31; 2.45]**	

Heterogeneity: I^2 = 99.9%, τ^2 = 2.6855, p = 0

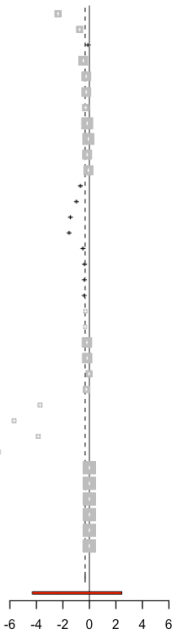


Figure A.2: Meta-analysis for estimated own-price elasticities.

Study	Country	Mode	Design	Model	Target group	Purpose	Type	Unit	Elasticity	N	95%-CI	Weight
Bursa (2024)	EU	CR	RP	MNL	Tourists	Leisure	Total	Hours	-0.50	807	-0.50 [-0.57; -0.43]	0.1%
Jung & Yoo (2014)	KR	HSR	SP	NL	General	Non-business	In-vehicle	Minutes	-0.26	3834	-0.26 [-0.29; -0.23]	0.4%
Jung & Yoo (2014)	KR	HSR	SP	NL	General	Business	In-vehicle	Minutes	-0.35	3834	-0.35 [-0.38; -0.32]	0.4%
Kristoffersson & Liu (2024)	EU	CR	RP	NL	General	Non-business	In-vehicle	Minutes	-0.29	324	-0.29 [-0.40; -0.18]	0.0%
Kristoffersson & Liu (2024)	EU	CR	RP	NL	General	Business	In-vehicle	Minutes	-1.07	717	-1.07 [-1.14; -1.00]	0.1%
Kristoffersson et al. (2025)	EU	CR	RP	NL	General	Non-business	In-vehicle	Minutes	-1.52	5270	-1.52 [-1.54; -1.49]	0.5%
Kristoffersson et al. (2025)	EU	CR	RP	NL	General	Business	In-vehicle	Minutes	-0.33	764	-0.33 [-0.40; -0.26]	0.1%
Rich and Mabit (2012)	EU	CR	RP	NL	Dist < 600 km	Short stay	In-vehicle	Minutes	-0.38	111867	-0.38 [-0.38; -0.37]	10.8%
Rich and Mabit (2012)	EU	CR	RP	NL	Dist > 600 km	Short stay	In-vehicle	Minutes	-0.45	111867	-0.45 [-0.46; -0.45]	10.8%
Rich and Mabit (2012)	EU	CR	RP	NL	Dist < 600 km	Leisure	In-vehicle	Minutes	-0.19	111867	-0.19 [-0.19; -0.18]	10.8%
Rich and Mabit (2012)	EU	CR	RP	NL	Dist > 600 km	Leisure	In-vehicle	Minutes	-0.15	111867	-0.15 [-0.16; -0.15]	10.8%
Rich and Mabit (2012)	EU	CR	RP	NL	Dist < 600 km	Business	In-vehicle	Minutes	-0.29	111867	-0.29 [-0.30; -0.29]	10.8%
Rich and Mabit (2012)	EU	CR	RP	NL	Dist > 600 km	Business	In-vehicle	Minutes	-0.28	111867	-0.28 [-0.28; -0.27]	10.8%
Rohr et al. (2013)	UK	CR	RP	NL	General	Commute	In-vehicle	-	-0.33	116039	-0.33 [-0.34; -0.33]	11.2%
Rohr et al. (2013)	UK	CR	RP	NL	General	Business	In-vehicle	-	-0.54	116039	-0.54 [-0.55; -0.54]	11.2%
Rohr et al. (2013)	UK	CR	RP	NL	General	VFR	In-vehicle	-	-0.36	116039	-0.36 [-0.36; -0.35]	11.2%
Zhou et al. (2024)	CH	HSR	SP	LC Class 1	Students	Leisure	In-vehicle	Hours	-0.25	999	-0.25 [-0.31; -0.19]	0.1%
Zhou et al. (2024)	CH	HSR	SP	LC Class 2	Students	Leisure	In-vehicle	Hours	-0.25	999	-0.25 [-0.31; -0.19]	0.1%
Zhou et al. (2024)	CH	CR	SP	LC Class 1	Students	Leisure	In-vehicle	Hours	-2.34	999	-2.34 [-2.40; -2.27]	0.1%
Zhou et al. (2024)	CH	CR	SP	LC Class 2	Students	Leisure	In-vehicle	Hours	-0.64	999	-0.64 [-0.70; -0.58]	0.1%
Common effect model											**-0.34 [-0.34; -0.34]**	**100.0%**
Prediction interval											**[-1.68; 0.60]**	

Heterogeneity: I^2 = 99.9%, τ^2 = 0.2821, p = 0

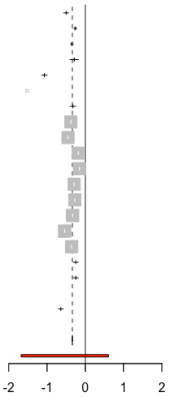


Figure A.3: Meta-analysis for reported own-time elasticities.

Study	Country	Mode	Design	Model	Target group	Purpose	Type	Unit	Elasticity	N	95%-CI	Weight
Abouelela et al. (2022)	EU	HSR	SP	MNL	General	General	Total	Minutes	-2.29	786	-2.29 [-2.36; -2.22]	3.2%
Cats et al. (2022)	EU	CR	SP	MNL	Academics	Business	In-vehicle	Hours	-0.56	104	-0.56 [-0.75; -0.37]	0.4%
Curtale et al. (2023)	EU	Night train	SP	MXL	General	Leisure	Total	Hours	-2.25	1671	-2.25 [-2.30; -2.20]	6.8%
Curtale et al. (2023)	EU	Night train	SP	MXL ext.	General	Leisure	Total	Hours	-2.21	1671	-2.21 [-2.26; -2.17]	6.8%
Curtale et al. (2023)	EU	Night train	SP	HC	General	Leisure	Total	Hours	-2.27	1671	-2.27 [-2.31; -2.22]	6.8%
Heufke Kantelaar et al. (2022)	EU	Night train	SP	MXL	General	General	In-vehicle	Hours	-0.74	804	-0.74 [-0.81; -0.67]	3.3%
Huan et al. (2023)	CH	HSR	SP	NL	Beijing travellers	General	In-vehicle	Hours	-0.68	2444	-0.68 [-0.72; -0.64]	10.0%
Huan et al. (2023)	CH	CR	SP	NL	Beijing travellers	General	In-vehicle	Hours	-2.22	2444	-2.22 [-2.26; -2.18]	10.0%
Huan et al. (2023)	CH	HSR	SP	NL	Shijiazhuang travellers	General	In-vehicle	Hours	-0.45	2444	-0.45 [-0.49; -0.41]	10.0%
Huan et al. (2023)	CH	CR	SP	NL	Shijiazhuang travellers	General	In-vehicle	Hours	-1.39	2444	-1.39 [-1.43; -1.35]	10.0%
Isler et al. (2024)	BR	CR	SP	MNL	General	Non-business	In-vehicle	Minutes	-0.68	143	-0.68 [-0.84; -0.51]	0.6%
Isler et al. (2024)	BR	CR	SP	MNL	General	Business	In-vehicle	Minutes	-0.73	143	-0.73 [-0.89; -0.56]	0.6%
Isler et al. (2024)	BR	HSR	SP	MNL	General	Non-business	In-vehicle	Minutes	-0.34	143	-0.34 [-0.50; -0.17]	0.6%
Isler et al. (2024)	BR	HSR	SP	MXL	General	Non-business	In-vehicle	Minutes	-0.18	143	-0.18 [-0.34; -0.02]	0.6%
Isler et al. (2024)	BR	HSR	SP	MNL	General	Business	In-vehicle	Minutes	-0.22	143	-0.22 [-0.39; -0.06]	0.6%
Isler et al. (2024)	BR	HSR	SP	MNL	General	Business	In-vehicle	Minutes	-0.17	143	-0.17 [-0.33; -0.00]	0.6%
Karlinova & Krcal (2022)	CZ	CR	SP	MXL	General	General	In-vehicle	Minutes	-6.25	232	-6.25 [-6.38; -6.12]	0.9%
Karlinova & Krcal (2022)	CZ	CR	SP	MXL	General	General	In-vehicle	Minutes	-5.91	232	-5.91 [-6.04; -5.78]	0.9%
Pan et al. (2023)	CH	HSR	SP	MNL	Tourists	Leisure	Total	Hours	-1.15	787	-1.15 [-1.22; -1.08]	3.2%
Pan et al. (2023)	CH	HSR	SP	MXL	Tourists	Leisure	Total	Hours	-1.03	787	-1.03 [-1.10; -0.96]	3.2%
Raux et al. (2021)	EU	CR	SP	MNL	General	Leisure	In-vehicle	Hours	-2.71	326	-2.71 [-2.82; -2.61]	1.3%
Raux et al. (2021)	EU	CR	SP	MXL	General	Leisure	In-vehicle	Hours	-3.70	326	-3.70 [-3.81; -3.60]	1.3%
Raux et al. (2021)	EU	CR	SP	LC Class 1	General	Leisure	In-vehicle	Hours	-3.10	326	-3.10 [-3.21; -2.99]	1.3%
Raux et al. (2021)	EU	CR	SP	LC Class 2	General	Leisure	In-vehicle	Hours	-2.03	326	-2.03 [-2.14; -1.92]	1.3%
Wang et al. (2016)	CH	Rail	RP	NL	Travellers	Business	In-vehicle	Minutes	-1.21	1247	-1.21 [-1.26; -1.15]	5.1%
Wang et al. (2016)	CH	Rail	RP	NL	Travellers	Non-business	In-vehicle	Minutes	-0.81	1247	-0.81 [-0.87; -0.76]	5.1%
Wang et al. (2016)	CH	Rail	RP	NL	Travellers	General	In-vehicle	Minutes	-0.84	1247	-0.84 [-0.89; -0.78]	5.1%
Common effect model											**-1.53 [-1.55; -1.52]**	**100.0%**
Prediction interval											**[-5.02; 1.60]**	

Heterogeneity: I^2 = 99.9%, τ^2 = 2.5009, p = 0

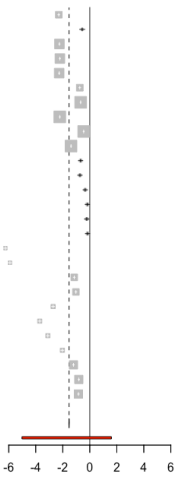


Figure A.4: Meta-analysis for estimated own-time elasticities.