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Dynamics and Heterogeneity in Working from Home Behaviour

A Latent Transition Analysis of Weekly Commuting Profiles

TU Delft

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DYNAMICS AND HETEROGENEITY IN WORKING FROM HOME BEHAVIOUR

A Latent Transition Analysis of Weekly Commuting Profiles

By

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PREFACE

Before you lies my Master's thesis: 'Dynamics and Heterogeneity in Working from Home Behaviour – A Latent Transition Analysis of Weekly Commuting Profiles', submitted in partial fulfilment of the requirements for the degree of Master of Science in Complex Systems Engineering and Management at Delft University of Technology. It marks the end of a research journey that began in February and kept me busy until June, and more broadly, the end of seven years of student life in Delft.

I like to think that I have lived by the motto 'leer wanneer het moet, en feest wanneer het kan', and looking back, I think I got the balance right. I have learnt an enormous amount, grown as a researcher and as a person, and made memories I would not trade for anything. But I am also ready for what comes next.

This thesis would not have been possible without the support of several people. First and foremost, I would like to thank my supervisor, Maarten Kroesen, for his guidance throughout this project. From our first meeting in February, when we mapped out the entire planning process, he expressed his confidence that I would graduate on June the 18th. Thank you for your trust, your positivity, the calm you brought to the process, and your remarkably quick email responses.

I would also like to thank Mariska van Essen from Goudappel, for her role as external supervisor. Your attention to detail, thorough chapter-by-chapter feedback, and the time you took to dive deep into my work have been invaluable in bringing this thesis to a higher level. And thank you to Oscar Oviedo Trespalacios, my second supervisor at TU Delft, for carefully reading the thesis and providing feedback that helped turn the separate parts into one coherent, flowing story.

Finally, thank you to everyone who supported me along the way – through comfort, distraction, genuine interest, and encouragement.

Eva Schepers
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ABSTRACT

Working from home (WFH) has changed commuting behaviour in the Netherlands, with office attendance increasingly concentrated on Tuesdays and Thursdays. This concentration poses a key challenge for Dutch peak-spreading policy, yet existing research consistently measures working from home as a frequency rather than a weekly structure, leaving the day-specific organisation of commuting behaviour largely unexplored. This study addresses this gap by conceptualising working from home as a weekly structure, applying latent class analysis (LCA) and latent transition analysis (LTA) to longitudinal survey data from the Landelijk Reizigersonderzoek (LRO). The data cover three annual waves (2023-2025) with a balanced panel of 1,026 respondents. Three distinct commuting profiles were identified: the Moderate Commuter (MC, 57%), the Intensive Full-Week Commuter (IFW, 30%), and the Tuesday and Thursday Commuter (TT, 13%). These profiles remained highly stable over time, with the vast majority of individuals staying in the same profile across consecutive measurement waves. None of the nine contextual policy factors examined reached statistical significance. However, directional patterns suggest that perceived improvements in working from home possibilities and public transport frequency are most strongly associated with transitions away from peak-day commuting among TT commuters. At the same time, perceived improvements in these factors reinforce peak-day concentration among IFW commuters. These findings suggest that generic improvements to working conditions or infrastructure are insufficient to redistribute peak commuting demand. Effective peak spreading may require targeted, day-specific interventions directed at the groups that contribute most to Tuesday and Thursday concentration.

Keywords: working from home, commuting behaviour, weekly structure, latent class analysis, latent transition analysis, peak spreading, hybrid work, commuting profiles, travel behaviour, the Netherlands.

EXECUTIVE SUMMARY

Working from home (WFH) has fundamentally reshaped commuting behaviour in the Netherlands. More than half of the Dutch working population now regularly works from home, with office attendance becoming increasingly concentrated on Tuesdays and Thursdays. This concentration puts disproportionate pressure on road and public transport networks on these peak days, presenting a key challenge for Dutch mobility policy. The national Aanpak Spreiden en Mijden 2025-2027 programme explicitly aims to spread commuting demand more evenly across the week. However, current policy monitoring focuses on how often people work from home, rather than which days they choose to do so. Consequently, it remains unclear whether the observed concentration on Tuesdays and Thursdays reflects a single behavioural pattern or several distinct groups, and how individuals can be steered away from peak days.

This study addresses this gap by conceptualising working from home not as a frequency, but as a weekly structure defined as the specific combination of office and WFH days from Monday to Friday. This operationalisation captures both how often individuals commute and which days they do so on. The central research question is:

How does the weekly structure of commuting behaviour evolve over time at the individual level, and which contextual policy factors are associated with transitions between distinct commuting profiles?

The analysis draws on longitudinal survey data from the Landelijk Reizigersonderzoek (LRO), a nationwide travel survey conducted annually by the Dutch Ministry of Infrastructure and Water Management. Three sub-questions were addressed sequentially: (SQ1) trends in commuting and WFH behaviour across waves, based on the complete working population per wave (8,169 in 2023, 8,330 in 2024 and 8,674 in 2025); (SQ2) identification of distinct commuting profiles using latent class analysis (LCA); and (SQ3) transitions between profiles and their associated contextual policy factors using latent transition analysis (LTA). SQ2 and SQ3 are based on a balanced panel of 1,026 respondents present in all three waves, reduced to 612 after excluding non-workers and full-time home workers.

Commuting behaviour remained largely stable across all three measurement waves. Peak arrivals were consistently highest on Tuesdays and Thursdays throughout the observation period, with the ranking of weekdays by peak arrival volume remaining unchanged. Fixed commuting patterns and increasingly fixed working hours left little scope for spontaneous redistribution of commuting demand, helping to explain the persistent peak concentration. WFH increased slightly, with the proportion of non-home workers falling from 53% in 2023 to 49% in 2025, while fixed WFH day patterns became slightly more common. Social motivations, particularly the desire for contact with colleagues, remained the dominant reason for office attendance. Conversely, only 2-3% reported working from home specifically to avoid peak hours. Employer policy and flexibility were consistently rated as the most influential factors in shaping commuting and WFH decisions across all waves.

The LCA identified three distinct weekly commuting profiles, illustrated in Figure 0.1. The Moderate Commuter (MC, 57%) commutes on all five working days at moderate frequencies. They work from home an average of 0.83 days per week and are mainly concentrated in healthcare. The Intensive Full-Week Commuter (IFW, 30%) commutes almost daily, works from home infrequently (M = 0.17) and has the shortest commute distance of all profiles. This profile is concentrated in agriculture and industry, and small organisations where physical presence is required. The Tuesday and Thursday Commuter (TT, 13%; relabelled Selective Commuter, SC, in the LTA) selectively commutes on Tuesdays and Thursdays, works from home most frequently (M = 1.77), has the longest commute distance (42.7 km) and is concentrated in large public sector organisations. Beyond these structural differences, the TT profile underwent a within-profile reorganisation between 2023 and 2024, in which Wednesday and Friday attendance dropped to near

zero while Tuesday attendance increased sharply – a shift invisible to frequency-based approaches, as the total number of commuting days remained constant.

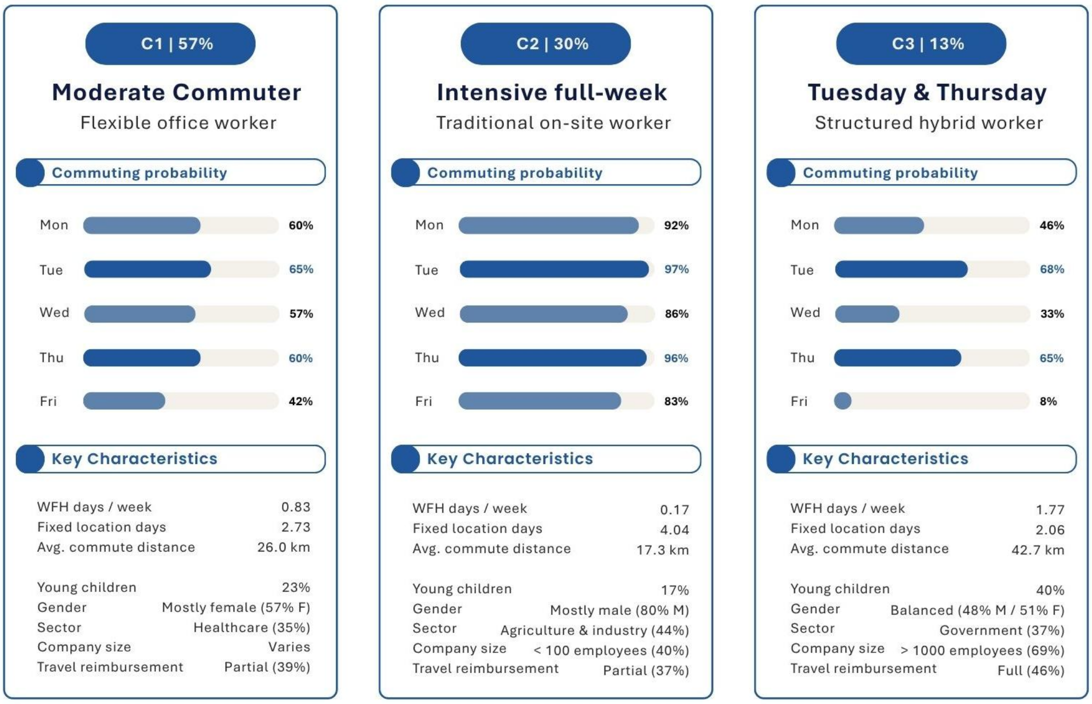

Figure 0.1 Overview of the three commuting profiles

The LTA revealed that weekly commuting patterns are highly resistant to change, with the vast majority of individuals remaining in the same profile across consecutive waves. None of the nine contextual policy factors reached statistical significance, which may be partly due to the small analytical sample size (N = 612). Nevertheless, directional patterns in the transition matrices were informative. The strongest associations with transitions from the SC to the MC profile were found with perceived improvements in WFH possibilities and public transport frequency (around 71% and nearly 100%, respectively), though both simultaneously pushed IFW commuters towards the SC profile, limiting their overall peak-spreading potential. The possibility to meet online was the only factor with a meaningful directional effect for IFW commuters (around 6% towards MC), though its overall effect was mixed due to simultaneous increases in commuting intensity among other profile groups. Financial incentives and scheduling flexibility had negligible redistributive effects, while infrastructure improvements were primarily associated with increasing peak-day concentration among IFW commuters.

These findings have direct implications for Dutch mobility policy. The high stability of commuting profiles suggests that improvements to working conditions or infrastructure are unlikely to substantially redistribute peak demand. Effective peak spreading may require targeted, day-specific interventions that reduce the incentive to be present on Tuesdays and Thursdays. The SC profile contributes most directly to peak demand and may have the greatest capacity to redistribute office attendance. Employer-level measures that make WFH genuinely possible on peak days, combined with team-level scheduling agreements and day-specific public transport improvements, may offer the most promising ways of redistributing commuting demand. Given the exploratory nature of the LTA findings, the recommendations in this study should be understood as evidence-informed directions rather than definitive prescriptions.

Several limitations apply. The small analytical sample (N = 612) may have reduced the statistical power in the LTA, the contextual policy factors reflect perceptions rather than objective measures, and the sample may not fully represent workers for whom WFH is a realistic option.

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NOMENCLATURE

LIST OF ABBREVIATIONS

Abbreviation	Definition
BIC	Bayesian Information Criterion
BVR	Bivariate Residual
CoSEM	Complex Systems Engineering and Management
LCA	Latent Class Analysis
LL	Log-likelihood
LRO	Landelijk Reizigersonderzoek
LTA	Latent Transition Analysis
PT	Public transport
WFH	Working from home

1. INTRODUCTION

1.1 BACKGROUND: COMMUTING BEHAVIOUR AND WORKING FROM HOME

Travel behaviour in the Netherlands has undergone a structural change in recent years, particularly with regard to commuting patterns. The traditional five-day working week, which was once characterised by fixed office days and predictable peak times, is no longer the norm (M. de Haas et al., 2020). Commuting demand is becoming increasingly concentrated on specific days of the week, putting disproportionate pressure on road and public transport networks. Tuesdays and Thursdays have become dominant office days, with substantially lower volumes on Mondays, Wednesdays and Fridays (M. de Haas, 2023).

A key driver of this transformation is the growing prevalence of working from home (WFH). Although remote working arrangements were gradually becoming more common prior to 2020 due to digitalisation and changes in labour market structures, the COVID-19 pandemic accelerated this development (Beck & Hensher, 2020; M. de Haas et al., 2020). Importantly, elevated levels of WFH have persisted since the pandemic ended, suggesting that it has become a structural feature of work organisation and mobility, rather than being a temporary response to exceptional circumstances (Jain et al., 2022).

According to recent statistics, over 5 million people in the Netherlands worked from home occasionally or regularly in 2023, accounting for around 52% of the working population (CBS, 2024). This proportion is higher than in any other EU country. Prior to the pandemic, the proportion of employees working from home was substantially lower at around 30% (Kennisinstituut voor Mobiliteitsbeleid, 2025). Additionally, in 2023, employees working from home spent an average of around 15 hours per week working remotely, equivalent to almost two full working days (CBS, 2024). These figures suggest that hybrid working has become the norm, with most employees now combining office attendance with WFH within the same week, rather than working remotely full-time.

Commuting accounts for a significant proportion of daily travel demand and is heavily concentrated during peak hours, resulting in reduced accessibility and unreliable travel times (Arnott et al., 1993). Managing this peak concentration on Tuesdays and Thursdays remains a central challenge in the Dutch transport system (Kennisinstituut voor Mobiliteitsbeleid, 2025; Small & Verhoef, 2007). In response, Dutch mobility policy is promoting flexible working arrangements as a key strategy for reducing peak congestion. The national programme Aanpak Spreiden en Mijden 2025-2027 encourages employers and employees to adopt more flexible working and commuting behaviours, with the explicit aim of steering commuters away from these peak days and distributing office attendance more evenly across the week (Ministerie van Infrastructuur en Waterstaat, 2025). Previous programmes, such as Beter Benutten, and various regional mobility management initiatives have similarly promoted flexible working and travel demand management to alleviate congestion (Rijkswaterstaat, 2015).

Working from home is not only a driver of peak concentration, but is also increasingly recognised as a promising instrument for spreading commuting demand across the week. When fewer commuters travel simultaneously during peak periods, the pressure on transport infrastructure can be alleviated without the need for major capacity expansions (Hensher et al., 2021; Small & Verhoef, 2007). However, WFH does not necessarily lead to less overall mobility; rather, it leads to a redistribution of travel over time (Buitelaar et al., 2021). The way in which commuting demand is redistributed depends on which days employees go to the office, and therefore on how WFH is structured across the week rather than just how frequently it occurs.

Existing research on WFH has predominantly focused on the frequency of remote working, typically measuring how many days per week are spent working from home (Barrero et al., 2021; Beck & Hensher, 2020; M. de Haas et al., 2020). While this provides insight into overall intensity, it offers limited understanding of how WFH days are arranged across specific weekdays. Consequently, it remains unclear whether the observed concentration of office attendance on Tuesdays and Thursdays reflects a single behavioural pattern or several distinct groups combining office and WFH days in different ways. Aggregate statistics may therefore mask meaningful variation in weekly routines, making it difficult to assess which segments of the working population contribute most to peak congestion on specific days.

Beyond identifying these distinct patterns, it is equally important to understand how people end up in them. The concentration of office attendance on Tuesdays and Thursdays is not random – it may reflect employer scheduling norms, social coordination among colleagues, or habitual behaviour that has solidified over time. Understanding how individuals adopt these patterns and why they persist is key to explaining how these undesirable concentrations arise, and whether policy can realistically steer people away from them. Therefore, a more detailed understanding of recurring weekly commuting patterns is needed to inform targeted interventions rather than one-size-fits-all approaches. This study addresses this gap by conceptualising WFH not as a frequency, but as a weekly structure – capturing which specific days individuals commute, rather than just how often.

1.2 Theoretical Background, Previous Research and Knowledge Gaps

The previous section established the societal relevance of this research by showing how working from home is reshaping commuting demand in the Netherlands and its implications for congestion management. This section addresses its academic relevance by outlining the theoretical background, synthesising existing empirical research on WFH and commuting behaviour, and identifying the scientific knowledge gaps this study addresses.

1.2.1 Theoretical Background

Working from home (WFH), also known as telecommuting or teleworking, is a work arrangement whereby employees perform their job tasks from home instead of travelling to a traditional workplace (Allen et al., 2015). Over the past decades, the development of information and communication technologies (ICT) has enabled WFH, as digital tools allow employees to communicate, collaborate, and access organisational systems from outside the office (Cheng et al., 2024).

Various teleworking arrangements exist, ranging from fully remote work to hybrid models, where employees divide their time between home and the office. Prior to the pandemic, WFH had only a limited influence on travel behaviour, as many organisations maintained strict remote work regulations and commuting patterns remained stable (Kasraian et al., 2018). The pandemic introduced many employees to working from home for the first time, and a significant proportion continued to do so afterwards, indicating that the shift was not merely situational, but reflected a genuine change in work preferences and organisational norms (Jain et al., 2022).

In this study, WFH is not conceptualised as a frequency-based measure indicating how many days per week an individual works from home, but rather as a weekly structure. This is defined as the specific combination of office and WFH days across the five working days of the week (Monday to Friday). This definition not only captures the number of days an individual works from home, but also the specific weekdays on which they commute or work from home – meaning two individuals with the same WFH frequency may have fundamentally different commuting patterns.

The relationship between working from home and commuting behaviour is multifaceted and is shaped by a variety of interconnected factors, including socio-demographic factors, contextual factors (such as job-related and mobility-related characteristics), and experiential factors (Ory & Mokhtarian, 2006). These determinants, in turn, shape various mobility effects, including changes in departure times, transport mode choices, commuting distance, and the number of trips made. Chapter 2 will address a deeper examination of the specific determinants and their effects, including how they interact and shape individual WFH behaviour.

The complexity and interplay of these factors reflect what travel behaviour research commonly refers to as behavioural heterogeneity. Heterogeneity refers to systematic differences in behavioural patterns across individuals or groups within a population (Train, 2002). Heterogeneity may be observed, explained by measurable characteristics, or unobserved, reflecting latent differences in preferences, constraints or decision-making processes (Greene & Hensher, 2003). In the context of WFH, this implies that individuals may organise their weekly work location choices in fundamentally different ways.

Beyond heterogeneity at a given point in time, WFH behaviour may also evolve. Mobility behaviour is not static and can change in response to life events, policy interventions, or changes in contextual conditions (Gärling & Axhausen, 2003; Schoenduwe et al., 2015). While behaviour may remain stable due to established habits or organisational routines, changes in external conditions may trigger behavioural adjustments (Schoenduwe et al., 2015). Capturing such dynamics requires a longitudinal approach, in which the same individuals are followed over multiple points in time, making it possible to observe whether and how commuting patterns change. In the context of this study, this raises the question of whether individuals transition between weekly commuting patterns over time and what motivates them to adopt or maintain patterns that concentrate office attendance on peak days.

1.2.2 Previous Research

This section examines how WFH behaviour has been studied empirically, with particular attention to its relationship with commuting behaviour, heterogeneity and dynamics. Chapter 2 will provide a more in-depth exploration of the literature on these topics.

To synthesise studies examining behavioural developments over time, this literature review focuses on research employing longitudinal or panel data designs. Based on a structured review of the literature, eleven academic studies were selected for inclusion. Appendix A provides an overview of the search strategy and the included longitudinal studies, while Table A.1 and Table A.2 summarise their key characteristics and analytical focus.

As shown in Table A.2, all of the reviewed studies operationalise WFH as either a binary indicator or a frequency-based measure. In other words, WFH is usually measured by whether an individual works from home, or by the number of days or hours worked from home per week. Therefore, none of the reviewed studies captures how WFH is distributed across specific weekdays within the working week.

Within this body of research, the majority of studies examine the associations between changes in WFH intensity and mobility outcomes. For instance, R. Faber et al. (2023) analyse the relationship between changes in WFH and commute travel time, and Böhnen & Kuhnimhof (2024) examine the link between sustained levels of WFH and changes in commuting distance over time. Similarly, Rüger et al. (2024) evaluate the reductions in weekly commuting time associated with an increase in WFH. Together, these studies consistently demonstrate that WFH is associated with measurable changes in commuting behaviour, although the size of the effect differs across contexts and population groups.

Heterogeneity across individuals is also acknowledged. For example, Victoriano-Habit & El-Geneidy (2024) demonstrate that the relationship between WFH and active travel is highly dependent on local residential accessibility. Meanwhile, Pedreira Junior & Pitombo (2024) identified three different substitution patterns of work trips by WFH, showing that these patterns differ in terms of the persistence with which WFH is adopted post-pandemic. Furthermore, Kroesen et al. (2023) reveal that different groups of travellers follow structurally different post-pandemic recovery trajectories in train usage, with WFH playing a key role in explaining how people adapted their travel habits. Together, these findings suggest that the effects of WFH are not uniform across the population.

Several studies explicitly address behavioural change over time. For example, Xie & Liao (2025) analyse the bidirectional effects of WFH, commute distance, mode preference, and car use. Similarly, Kroesen et al. (2022) investigate the dynamic interactions between WFH, train use, and attitudes, capturing the reciprocal relationships between attitudes and behaviour over time. Meanwhile, Magriço et al. (2024) compared pre-pandemic rail commuting with 2023 survey data, finding that employer policies on office attendance significantly moderated whether patterns returned to pre-pandemic levels. Together, these studies emphasise that commuting behaviour is not fixed and that policy interventions, such as employer scheduling norms, can actively drive transitions.

> Overall, existing research shows that WFH is systematically related to commuting behaviour, that workers do not respond uniformly and that their travel patterns may evolve over time. At the same time, however, WFH is consistently operationalised as a binary or frequency-based variable, focusing on how often individuals work from home rather than on how WFH behaviour is structured across specific weekdays.

1.2.3 Scientific Knowledge Gaps

Despite the empirical advances outlined in Section 1.2.2, three interrelated gaps remain in the existing literature.

1. **Operationalisation: WFH as a weekly structure**
   Firstly, there is a conceptual gap in the way that WFH is operationalised. WFH is consistently measured as either a binary indicator or a frequency-based variable. However, it does not capture how work is distributed across specific weekdays. Whether someone works from home on Mondays and Fridays, or on Tuesdays and Thursdays, is behaviourally and policy-relevant, yet this distinction is absent from existing measurement frameworks.
2. **Heterogeneity: Individual differentiation in weekly commuting patterns**
   Secondly, the lack of a weekly structure perspective means that behavioural heterogeneity in commuting patterns has not been systematically investigated. While studies acknowledge that individuals respond differently to WFH, these differences are analysed in terms of effect size rather than qualitative, distinct weekly patterns. Therefore, it remains unclear whether individuals can be grouped into meaningful profiles of weekly commuting behaviour, and what factors shape membership of each group.
3. **Dynamics: Stability and transitions of commuting patterns**
   Thirdly, although some studies analyse behavioural change over time, their focus is primarily on changes in WFH intensity or mobility outcomes. It remains unclear whether individuals maintain stable weekly routines or transition between different commuting patterns over time. Moreover, it remains unclear which factors drive these transitions, particularly contextual policy factors, as these are most amenable to policy intervention.

1.3 Research Objective and Research Questions

This section outlines the research objectives and the corresponding research questions, which have been formulated based on the societal and scientific relevance as identified in previous sections.

1.3.1 Research Objective

Building on the identified knowledge gaps in Section 1.2.3, the following research objective is formulated:

> To gain insight into the weekly structure of individuals' commuting behaviour by identifying distinct commuting profiles and examining whether and how individuals transition between these profiles over time. Additionally, this study analyses the contextual policy factors associated with these transitions, particularly those amenable to policy intervention, in order to understand their implications for commuting demand and peak congestion management in the Netherlands.

1.3.2 Research Questions

Based on the research objective, as defined in Section 1.3.1, the following main research question is formulated:

> **How does the weekly structure of commuting behaviour evolve over time at the individual level, and which contextual policy factors are associated with transitions between distinct commuting profiles?**

To answer the main research question in a structured manner, three sequential sub-questions are formulated.

1. **SQ1:** What are the observed trends in commuting and working from home behaviour, and the factors associated with these behavioural decisions, across the three measurement waves (2023, 2024 and 2025)?
2. **SQ2:** Which distinct commuting profiles can be identified based on individuals' commuting behaviour per day of the week?
3. **SQ3:** How do individuals transition between commuting profiles over time, and which contextual policy factors are associated with these transitions?

Together, these sub-questions address the main research question. The first sub-question examines observed trends across the three measurement waves: 2023, 2024 and 2025. The analysis focuses on changes in commuting and WFH behaviour, as well as trends in the factors associated with decisions for this behaviour. This provides a descriptive foundation for the study and establishes whether these patterns have remained stable or shifted within the working population.

The second sub-question focuses on identifying distinct commuting profiles based on individuals' commuting behaviour throughout the week. By grouping individuals with similar configurations of commuting patterns across the week, this step captures the heterogeneity in weekly WFH behaviour within the working population.

The third sub-question builds on these profiles by examining how individuals transition between the commuting profiles over time. This analysis provides insight into the temporal dynamics of weekly commuting behaviour by investigating which contextual policy factors are associated with transitions between the profiles. This information can be used to inform evidence-based commuting policy.

1.4 Research Approach and Research Scope

Building on the research definition presented in previous sections, this section outlines the study's overall approach and scope. First, it introduces the research approach in Section 1.4.1, including a research overview. Then, the specific scope and boundaries of the research are outlined in Section 1.4.2.

1.4.1 Research Approach

Figure 1.1 provides an overview of the research process and explains the research approach, which is structured in three phases: 1) Conceptualisation, 2) Operationalisation and 3) Integration.

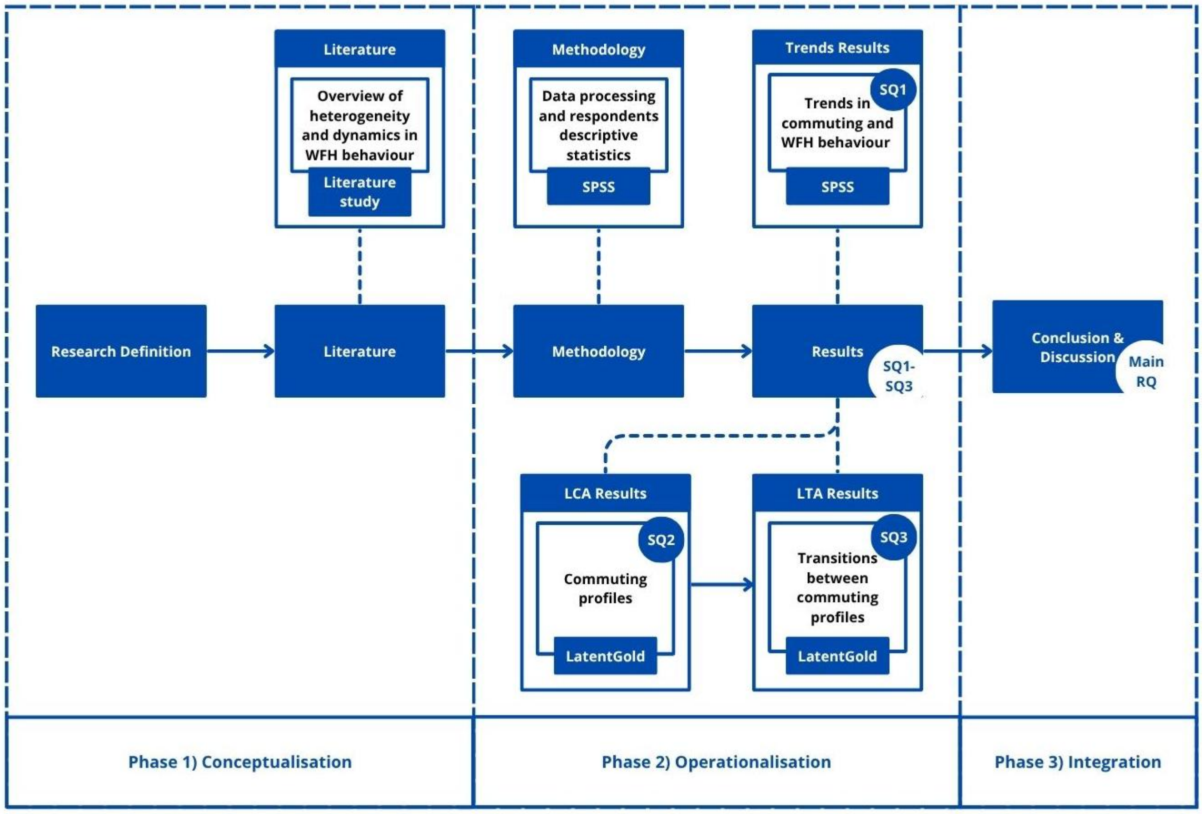

Figure 1.1 Research overview

Phase 1 (Conceptualisation) encompasses the research definition presented in this chapter and the literature review in Chapter 2. The literature review examines the determinants of WFH behaviour, the drivers of behavioural change, the mobility implications of WFH, and the heterogeneity and dynamics observed across the working population. Based on a synthesis of longitudinal studies, analytical limitations in existing approaches are identified, informing the conceptual framework introduced in Chapter 2.

Phase 2 (Operationalisation) includes the methodology and empirical analysis. This study adopts a quantitative, longitudinal research approach based on secondary survey data from the Landelijk Reizigersonderzoek (LRO) to analyse the weekly structure of commuting behaviour and its development over time. Quantitative longitudinal approaches are particularly well suited to studying behavioural heterogeneity and temporal dynamics at the individual level, as they enable the systematic analysis of behavioural patterns and changes within individuals across multiple time points (Creswell, 2009; Vij et al., 2013). In mobility research, latent variable modelling techniques are commonly used to identify unobserved behavioural heterogeneity in large-scale survey data, enabling latent behavioural profiles to be inferred from patterns in observable variables (McCutcheon, 2011; Rafiq & McNally, 2021).

The methodology chapter outlines the research methods and data used in this study. First, the analytical methods are discussed, followed by a description of the data source, how the data was prepared, how the key variables were operationalised, and how representative the data is.

The empirical analysis proceeds in three steps. First, descriptive statistics are used to analyse trends in commuting and working from home behaviour across the three measurement periods: 2023, 2024 and 2025. Examining these trends provides insight into the current state of commuting and WFH behaviour within the working population, as well as how factors associated with these behavioural decisions have developed over time. This establishes the broader behavioural context in which the commuting profiles identified in the subsequent analyses are situated.

Secondly, latent class analysis (LCA) is employed to identify different weekly commuting profiles based on individuals' commuting behaviour throughout the week. LCA groups individuals with similar commuting patterns into latent profiles, thereby capturing heterogeneity in weekly commuting behaviour within the working population (Collins & Lanza, 2010). This step corresponds to the second research sub-question, which focuses on identifying distinct commuting profiles.

Thirdly, latent transition analysis (LTA) is employed to analyse how individuals transition between these commuting profiles over time. LTA extends LCA by modelling changes in latent class membership across multiple observation moments and estimating transition probabilities between the profiles (Collins & Lanza, 2010). This enables the temporal dynamics of weekly commuting behaviour to be analysed, and contextual policy factors associated with these transitions to be examined (M. C. de Haas et al., 2018; Haustein & Kroesen, 2022). This step corresponds to the third research sub-question, which focuses on transitions between commuting profiles over time. Both LCA and LTA are conducted using the LatentGOLD software.

Phase 3 (Integration) synthesises the findings in the conclusion and discussion chapter, where the results are interpreted and related to broader research context. The main research question is addressed, scientific contributions are outlined, policy recommendations are formulated, and limitations and directions for future research are discussed.

1.4.2 Research Scope

This study focuses on the Netherlands, given the high prevalence of WFH arrangements and their potential impact on commuting demand and mobility patterns (CBS, 2024). It analyses the structure and evolution of weekly commuting behaviour among the Dutch working population aged 18 years and older. The empirical analysis draws on data from the Landelijk Reizigersonderzoek, a national panel survey conducted annually since 2019. The study focuses on respondents who participated in three consecutive waves (2023, 2024, and 2025), enabling a longitudinal analysis of the same individuals over time.

The study is further limited to individuals who are employed and commute to a fixed or external work location outside the home on at least some days of the week, as fully remote workers do not make commuting trips and therefore cannot be assigned a weekly commuting profile. The analysis focuses exclusively on whether a commuting trip is made on each day of the working week, from Monday to Friday. The mode of transport used on commuting days is outside the scope of this study, as the focus is on the day-specific structure of commuting behaviour rather than modal choices. Furthermore, while various factors may shape commuting behaviour, this study focuses specifically on contextual policy factors, as these are most directly amenable to policy intervention.

Although the empirical analysis is specific to the Netherlands, the analytical approach and resulting insights could be applicable to other countries experiencing comparable shifts in WFH and commuting behaviour.

1.5 CoSEM Relevance

This research is conducted as part of the MSc programme in Complex Systems Engineering and Management (CoSEM) at Delft University of Technology. The study examines commuting and working from home behaviour as a complex socio-technical system shaped by the interactions of individuals, organisations and policy frameworks.

Adopting a longitudinal approach reflects the CoSEM emphasis on analysing dynamic and heterogeneous behaviour in interconnected systems. The focus on behavioural change and policy-relevant outcomes is consistent with the programme's goal of supporting informed decision-making in complex, real-world situation contexts by integrating technical analysis with institutional and societal considerations.

1.6 Reading Guide

Figure 1.2 presents the overall structure of this thesis. Chapter 1 establishes the research definition, including the background, theoretical background, research objectives and questions, research approach and scope, and the CoSEM relevance. Chapter 2 provides a literature review examining the determinants and mobility implications of WFH, previous research on WFH and commuting behaviour, the limitations of existing approaches, and the conceptual framework. Chapter 3 outlines the methodology, covering the research methods – including latent class analysis and latent transition analysis – as well as the research data, including the data source, preparation, operationalisation, and representativeness. Chapter 4 presents the empirical results in three stages. First, observed trends in commuting and WFH behaviour are examined across the three measurement waves. Second, the results of the latent class analysis are presented, including the identification of distinct commuting profiles. Third, the results of the latent transition analysis are discussed, examining transitions between profiles over time and the contextual policy factors associated with these transitions. The chapter concludes with a discussion of the results, reflecting on the key findings in relation to existing literature. Finally, Chapter 5 presents the conclusion and discussion, addressing the main research question, outlining the scientific contributions of this study, providing policy recommendations, reflecting on the limitations of the study and directions for future research, and closing with a personal reflection and final remarks.

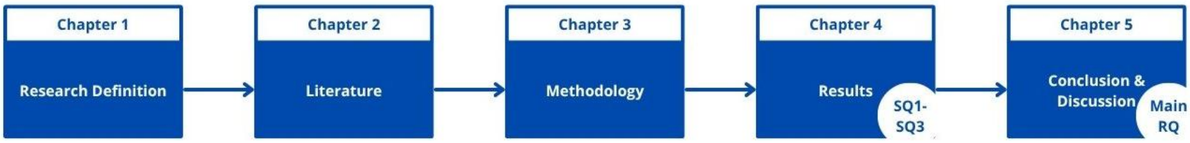

Figure 1.2 Reading guide

Chapter Summary

What do we know? Travel behaviour in the Netherlands has undergone a structural shift, driven by the increasing popularity of working from home. Currently, over half of the Dutch working population works from home regularly, with office attendance increasingly concentrated on Tuesdays and Thursdays. This concentration puts disproportionate pressure on road and public transport networks on these days, making peak congestion a key policy challenge. Dutch mobility policy actively promotes flexible working arrangements to spread commuting demand more evenly across the week.

What do we not yet know? Existing research confirms that WFH is systematically associated with changes in commuting behaviour, that individuals do not respond uniformly and that behavioural patterns may evolve over time. However, WFH is consistently measured as a frequency-based variable – indicating how often individuals work from home – rather than as a weekly structure capturing which specific days they work from home. Consequently, it remains unclear whether the observed concentration of office attendance reflects a single behavioural pattern or several distinct groups, how individuals end up in patterns that concentrate commuting on peak days, how stable these patterns are, and what factors drive transitions between them.

Why does this research fill that gap? This study addresses these gaps by reconceptualising WFH not as a frequency, but as a weekly structure – capturing which specific days individuals commute, rather than just how often. This distinction matters: two individuals working from home the same number of days may have fundamentally different commuting patterns depending on which days they choose – a difference that frequency-based approaches cannot detect. By applying latent class and latent transition analysis to longitudinal survey data from the Dutch working population, the study identifies distinct commuting profiles and examines how and if individuals transition between them, providing insight into the behavioural heterogeneity and dynamics underlying peak-day concentration. This allows for the design of more targeted policy interventions to effectively manage peak congestion in the Netherlands.

2. LITERATURE REVIEW

Working from home has fundamentally reshaped commuting behaviour, yet existing research leaves important questions about its structure and dynamics unanswered. This chapter reviews the empirical and conceptual literature on WFH in the context of travel behaviour research. It examines the determinants that influence individual WFH behaviour, the drivers of behavioural change, the mobility implications of WFH, and the heterogeneity and dynamics observed across the working population. Based on a synthesis of longitudinal studies, analytical limitations in existing approaches are identified. These limitations inform the conceptual framework introduced in Section 2.4, which conceptualises WFH as a structured weekly pattern integrating behavioural profiles and transitions.

2.1 WORKING FROM HOME: DETERMINANTS AND MOBILITY IMPLICATIONS

WFH is not randomly distributed across the working population. Its likelihood and frequency are shaped by a range of structural determinants that vary between individuals and contexts. Section 2.1.1 examines these determinants of WFH, Section 2.1.2 discusses drivers of behavioural change, and Section 2.1.3 examines the mobility implications of WFH. Together, these sections provide the individual-level foundation for understanding the heterogeneity and dynamics of commuting behaviour, as discussed in subsequent sections.

2.1.1 DETERMINANTS OF WORKING FROM HOME BEHAVIOUR

Previous studies have shown that the likelihood and frequency of WFH are influenced by a combination of socio-demographic, job-related, residential and experiential factors (Ory & Mokhtarian, 2006). These factors do not operate in isolation: together, they determine whether WFH is both possible and desirable for an individual.

Socio-demographic characteristics are among the most consistent predictors of WFH adoption. Employees with higher levels of education tend to work in knowledge-intensive occupations that offer greater opportunities for WFH, and higher incomes are often associated with greater job autonomy and access to flexible working arrangements (Mokhtarian & Salomon, 1997). Gender may also play a role, as women are more likely to encounter cultural barriers to WFH, particularly in workplaces with a strong ideal worker culture (Lott & Abendroth, 2020). Age is another factor, with younger professionals generally being more likely to work from home. Furthermore, household composition and size matter: individuals with caregiving responsibilities may be more inclined to work from home in order to balance work and private life. However, the presence of young children can introduce distractions that make WFH more challenging (Dunatchik et al., 2021).

Job-related characteristics are another important factor that enables WFH. Companies that require physical presence are, by definition, incompatible with WFH. In contrast, knowledge-intensive sectors, such as IT and business services, demonstrate higher levels of WFH due to greater job autonomy and digitalisation (Elldér, 2019). At an organisational level, larger firms tend to have the digital infrastructure and formal policies in place to support flexible working. In contrast, smaller firms may rely more on direct oversight, which limits the uptake of WFH (Criscuolo et al., 2021). Financial arrangements can reinforce this: commuting reimbursement policies may reduce the financial incentive to avoid commuting, making WFH less attractive for some employees (Reiffer et al., 2023).

Residential characteristics introduce a spatial dimension. Commute distance affects the appeal of WFH, as greater distances make avoiding the daily commute more attractive (Moeckel, 2017). Furthermore, the urbanisation level of an individual's place of residence may affect WFH adoption, as individuals living in more urbanised areas typically have better access to workplaces and public transport, potentially reducing the incentive to work from home.

Finally, ongoing behaviour is shaped by experiential factors, which refer to individuals' subjective assessments of prior WFH experiences. Positive experiences, such as increased productivity or a better work-life balance, encourage the willingness to continue WFH, whereas negative experiences, such as social isolation or difficulty separating work and private life, may discourage it (Mokhtarian & Salomon, 1997).

As shown in Figure 2.1, individual WFH behaviour arises from the interaction between socio-demographic, contextual (job-related and residential) and experiential factors. It is, in turn, associated with various mobility effects, including changes in departure times, transport mode choice, commuting distance, and number of trips (Ory & Mokhtarian, 2006). Although WFH has also been linked to broader effects on mental well-being and work-life balance (Allen et al., 2015; Gajendran & Harrison, 2007), this study exclusively examines its implications for travel behaviour.

> Taken together, these determinants mean that WFH adoption is unevenly distributed across the population. From a policy perspective, this is important because if certain groups are more or less likely to work from home, commuting demand will not spread evenly, even as overall WFH rates increase. Therefore, understanding who works from home and why is a necessary starting point for analysing how commuting patterns are distributed across the week.

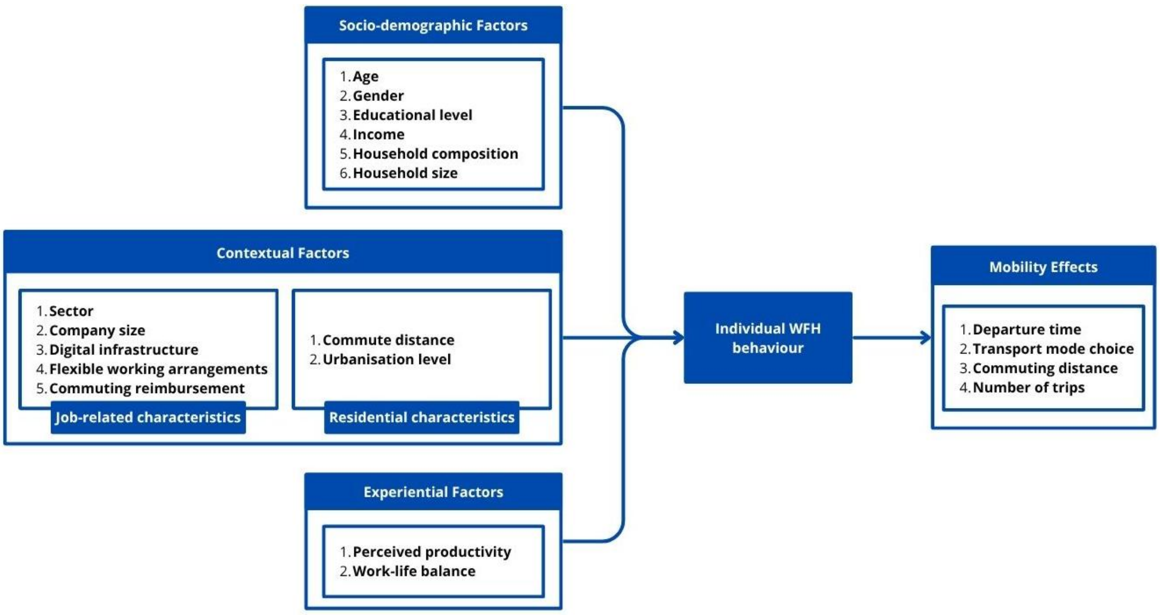

Figure 2.1 Conceptual framework of determinants and mobility effects of individual WFH behaviour

2.1.2 Drivers of Behavioural Change

Beyond the individual-level determinants discussed above, WFH behaviour is not static. Research on mobility behaviour has shown that behavioural change is often triggered by life events, such as changing jobs, moving house, or having a child, that disrupt established routines and create opportunities for new patterns to emerge (Gärling & Axhausen, 2003; Schoenduwe et al., 2015). In the context of WFH, such events may prompt individuals to reconsider their work location choices and transition between commuting patterns.

The Theory of Planned Behaviour helps to explain why patterns remain stable in the absence of such triggers (Ajzen, 1991). According to this theory, behaviour is shaped not only by objective circumstances, but also by attitudes towards the behaviour, perceived behavioural control, which refers to the degree to which individuals feel able to change their behaviour, and subjective norms, which reflect the perceived social pressure from others to behave in a certain way. When colleagues consistently attend the office on the same days, these norms can reinforce existing patterns and make transitions less likely, even when individuals have the formal flexibility to change.

However, not all triggers of change are amenable to policy intervention. Life events and individual circumstances are largely beyond the control of policymakers. Contextual policy factors operating at organisational or transport system levels can directly affect perceived behavioural control and are therefore more actionable. As illustrated in Figure 2.2, two categories are particularly relevant. Employer-level factors, such as the possibility to work from home, the possibility to meet online, flexible working hours, WFH allowances, travel reimbursements and parking tariffs, may shift as a result of policy revisions or changes in organisational norms (Reiffer et al., 2023). Commute route conditions, including car travel conditions, public transport availability, cycling infrastructure and park-and-ride options, are shaped by the broader transport environment and fall outside the direct control of individual commuters (Ashour & Shen, 2025).

This study therefore focuses on these contextual policy factors as the primary drivers of transitions between commuting profiles. Chapter 3 discusses how these factors are operationalised in this study.

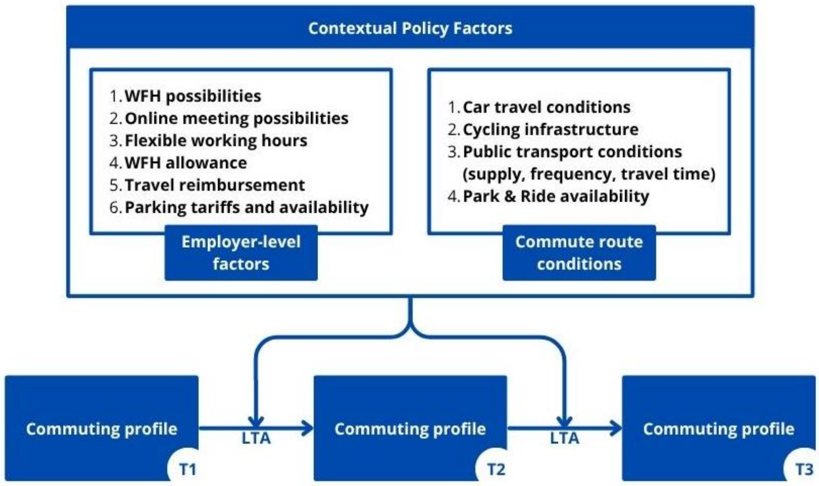

Figure 2.2 Contextual policy factors associated with changes in commuting behaviour over time

2.1.3 Mobility Implications of Working from Home

WFH influences travel behaviour through three main mechanisms: substitution, complementarity and modification. Together, these mechanisms help to explain why the relationship between WFH and travel demand is more complex than simply a reduction in commuting trips.

The substitution effect refers to the replacement of physical commuting with remote working, which reduces the total number of commuting trips (Andreev et al., 2010). The complementarity effect, however, suggests that time saved from commuting may be spent on additional non-work travel. This is linked to the concept of a constant travel time budget: individuals tend to maintain a relatively stable amount of daily travel time. This means that reductions in commuting time may be partially offset by an increase in the time spent on other trips, resulting in the so-called 'rebound effect' (Andreev et al., 2010; Elldér, 2020). However, as these additional trips typically occur outside peak hours, they may still contribute to spreading peak demand, even if total travel time remains constant.

Beyond changes in trip frequency, WFH may also modify the characteristics of commuting behaviour without necessarily reducing its overall volume. For example, flexible working arrangements can shift departure times towards off-peak periods, encourage the use of active transport modes such as walking and cycling, or alter commuting distances (Andreev et al., 2010). These modification effects mean that WFH does not uniformly reduce travel demand, but instead reshapes how, when and by what means people travel. Therefore, the modification effect is particularly relevant: if WFH leads to more dispersed departure times and greater use of active travel, it could help to spread peak demand without reducing the total number of commuting trips.

2.2 Previous Research on Working from Home and Commuting Behaviour

The conceptual relationships outlined in the previous section raise an important practical question: to what extent does WFH actually reduce commuting demand, and does this effect apply equally across the population? To answer this question, three issues must be addressed sequentially: first, whether WFH reduces commuting at all; second, whether this effect is uniform across the population; and third, whether these patterns are stable over time or subject to change. This section reviews the empirical evidence on each of these questions, drawing on longitudinal studies selected through a structured search procedure (see Appendix A). Together, they reveal what is currently known and where important gaps remain.

2.2.1 Working from Home and Commuting Outcomes

From a policy perspective, one of the most basic questions is whether working from home actually reduces the pressure on transport networks. If WFH leads to fewer or shorter commutes, it could help to relieve congestion during peak hours, which is a key objective of Dutch mobility policy. The empirical evidence broadly supports this expectation, though important qualifications must be made regarding the scale, timing and longer-term consequences of WFH adoption.

In terms of overall time savings, Rüger et al. (2024) found that any level of WFH was associated with an average reduction in weekly commuting time of around 14%, drawing on nearly two decades of Australian panel data. However, meaningful reductions only occurred when WFH accounted for a substantial proportion of working time. This is particularly relevant in the Dutch context, where the majority of the working population now combines office attendance with WFH within the same week, rather than working fully remotely.

A related question is how stable this relationship is over time, and whether findings from one period can be applied to another. R. M. Faber et al. (2023) address this directly by tracking Dutch workers throughout the pandemic using panel data from the Netherlands Mobility Panel (2017-2021) and separating the effects that occurred between and within individuals. They found that WFH reduced commute travel time consistently, both before and during the pandemic, while a positive effect on leisure travel was only observed before the pandemic. These findings demonstrate that the relationship between WFH and travel behaviour changed during this period and that pre-pandemic data should not be extrapolated uncritically to predict current travel patterns. For policymakers seeking to estimate future commuting demand, this is an important consideration. The behavioural consequences of WFH are not fixed, and the context in which it occurs shapes its effects.

Building on this, R. Faber et al. (2023) conducted a distinct study which looked further ahead by modelling the expected long-term effects of the structural increase in WFH and teleconferencing in the Netherlands. They noted that the average number of WFH hours has doubled compared to pre-pandemic levels. Their projections suggest reductions in distances travelled by train, car, and public transport of up to 9%, 5%, and 5%, respectively. Notably, the impact on cycling and walking is smaller, or even slightly positive, due to additional local trips made on WFH days. For peak-spreading policy, this distinction matters: while WFH may reduce motorised commuting, it does not eliminate local travel, and its net effect on network pressure depends on which trips and which days are affected.

A further complication concerns the longer-term residential adjustments that WFH may trigger. While the above studies focus on the direct effects on commuting time and distance, Böhnen & Kuhnimhof (2024) demonstrate that WFH also influences residential choices, and vice versa. Using German panel data, they found that workers with persistently high levels of WFH tended to accept longer commuting distances over time, while those with long commutes were more likely to increase their WFH. Crucially, these effects only show up when residential relocation occurred, meaning they unfold over years rather than immediately. For policymakers monitoring short-term trends, this is a relevant caution: the full consequences of WFH normalisation on travel demand may still be unfolding, and aggregate statistics may not yet reflect them.

2.2.2 Heterogeneity in Working from Home

The above studies treat the working population as a broadly homogeneous group, focusing on average effects. However, the consequences of WFH depend heavily on who is doing so and where. This distinction matters for peak-spreading policy, since uniform measures may affect different groups in very different ways.

A first illustration of this comes from the spatial context. Victoriano-Habit & El-Geneidy (2024) examined the effect of telecommuting during the pandemic on the frequency of active travel for non-work utilitarian purposes among Montreal workers. They found that this effect depended almost entirely on the level of local accessibility around the person's household. In neighbourhoods with high accessibility, increased WFH led to more active trips for non-work purposes, whereas in neighbourhoods with low accessibility, the effect was the opposite. This finding has broader implications: aggregate statistics on WFH and travel behaviour may obscure meaningful variations between groups, and policies designed around average effects may be ineffective for large segments of the population.

A second illustration comes from behavioural patterns themselves. Pedreira Junior & Pitombo (2024) tracked Brazilian workers throughout the pandemic, identifying three distinct substitution patterns: no or low, moderate, and intense. These groups differed in how much in-person work was replaced by WFH, and in how durable this change proved to be. While the no or low and moderate substitution groups had largely returned to pre-pandemic commuting patterns by late 2021, the intense substitution group continued to work from home. This finding is relevant beyond the Brazilian context as it suggests that the adoption of WFH does not follow a single trajectory within the working population but instead reflects qualitatively different pathways. For peak-spreading policy, it is important to realise that measures that work for one group may have little effect on another.

A third example comes from the Netherlands itself and is particularly relevant to this study. Kroesen et al. (2023) tracked train travel behaviour at eight different points in time after the onset of the pandemic, identifying six distinct recovery trajectories. Those with low levels of education who commuted frequently returned to near-pre-pandemic levels of train use, while highly educated commuters and those who travelled for mixed purposes continued to travel significantly less, even after all restrictions were lifted. This suggests a structural rather than temporary behavioural shift among specific groups. Interestingly, the shift towards WFH was found to be more pronounced than the shift towards private car use, indicating that WFH is a key driver of these diverging recovery pathways. For the Netherlands' peak-spreading policy, this finding is directly relevant: if different groups of commuters respond to WFH in structurally different ways, policies aimed at redistributing peak demand must account for this heterogeneity rather than assuming a uniform response.

While the above studies reveal meaningful heterogeneity in WFH adoption and its consequences for mobility, none of them examine how individuals organise their working days throughout the week.

Nevertheless, evidence from descriptive mobility statistics suggests that commuting demand is increasingly concentrated on specific weekdays. Using mobility data from the Netherlands Mobility Panel, M. de Haas (2023) demonstrates that office attendance is now more prevalent on Tuesdays and Thursdays, with substantially lower commuting volumes on Mondays, Wednesdays and Fridays. Similar patterns have been observed internationally. Barrero et al. (2023) analysed large-scale survey data on post-pandemic work arrangements in the United States and reported that hybrid workers tend to coordinate their office attendance in the middle of the week. This results in pronounced peaks in commuting demand between Tuesday and Thursday.

2.2.3 Behavioural Dynamics in Working from Home

Beyond heterogeneity in effect size, another question is whether WFH behaviour and its mobility consequences remain stable over time or evolve dynamically. Knowing that certain groups tend to be in the office on Tuesdays and Thursdays is only part of the picture. It is equally important to understand how individuals end up in these patterns, whether they persist over time and what might prompt a transition away from them. Without this dynamic perspective, policies can identify those who contribute to peak demand, but cannot steer them towards different behaviour.

Kroesen et al. (2022) examined precisely this dynamic using a four-wave longitudinal dataset from the Netherlands. They focused on the reciprocal relationships between WFH, train use, and travel-related attitudes during the pandemic. Their results showed that WFH and train use were substitutes for each other: working from home more frequently in one period was associated with using the train less in the next period, and vice versa. In addition to this substitution effect, they found that individuals who worked from home more frequently developed a greater fear of infection over time, which further reduced their train use. This reciprocal dynamic is consistent with cognitive dissonance theory, whereby people develop attitudes that align with their behaviours rather than the other way around. For policymakers, this finding is relevant because it suggests that behavioural change can be self-reinforcing: once commuting patterns shift, attitudes may follow and consolidate the new behaviour, making transitions between patterns less likely over time.

Building on this, Xie & Liao (2025) present the most comprehensive temporal evidence to date. They examined the dynamic relationships between WFH, commute distance, mode preference, and car use over a six-year period in the Netherlands. Their results confirm that WFH and car use are bidirectionally linked. WFH was associated with reduced car use frequency, while a preference for cars was linked to sustained car use over time. Furthermore, higher levels of WFH were related to longer commuting distances during the pandemic, suggesting that people became more willing to live further from the office as they worked from home more frequently. Beyond WFH itself, characteristics of the built environment and life events such as job changes, childbirth and relocation also shaped these relationships. Together, these findings reinforce the picture emerging from Kroesen et al. (2022), which is that commuting behaviour is not a static outcome, but rather part of a dynamic system of mutual influences in which WFH, residential choices, mode preferences, and attitudes continuously interact and reshape one another over time.

A third perspective emerges from considering the role of organisational constraints. While previous studies have focused on individual behaviour and attitudes, Magriço et al. (2024) demonstrate that commuting patterns are also significantly influenced by decisions made above the individual level. By comparing pre-pandemic commuting behaviour with survey data from 2023 among British rail commuters, they discovered that commuting days per week had decreased by 1.18, while WFH days had increased by 0.85. Crucially, if employers had not imposed workplace attendance requirements, the return to commuting would have been 12% lower. This finding complements the dynamic picture emerging from previous studies: even when individuals have developed new commuting patterns and attitudes, organisational constraints can override personal preferences and force a return to previous behaviour. For peak-spreading policy, this is a double-edged finding: employer restrictions can both accelerate and reverse behavioural change, making them a powerful but unpredictable lever.

2.3 Limitations of Existing Approaches

The studies reviewed in Section 2.2 confirm that WFH affects commuting demand, that the effects differ across individuals, and that both WFH adoption and mobility outcomes evolve over time. However, collectively, they have a fundamental limitation: none of them examine how WFH is structured across specific weekdays. This limitation is inherent in the way that WFH is conceptualised and operationalised throughout the existing literature, and it manifests in three interrelated ways: in how WFH is measured, in how heterogeneity is captured, and in how behavioural change is tracked over time. Each of these issues is discussed in turn.

2.3.1 Frequency-Based Measurement of Working from Home

All eleven of the reviewed studies operationalise WFH as either a binary indicator or a frequency-based variable (see Appendix A). While this captures the overall intensity of remote working, it reveals nothing about how those days are distributed across the working week. Rüger et al. (2024) measure commuting savings in total weekly hours; Böhnen & Kuhnimhof (2024) examine changes in overall commuting distance; and R. Faber et al. (2023) estimate modal shifts across the entire week. However, none of these analyses reveal which days commuting trips are made or avoided. Consequently, two individuals who both work from home two days per week, but on different days, are treated as equivalent even though their contributions to peak demand on specific weekdays may differ substantially.

2.3.2 Individual Heterogeneity Without Weekly Structure

The studies reviewed in Section 2.2.2 demonstrate that WFH affects different people in different ways. Spatial context, behavioural trajectory and educational background all influence how individuals respond. However, knowledge of which groups reduced train use more persistently than others, or that intense substituters continued working from home while moderate substituters returned to the office, does not reveal whether these groups concentrate their office attendance on the same weekdays. While Victoriano-Habit & El-Geneidy (2024), Pedreira Junior & Pitombo (2024) and Kroesen et al. (2023) capture meaningful heterogeneity in WFH adoption and its consequences, none examine which days different groups commute on. Without this weekly dimension, it is impossible to assess which groups contribute most to congestion on specific days and which might be most responsive to policies aimed at redistributing peak demand.

2.3.3 Temporal Dynamics Without Weekly Patterns

The studies reviewed in Section 2.2.3 show that commuting behaviour does not remain the same over time. WFH intensity, train use, car use and residential choices all shift over time in response to changing circumstances. However, Kroesen et al. (2022), Magriço et al. (2024), and Xie & Liao (2025) all track changes in aggregate frequency or intensity, rather than shifts in the internal structure of the working week. For example, an individual could transition from WFH on Mondays and Fridays to WFH on Tuesdays and Thursdays, which is a structural shift with direct consequences for peak congestion, but it would remain invisible to frequency-based measurement.

> Taken together, the reviewed literature demonstrates that WFH is systematically associated with changes in commuting behaviour, that the effects of WFH differ across individuals, and that behavioural patterns evolve over time. However, despite this progress, a fundamental blind spot remains: by consistently measuring WFH frequency, existing approaches obscure the structure of WFH and commuting behaviour within the working week. Knowing whether someone works from home on Mondays and Fridays or on Tuesdays and Thursdays is precisely the kind of information that peak-spreading policy requires. Yet, it remains absent from current measurement frameworks. This study addresses this gap directly.

2.4 Conceptual Framework

The three limitations identified in Section 2.3 suggest a common solution: a framework that considers not how frequently individuals work from home, but how their commuting behaviour is organised throughout the working week. This shift is grounded in the observation that commuting and WFH are inherently linked. By definition, a day worked from home is a day without a commute. Rather than treating WFH as a frequency, this study therefore examines whether a commute trip is made on each specific day of the working week. Within this framework, two analytical constructs are central: behavioural profiles to capture heterogeneity in weekly commuting patterns and behavioural transitions to capture how these patterns evolve over time.

A behavioural profile is defined as a distinct and consistent pattern of behaviour shared by a subgroup within a population (Collins & Lanza, 2010). In the context of this study, these profiles correspond to recurring weekly commuting patterns, defined by whether or not an individual made a commute trip on each day of the working week. Identifying these profiles enables the analysis to capture both observed and unobserved heterogeneity in individuals' commuting behaviour. In this study, these profiles are identified using latent class analysis (LCA).

A behavioural transition refers to a change in profile membership between two points in time, modelled probabilistically as the likelihood of moving from one profile to another (Collins & Lanza, 2010). Transitions capture behavioural dynamics by modelling the probability of remaining in or moving between profiles. Individuals may maintain stable weekly routines, consistent with the habit formation literature discussed in Section 2.1, or transition between profiles in response to changes in employer policies or commute route conditions. Analysing these transitions enables the study of how commuting patterns evolve over time. In this study, these dynamics are analysed using latent transition analysis (LTA).

Figure 2.3 illustrates how these two constructs are integrated, showing that heterogeneity and dynamics together capture the full structure of WFH behaviour. Heterogeneity is captured through distinct weekly commuting profiles identified by LCA, while dynamics are captured through transitions between these profiles modelled by LTA. Both methods are introduced and elaborated in Chapter 3.

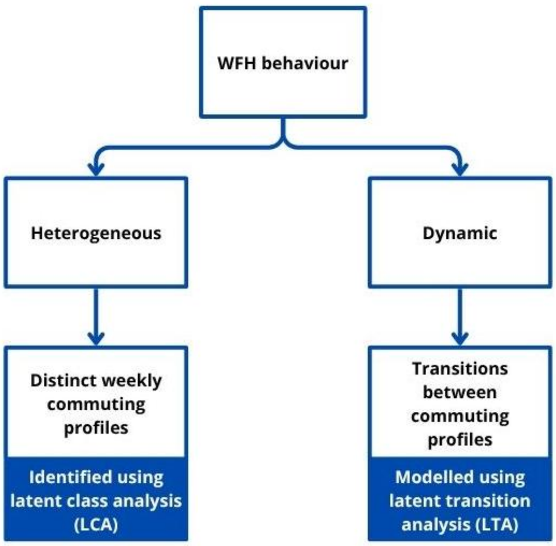

Figure 2.3 Conceptual framework of WFH behaviour in this study

Chapter Summary

What do we know? Working from home is not randomly distributed across the population. Its likelihood and frequency are influenced by a combination of socio-demographic, job-related, residential, and experiential factors. It is also linked to reductions in commuting time and distance. However, the size of these effects depends strongly on the context, including the proportion of time spent working from home, the stage at which it is adopted, and the longer-term residential adjustments it may trigger. Furthermore, the effects of WFH are not uniform across the population. Spatial context, educational background, and behavioural trajectory all influence how individuals respond. Commuting behaviour is also not static. WFH adoption, travel attitudes and residential choices interact and reshape one another over time, while organisational constraints can accelerate or reverse behavioural change.

What do we not yet know? Despite this body of evidence, existing research consistently treats WFH as a frequency-based variable, capturing how often individuals work from home, rather than on which specific days. As a result, the day-specific structure of commuting behaviour remains analytically invisible in current measurement frameworks. It is therefore unclear whether the observed concentration of office attendance on Tuesdays and Thursdays reflects a single behavioural pattern or several distinct groups, how stable these patterns are over time, and which factors drive transitions between them.

Why does this research fill that gap? This study addresses these gaps by conceptualising WFH as a weekly structure, as formalised in the conceptual framework presented in Section 2.4. This framework integrates two analytical constructs: behavioural profiles to capture heterogeneity in weekly commuting patterns, and behavioural transitions to capture how these patterns evolve over time. Together, they provide the analytical foundation for the empirical analysis in the following chapters.

3. Methodology

This chapter outlines the methodology adopted to address the sub-questions. It is divided into two main sections. Section 3.1 describes the research methods, introducing latent class analysis and latent transition analysis, discussing their limitations, and presenting the model conceptualisation. Section 3.2 describes the research data, covering the data source and panel, how the data were prepared, how the variables were operationalised, and a description of the sample and its representativeness.

3.1 Research Methods

Two related statistical methods are employed to identify distinct weekly commuting profiles and analyse how individuals transition between these profiles over time: latent class analysis (LCA) and latent transition analysis (LTA). LCA identifies distinct commuting profiles based on individuals' commuting behaviour on specific weekdays. LTA then extends this framework to model how individuals transition between these profiles across the three measurement waves. All latent class and latent transition models are estimated using the LatentGOLD software package (Vermunt & Magidson, 2005). The following sections introduce these methods and discuss their limitations, as well as presenting the model conceptualisation.

3.1.1 Latent Class Analysis

This section introduces the latent class analysis (LCA) and discusses why it is suitable for this study. It also describes the estimation procedure.

Latent Class Analysis (LCA)

LCA is a probabilistic, model-based clustering technique used to identify unobserved subgroups within a heterogeneous population (McCutcheon, 2011). These subgroups are referred to as latent classes, where the term latent indicates that the class structure cannot be observed directly in the data. Instead, it must be inferred from patterns observed in variables, known as indicators. In this study, the indicators are individuals' commuting behaviour on each day of the week, from Monday to Friday. It is therefore not whether someone commutes on any single day, but the configuration of their commuting behaviour across the full working week, that reveals their underlying profile.

The model assumes that an underlying categorical latent variable, in this case the commuting profile, drives the observed indicator values. In the data, day-specific commuting indicators will naturally correlate: someone who commutes on Monday is likely to also commute on Tuesday. These are the observed correlations between the indicators. LCA attempts to explain these correlations by positioning an underlying latent variable: the commuting profile. Conditional on this latent variable, the indicators are assumed to be independent. Therefore, it is assumed that all remaining correlations between the indicators are zero. This is known as the local independence assumption: given class membership, the indicators are assumed to be independent of each other (Magidson & Vermunt, 2004). In other words, once an individual's commuting profile is known, their commuting behaviour on one day provides no additional information about their behaviour on another day. All meaningful associations between the indicators are assumed to be fully explained by the latent class structure itself.

The objective of LCA is to maximize homogeneity within classes and heterogeneity between them (Magidson & Vermunt, 2004). In other words, it is preferred to obtain a class solution in which individuals within the same class are as similar as possible in their indicator patterns, while individuals across different classes are as distinct as possible. In this study, this means identifying groups of individuals who exhibit similar patterns of commuting behaviour on a weekly basis, while ensuring that those profiles are clearly distinguishable from one another.

LCA suitability

Empirical evidence consistently demonstrates that WFH behaviour is characterised by heterogeneity across the working population (see Section 2.2.2). Individuals not only differ in how often they work from home, but also in the specific days on which they do so. This gives rise to the qualitatively distinct weekly routines. This heterogeneity can be captured using a person-oriented clustering approach that groups individuals based on the configuration of their behaviour across the full working week, rather than examining the average effect of a single variable (Collins & Lanza, 2010). A variable-oriented approach, such as regression analysis, would obscure precisely the kind of within-person patterning that this study aims to detect.

Among the available clustering methods, latent class analysis is the most appropriate for this study. As described above, the core premise of LCA is that a population consists of discrete, unobserved subgroups that drive observed patterns across indicators. This directly mirrors the conceptual framework introduced in Section 2.4, which posits that distinct commuting profiles exist within the working population and that these profiles, rather than isolated day-level decisions, shape individuals' weekly commuting behaviour. Therefore, LCA is not only statistically suitable, but also conceptually aligned with the framework introduced in Section 2.4.

Beyond this conceptual fit, LCA has several methodological advantages over traditional clustering methods, such as K-means. Both approaches are person-oriented, grouping individuals based on patterns across multiple observed variables. However, K-means clustering has three fundamental limitations that LCA avoids (Vermunt & Magidson, 2002).

Firstly, K-means uses a deterministic method, whereby each individual is assigned to exactly one cluster based on the Euclidean distance – the straight-line distance between an observation and the nearest cluster centre in variable space – to the nearest cluster centroid. This can be problematic for observations that do not clearly belong to any single cluster, as forcing such cases into the nearest cluster can bias the centroid positions of all clusters. By contrast, LCA assigns each individual a posterior probability of belonging to each class, conditional on their observed indicator values. By probabilistically distributing cases across classes, LCA minimises the bias and explicitly accounts for uncertainty in class membership (Vermunt & Magidson, 2002).

Secondly, as K-means relies on Euclidean distance, it can only process continuous variables, where distances between nominal categories are mathematically undefined. LCA imposes no such constraint. It can accommodate indicators of any measurement scale, including nominal, ordinal and count variables, or mixtures thereof (Vermunt & Magidson, 2002). In this study, the indicators are binary variables representing whether an individual commuted to the office on each day of the working week, making LCA the only appropriate method of the two.

Thirdly, K-means is a sample-based technique that requires the researcher to specify the number of clusters in advance, with only subjective criteria available to guide that choice. In contrast, LCA is a model-based technique in which parameters are estimated by maximum likelihood. Rigorous statistical criteria can be applied to determine the optimal number of classes (Vermunt & Magidson, 2002).

Taken together, these characteristics make LCA a more appropriate method for identifying distinct commuting profiles than traditional approaches.

LCA estimation procedure

In practice, applying LCA involves the following steps. First, the model is estimated for a range of class solutions, typically from one class up to eight. At each stage of this process, the model estimates two sets of parameters. The first set are the item-response probabilities, which are the conditional probabilities of observing a given indicator value given class membership. The second set of parameters are class prevalences, representing the proportion of the population belonging to each class. The parameters are estimated iteratively using the Expectation-Maximisation (EM) algorithm, which alternates between estimating class membership probabilities and updating the model parameters until convergence is achieved (McCutcheon, 2011; Vermunt & Magidson, 2005).

Secondly, the appropriate number of classes must be determined. Several criteria are applied to select the optimal class solution. The primary statistical criterion is the Bayesian Information Criterion (BIC). The BIC balances model fit and complexity by penalising models with additional parameters. A lower BIC indicates a better balance between fit and parsimony and is therefore preferable (Magidson & Vermunt, 2004). Additionally, the likelihood ratio chi-squared statistic (L^2) from the one-class model is used as a baseline measure of the total amount of association present in the data. By comparing the L^2 values of models with multiple classes to the one-class solution, the reduction in L^2 represents the total association that is explained by the model. When the reduction in L^2 becomes relatively small after adding an extra class, it is no longer justified to add an extra class to the model (Magidson & Vermunt, 2004).

Furthermore, bivariate residuals (BVRs) are examined to assess whether the local independence assumption holds between pairs of indicators. BVRs measure the residual association between two indicators after conditioning on a latent class variable. A BVR below 3.84 indicates a non-significant residual association, suggesting that the local independence assumption is satisfied and that the latent class structure adequately accounts for the associations in the data (Magidson & Vermunt, 2004). Conversely, a significant BVR indicates unexplained heterogeneity between two indicators, which may suggest that an additional class is needed. Finally, a minimum class size of 5% of the total sample is required to ensure that each identified profile is sufficiently represented for stable parameter estimation and meaningful interpretations of the results (Weller et al., 2020).

Additionally, Entropy R^2 is reported as a supplementary measure of classification quality. It reflects the extent to which the model unambiguously assigns respondents to a single class. Values range from 0 to 1, with higher values indicating clearer separation between classes (Weller et al., 2020). While Entropy R^2 is not used as a primary selection criterion, it provides useful context for interpreting the distinctiveness of the identified profiles. Beyond these statistical criteria, interpretability is also a factor in selecting the final class solution. The chosen model must produce profiles that are theoretically meaningful and distinct enough from one another to support substantive interpretation and to support the subsequent latent transition analysis.

In order to apply LCA in LatentGOLD, several specification decisions were made. Indicators were specified as nominal rather than ordinal variables, as the binary nature of the commuting indicators does not imply an ordered structure. This allows the model to estimate response probabilities freely across categories, without imposing unnecessary constraints on the class solution. To reduce the risk of converging on a local rather than a global maximum likelihood solution, the number of random sets was increased from the default value of 16 to 200 (Vermunt & Magidson, 2005). Additionally, the ‘include all’ option was enabled in LatentGOLD, allowing respondents with missing values on some covariates to be retained in the analysis rather than being excluded through listwise deletion.

3.1.2 Latent Transition Analysis

As discussed in the research approach in Section 1.4, latent transition analysis (LTA) is applied to examine how individuals transition between commuting profiles over time.

Latent Transition Analysis (LTA)

While LCA identifies distinct commuting profiles at a single point in time, LTA extends this framework to model changes in latent class membership across consecutive measurement waves. LTA can be understood as a series of latent class analyses estimated at multiple time points, where the same underlying profiles are defined at each wave to enable analysis of movement between them (Collins & Lanza, 2010). In this study, LTA is used to examine transitions between commuting profiles over three measurement waves in 2023, 2024 and 2025.

A key assumption of LTA is measurement invariance over time. This means that the latent profiles, which are defined by the indicator-response probabilities, remain consistent over time (M. C. de Haas et al., 2018). This assumption is necessary to ensure that a transition from one profile to another reflects a change in an individual's commuting behaviour, rather than a change in the composition or definition of the profiles themselves between waves.

The model also assumes a first-order Markov structure (Collins & Lanza, 2010). This means that class membership at time t is fully determined by class membership at $t-1$. In other words, knowing which commuting profile an individual belongs to in one wave is sufficient to predict their profile membership in the next wave. So, earlier waves influence later membership only through the intermediate wave.

LTA suitability

There are several reasons why LTA is the most appropriate method for examining transitions in commuting profiles over time.

Firstly, LTA is the only method that maintains methodological continuity within the LCA framework used to identify commuting profiles. Approaches that first assign individuals to their modal class and then analyse transitions using multinomial logistic regression are guilty of the 'classify-then-analyse' fallacy. These approaches treat probabilistic class assignments as error-free observations, disregarding classification uncertainty and producing biased transition estimates. LTA avoids this issue by integrating the measurement and transition models into a single estimation framework that propagates classification uncertainty (Collins & Lanza, 2010).

Secondly, in contrast to cross-sectional approaches, which can only detect distributional shifts at an aggregate level, LTA estimates transition probabilities at the individual level over consecutive measurement waves. This is crucial for answering the third sub-question, which asks how individual respondents' commuting profiles change over time, rather than how the overall distribution of profiles changes between 2023 and 2025. It therefore allows heterogeneity in transition behaviour across individuals to be captured (Collins & Lanza, 2010).

Thirdly, and most importantly in terms of the policy orientation of this study, LTA allows time-varying covariates to be incorporated as predictors of transitions. This makes it possible to compute separate transition matrices conditional on specific covariate values and allows for direct comparison of transition dynamics across different policy conditions. This combination of features makes LTA particularly well-suited to the policy-oriented aims of this study, as it allows transition dynamics to be compared directly across different contextual conditions within a single, unified framework (Collins & Lanza, 2010; Magidson & Vermunt, 2004).

LTA estimation procedure

The main output of LTA is a transition probability matrix. Each row of this matrix corresponds to a latent class at time *t*. Each cell represents the probability of transitioning to a particular class at time *t+1*. The diagonal cells represent the probability of remaining in the same class, while the off-diagonal cells represent the probability of moving to a different class. The transition probabilities are estimated using a multinomial logit parameterisation, in which the log-odds of transitioning to a particular class are modelled as a linear function of the covariates. The resulting probabilities for each row sum to one because each individual must belong to exactly one class at each time point (Collins & Lanza, 2010). These probabilities are derived from the parameter estimates of the transition model and can be computed separately for different covariate values, enabling comparison of transition patterns across subgroups (M. C. de Haas et al., 2018).

There are two ways in which covariates can be incorporated into the LTA model. Active covariates influence the model directly by predicting class membership or transitions. In contrast, inactive covariates are included solely to describe the composition of the classes, with no influence on the class structure or transition probabilities. In this study, these comprise four work location variables: days at a fixed location, days at home, days at an external location, and total days worked.

In this study, the active covariates are used in two distinct roles. Exogenous variables – socio-demographic, residential and job-related characteristics – are included as predictors of initial class membership in 2023, capturing baseline heterogeneity in commuting profiles across the population. Contextual policy factors, specifically employer-level factors and commute route conditions, as identified in Section 2.1.2, are included exclusively as predictors of transitions between profiles across waves. This reflects the expectation that changes in these conditions will prompt individuals to change their commuting behaviour over time. The operationalisation of all variables is discussed in Section 3.2.3.

Given the complexity of the LTA model, as it simultaneously estimates measurement parameters across three waves and transition probabilities between profiles, the number of random sets was set to 200. This was done to further reduce the risk of converging on a local rather than a global maximum likelihood solution (Vermunt & Magidson, 2005).

3.1.3 Method Limitations

As outlined in Section 3.1.1 and Section 3.1.2, LCA and LTA are suitable methods for capturing heterogeneity and modelling behavioural dynamics over time. However, there are several inherent limitations that should be considered when interpreting the results.

Firstly, since individuals are assigned to classes based on posterior probabilities rather than direct observation, it is impossible to guarantee correct class assignment and the exact composition of classes remains uncertain (Weller et al., 2020). This limitation is inherent in all probabilistic clustering methods and is exacerbated by the relatively small sample size of the panel used in this study, which increases classification uncertainty.

Secondly, the class solution depends on modelling decisions, including the selection of indicators and the number of classes estimated. As there is no single optimal statistical criterion for comparing solutions with different number of classes, the approach remains partly exploratory (Weller et al., 2020). To address this issue, the final class solution is selected by combining statistical fit criteria – most notably the BIC and the reduction in L^2 – with substantive interpretability, as recommended by Magidson & Vermunt (2004).

Thirdly, qualitative labels are assigned to classes based on their indicator profiles, which introduces the risk of a naming fallacy whereby the label may oversimplify or misrepresent the full complexity of the class

(Weller et al., 2020). This risk can be mitigated by basing the naming of profiles on the substantive characteristics of the indicators rather than a single defining feature.

Fourthly, the relatively small size of the panel sample and the limited number of transitions observed across waves mean that the LTA results should be treated with caution and regarded as exploratory and indicative rather than definitive.

Fifthly, restricting the analysis to respondents who participated in all three waves introduces the risk of attrition bias. Respondents who completed all three waves may differ systematically from those who dropped out, for instance with regard to commuting intensity or WFH behaviour. This could affect the generalisability of the identified profiles and transition probabilities (Olde Kalter et al., 2020).

Finally, associations between covariates and class membership or transitions should not be interpreted as causal effects. Although covariate selection is theory-driven, it is also constrained by data availability, and unobserved factors may influence both commuting behaviour and the included covariates. Therefore, the findings should be interpreted as descriptive and exploratory patterns that support an understanding of commuting behaviour and inform policy discussions, rather than as causal estimates (M. C. de Haas et al., 2018).

3.1.4 Model Conceptualization

As explained in the previous sections, latent class and latent transition analyses are conducted to identify distinct commuting profiles and examine transitions between them over time. Figure 3.1 shows the conceptual model of the latent transition analysis, with T1 representing 2023, T2 representing 2024, and T3 representing 2025.

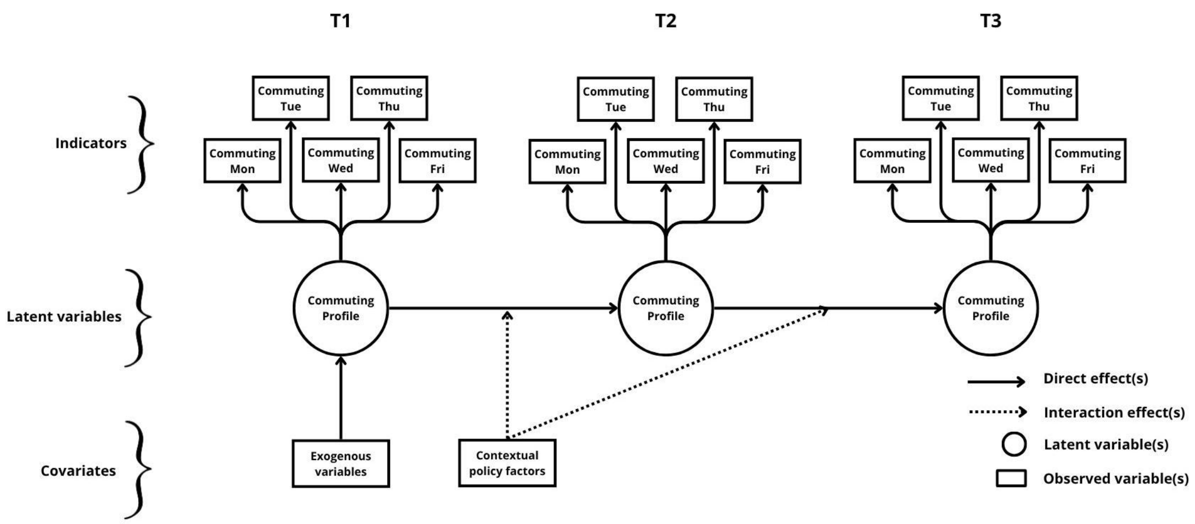

Figure 3.1 Conceptual model of the latent class and transition analysis

At each time point, the commuting profile is inferred from five binary indicators representing whether an individual commuted on each day of the week (Monday to Friday). The latent variable, i.e. the commuting profile, is not directly observable, but is derived from patterns observed in these indicators, as described in Section 3.1.1. Although models were also estimated including weekend days (Saturday to Sunday), these were excluded from the final analysis given the study's focus on peak-hour commuting behaviour on working days.

As discussed in Section 3.1.2, the model is extended to a latent transition model, which van be conceptualised as repeated latent class analyses over time, where the same commuting profiles are defined at each time point and transitions between them are assessed (Collins & Lanza, 2010) .

Two types of covariates are incorporated in the model. First, exogenous variables capturing socio-demographic, residential and job-related characteristics are included as predictors of initial profile membership at T1 (2023). Specifically, eleven covariates are included: age, gender, educational level, income, household composition, household size, urbanisation level, commute distance, sector, company size, and commuting reimbursement.

Second, contextual policy factors comprising employer-level factors and commute route conditions, as identified in Section 2.1.2, are included exclusively as predictors of profile transitions rather than initial membership. These factors are expected to directly constrain or enable shifts in commuting behaviour between waves. In total, nine contextual policy covariates are included: six employer-level factors (possibility to work from home, possibility to meet online, flexible working hours, WFH allowance, travel reimbursement for car, and travel reimbursement for PT) and three commute route conditions (car travel time reliability, PT frequency, and PT travel time reliability). Section 3.2.3 discusses the specific operationalisation of all indicators and covariates, as well as the rationale for their inclusion and exclusion.

3.2 Research Data

This section outlines the data used for the analyses detailed in the previous section. Section 3.2.1. introduces the data source and panel structure. Section 3.2.2 details the steps taken to prepare the data for analysis. Section 3.2.3 presents the operationalisation of all the variables included in the models. Finally, Section 3.2.4 describes the sample and assesses its representativeness in relation to the wider Dutch population.

3.2.1 Data Source and Data Panel

This study uses data from the Landelijk Reizigersonderzoek (LRO), a nationwide travel survey commissioned by the Dutch Ministry of Infrastructure and Water Management. The LRO serves as a national monitoring tool within the Directorate-General for Mobility (DGMo), supporting the evaluation of mobility policies aimed at enhancing accessibility, promoting sustainability, and optimising the use of existing infrastructure (Ministerie van Infrastructuur en Waterstaat et al., 2025). By systematically collecting data on commuting behaviour and working from home, the survey enables national mobility trends and the impact of policies to be assessed over time.

The LRO is an annual online questionnaire conducted among the Dutch population aged 18 years and older. The first wave was implemented in autumn 2019, and the survey has been repeated each year since then, enabling trends in travel behaviour to be analysed from 2019 to 2025. The LRO's primary objectives are to (1) identify changes in commuting behaviour, including attitudes, motivations and barriers, and (2) translate these behavioural developments into implications for accessibility, liveability, and safety (Ministerie van Infrastructuur en Waterstaat et al., 2025).

The questionnaire consists of a core module that remains unchanged and additional thematic modules that vary annually. The core module contains detailed questions about commuting frequency, working from home, employer regulations, parking conditions, use of shared mobility, perceived accessibility and socio-demographic and household characteristics. In addition, retrospective questions are included to capture self-reported changes in behaviour compared to the previous year. The questions relevant to this study are included in Appendix B.

A total of 15,126 respondents completed the questionnaire in 2025. After data cleaning, a final dataset of 12,605 respondents remained. Since 2023, respondent identities have been consistently tracked across waves, enabling the construction of a longitudinal panel. Of the 2024 sample, 3,146 respondents had also participated in 2023. In 2025, 1,781 respondents had participated in 2024, while 3,059 had participated in 2023 (see Table 3.1).

Table 3.1 Overlap of respondents across LRO survey waves

Survey Wave	2024	2025	2024 – 2025
2023	3,146	3,059	1,026
2024		1,781	

The LRO measures behaviour during a single reference week, which falls in late October or early November each year. Respondents are asked to report their commuting and WFH behaviour during this specific week, which is assumed to be representative of their typical working week. However, this assumption has limitations, as behaviour during this period may not fully reflect annual patterns. Seasonal factors such as shorter daylight hours and weather conditions may influence commuting and WFH decisions. This should be considered when interpreting the results.

The analyses in this study are based on different subsamples, depending on the research question. For the descriptive trend analyses (SQ1), the complete set of working respondents per wave is used, rather than being restricted to the longitudinal panel. The working population comprised 8,169 respondents in 2023, 8,330 in 2024, and 8,674 in 2025. This approach was chosen to maximise the representativeness of the descriptive trends per measurement wave. In contrast, the latent class analysis (SQ2) and latent transition analysis (SQ3), only include respondents who participated in all three waves (2023-2025). This balanced panel of 1,026 respondents ensures temporal consistency at the individual level and provides the necessary structure for identifying commuting profiles using LCA and modelling transitions between these profiles using LTA. However, two groups were excluded from these analyses. Firstly, respondents who were not in paid employment were excluded, since the behavioural constructs under investigation only apply to working individuals. Secondly, full-time home workers – defined as respondents who did not commute to a fixed or external work location at any time during the reference week – were excluded because their commuting patterns do not vary across days and therefore do not provide meaningful information about the latent class structure. After applying these exclusions consistently across all three waves, a final analytical sample of 612 respondents remained.

3.2.2 Data Preparation

As discussed in Section 3.2.1, this study uses a dataset derived from the Landelijk Reizigersonderzoek (LRO), which is a longitudinal panel survey that was conducted in three consecutive waves in 2023, 2024 and 2025. To enable consistent longitudinal analysis at the individual level, a structured data preparation process was carried out.

Dataset construction

The Dutch Ministry of Infrastructure and Water Management provided three separate annual LRO datasets for 2023, 2024 and 2025, as well as a linkage file in which the identities of respondents were matched across those three waves. This file enabled the identification of the 1,026 respondents who participated in all three consecutive waves. A new dataset containing only these 1,026 panel respondents was constructed using this file as a basis.

The relevant variables were then extracted from each of the three annual LRO datasets and added to this new file, resulting in a single longitudinal dataset in which each respondent is represented at all three time points. The selected variables relate to five central thematic domains of this study: commuting situation, commuting behaviour, working from home, employer regulations and socio-demographic characteristics. Variables relating to mobility resources, general travel behaviour, parking, shared mobility, perceived accessibility, vehicle specifications and motivations or barriers for commuting were excluded as they fall outside the scope of this research. As noted in Section 3.2.1, the specific LRO questions used in this study are presented in Appendix B.

While Figure 3.1 illustrates the analytical structure of the model, Figure 3.2 provides a more detailed overview of the specific variables included and excluded from the analysis. The variables in bold are included in the analysis, while the grey variables are available in the LRO dataset but have been excluded to limit model complexity. The number of covariates included in the LTA has been restricted to avoid overparameterising the model. Section 3.2.3 discusses the rationale for including or excluding specific variables.

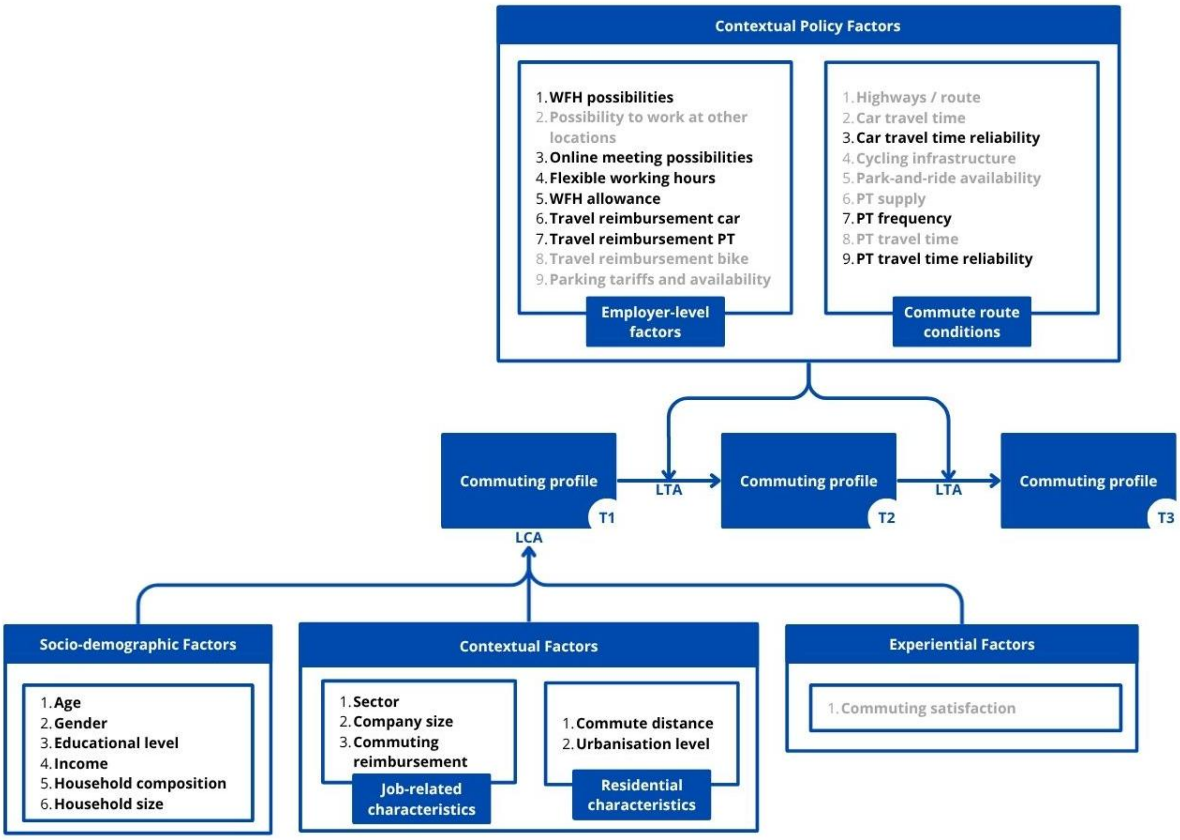

Figure 3.2 Conceptual overview of included and excluded variables

Variable harmonisation

To ensure longitudinal comparability, several variables required harmonisation across the three waves. Where response formats or question structures differed between datasets, the variables were recoded to ensure consistency. Two of the harmonisation steps involved making explicit assumptions.

Firstly, household income, which was only recorded in 2025, was assumed to be stable across the three years, and was therefore applied to 2023 and 2024. Income was measured in broad categorical groups rather than exact values and was subsequently recoded into three categories (low, intermediate and high). This assumption is considered reasonable, as meaningful changes in income category over a three-year period are unlikely for the majority of respondents. Secondly, household size, which was absent from the 2024 dataset, was imputed from the identical values in the 2023 and 2025 datasets, or otherwise treated as missing.

A detailed account of all harmonisation steps is provided in Appendix C.1.

Variable simplification and category reduction

Several variables were recoded into fewer categories to improve interpretability. These transformations are summarised in the table below, Table 3.2. Appendix C.2 provides a more detailed overview of the original and recoded categories for each variable.

Age was recoded from a continuous variable into four ordinal groups that reflect life stages which are commonly distinguished in labour and mobility research: young workers (18-34 years old), mid-career workers (35-49 years old), pre-retirement workers (50-64 years old) and retirement-age workers (65 years old and over).

Gender was recoded into a binary variable (male or female). Respondents who identified as non-binary or who preferred not to disclose their gender were assigned missing values.

Educational level was consolidated from eight original categories into three (low, intermediate and high), based on their position in the Dutch education system. Although HAVO and VWO provide access to higher education, they constitute general upper secondary qualifications and do not themselves confer a higher education degree. Therefore, they are placed in the intermediate category. Respondents selecting 'other' were treated as missing values.

Household income was reduced from eight original categories into three: low (up to €33,500), intermediate (€33,500-€83,000) and high (€83,000 or more). These boundaries reflect the modal income thresholds as defined in the LRO questionnaire and are consistent with how income distributions are commonly reported in Dutch socio-economic research. Respondents who indicated that they did not know or preferred not to disclose their income were treated as missing values.

Household composition was reduced from eight original categories into three broader groups: without children (living alone or with a partner but no children), young children (living with at least one child aged 17 or younger, with or without a partner), and older children or other (living with children aged 18 or older, or living with others such as family members or housemates). When respondents indicated living with both young and older children, they were classified as having young children, as this is considered the most relevant factor for WFH behaviour. Respondents who preferred not to answer, or who selected 'other', were treated as missing values.

The employment sector was recoded from the original fifteen categories into six broader groups: agriculture and industry, services, government, education, healthcare, and other. This consolidation follows the sectoral grouping applied in the LRO monitoring reports (Ministerie van Infrastructuur en Waterstaat et al., 2025). Although a more detailed classification was available, the fifteen original categories yield cell sizes too small for meaningful interpretation, while the six-category solution retains theoretically relevant distinctions between sectors.

The urbanisation level was recoded from six categories into three: (very) strongly urban, moderately urban, and low/non-urban. In 2024 and 2025, a pre-recoded three-category version was available and was used directly. In 2023, however, only the six-category version was available, so it was recoded into the same three categories to ensure consistent operationalisation across all three waves.

Commute distance was converted from metres to kilometres in all three datasets to improve interpretability and align with the conventional distance units used in mobility research.

Finally, the variables measuring changes in employer regulations and commute route conditions were each recoded from a five-point scale into three categories: improved, unchanged, and worsened. The original extreme categories were merged with their adjacent categories. Respondents who selected ‘don’t know/not applicable’ were treated as missing values.

Table 3.2 Overview of recoded variables and their reduced categories

Variable	Original Categories	Recoded Categories
Age	Continuous (years)	(1) 18 – 34 (2) 35 – 49 (3) 50 – 64 (4) 65+
Gender	4 categories	(1) Male (2) Female (99) Missing
Educational level	8 categories	(1) Low (2) Intermediate (3) High (99) Missing
Income	8 categories	(1) Low (2) Intermediate (3) High (99) Missing
Household composition	8 categories	(1) No children (2) Young children (≤ 17 years) (3) Older children or other
Sector	15 categories	(1) Agriculture and industry (2) Services (3) Government (4) Education (5) Healthcare (6) Other
Urbanisation level	6 categories	(1) (Very) strongly urban (2) Moderately urban (3) Low/non-urban
Changes to regulations	6 categories	(1) Improved (2) Unchanged (3) Worsened (99) Missing
Changes to commute	6 categories	(1) Improved (2) Unchanged (3) Worsened (99) Missing

> Following these data preparation steps, a single longitudinal dataset was obtained containing the 1,026 panel respondents observed across three time points, with harmonised and recoded variables ready for analysis. The resulting dataset forms the basis for the operationalisation of variables presented in Section 3.2.3, the data description and representativeness assessment in Section 3.2.4, and the subsequent analyses reported in Chapter 4.

3.2.3 Data Operationalisation

This section outlines how all the variables included in the latent class and latent transition models were operationalised. These variables are organised into four groups: indicators, active covariates, inactive covariates, and contextual policy factors. Table 3.3 provides an overview of all variables and their respective categories.

Table 3.3 Operationalised variables

	Variable	Category
Indicators		
Commuting day	Monday	(0) No (1) Yes
	Tuesday	(0) No (1) Yes
	Wednesday	(0) No (1) Yes
	Thursday	(0) No (1) Yes
	Friday	(0) No (1) Yes
Active covariates		
Socio-demographic characteristics	Age	(1) 18 – 34 years (2) 35 – 49 years (3) 50 – 64 years (4) 65+
	Gender	(1) Male (2) Female
	Educational level	(1) Low (2) Intermediate (3) High
	Income	(1) Low (2) Intermediate (3) High
	Household composition	(1) No children (2) Young children (≤ 17 years) (3) Older children or other
	Household size	Continuous
Residential characteristics	Urbanisation level	(1) (Very) strongly urban (2) Moderately urban (3) Low/non-urban
	Commute distance	Continuous
Job-related characteristics	Sector	(1) Agriculture and industry (2) Services (3) Government (4) Education (5) Healthcare (6) Other
	Company size	(1) < 100 employees (2) 100 – 250 employees (3) 250 – 500 employees (4) 500 – 1000 employees (5) > 1000 employees (6) Don't know
	Commuting reimbursement	(1) Full (2) Partial (3) None
Inactive covariates		
Work location	Days at fixed location	Continuous
	Days at external location	Continuous
	Days at home	Continuous
	Total days worked	Continuous

Contextual policy factors			
	Employer-level factors	Possibility to work from home	(1) Improved (2) Unchanged (3) Worsened (99) Missing
		Possibility to meet online	
		Flexible working hours	
		WFH allowance	
		Commuting reimbursement car	
		Commuting reimbursement PT	
	Commute route conditions	Car travel time reliability	(1) Improved (2) Unchanged (3) Worsened (99) Missing
		PT frequency	
		PT travel time reliability	

Indicators

The indicators are the variables from which the latent commuting profiles are derived. Five binary variables are included, representing whether an individual commuted to their fixed or external work location on each day of the working week (Monday to Friday). Saturday and Sunday are excluded as the policy objective concerns the redistribution of peak-hour commuting on working days, not on weekends. This is further supported by the negligible commuting shares observed on these days across all three waves, with peak-hour commuting not exceeding 4% during the morning and evening peak (see Figure 4.1 and Figure 4.2). A value of 1 indicates that a commute took place on that day, while a value of 0 indicates that it did not.

Active and inactive covariates

In the model conceptualisation presented in Section 3.1.4, a distinction is made between exogenous variables and contextual policy factors. Exogenous variables are further divided into active and inactive covariates: active covariates directly influence class membership or transitions, whereas inactive covariates are included solely to describe the composition of the classes without affecting the class structure or transition probabilities. The selection of active covariates is grounded in the determinants of WFH behaviour identified in Section 2.1.1. Variables available in the dataset but not included are shown in grey in Figure 3.2. In total, eleven active covariates are included in the latent transition model to predict initial class membership, organised into three groups.

Socio-demographic characteristics include age, gender, educational level, income, household composition and household size. These variables are included because they have been identified in the literature as key determinants of WFH adoption and commuting behaviour (see Section 2.1.1). They are expected to explain baseline heterogeneity in commuting profiles at T1.

Residential characteristics include urbanisation level and commute distance. These variables are included because the residential context influences the feasibility and appeal of commuting. Greater distances and lower levels of urbanisation are associated with a higher adoption of WFH (see Section 2.1.1).

Job-related characteristics include sector, company size, and commuting reimbursement. These variables are included because organisational context directly constrains or enables WFH. Sector and company size reflect the degree of job autonomy and digitalisation, while commuting reimbursement captures a key financial factor in the trade-off between working from home and commuting to the office.

Four work location variables are included as inactive covariates: days at a fixed location, days at home, days at an external location and total days worked. Together, these variables provide a comprehensive overview of how individuals organise their working week across different locations, allowing for a more detailed interpretation of the commuting profiles identified by the model.

Contextual policy factors

Contextual policy factors form a separate category of active covariates that are included exclusively as predictors of transitions between profiles rather than as predictors of initial class membership. This distinction reflects the theoretical expectation that contextual conditions change over time and therefore drive transitions, whereas exogenous variables capture stable baseline differences between individuals and therefore predict initial class membership.

The selection of covariates was guided by three principles: minimising the number of covariates to avoid estimation issues (M. C. de Haas et al., 2018); selecting direct behavioural enablers of profile change rather than variables on statistical grounds alone (Olde Kalter et al., 2020); and ensuring relevance to identifiable policy actors (M. C. de Haas et al., 2018). For these reasons, the variables are based on questions B2 and B3 of the LRO questionnaire. The full question wording is provided in Appendix B. It should be noted that the contextual policy factors are measured as self-reported perceived changes relative to the previous year rather than absolute values.

The selection was further informed by the conceptual framework presented in Chapter 2, which identified redistributing commuting days across the week as the main way to achieve peak spreading. This served as the core inclusion criterion: a variable was retained only if it plausibly influences which days individuals travel to the office, rather than how or when they travel. All 26 candidate variables, from B2 and B3, were systematically screened against this criterion, and the full screening process is presented in Appendix C.3.

Based on this screening, nine contextual covariates were selected for inclusion in the LTA (see Table 3.4). The employer-level variables – the possibility to WFH, the possibility to meet online, flexible working hours, a WFH allowance, and travel reimbursements for car and public transport (PT) – reflect organisational policies that may influence how employees schedule their commuting days. The commute route variables – car travel time reliability, PT frequency, and PT travel time reliability – reflect broader transport system conditions that may affect day-to-day commuting decisions. Unlike travel time itself, which is largely determined by geographical distance, travel time reliability can be influenced through traffic management and PT scheduling and is therefore an actionable factor for transport authorities. Together, these nine variables cover the two domains of actors most relevant to peak spreading: employers and national transport authorities.

Table 3.4 Overview of included contextual policy covariates in LTA

Contextual Policy Factor	Actor	Reason
Employer-level factors (B2)		
Possibility to WFH	Employer	Directly enables reduction in commuting days
Possibility to meet online	Employer	Reduces obligation to commute for meetings
Flexible working hours	Employer	Enables commuting on non-peak days
WFH allowance	Employer	Financial incentive to increase WFH days
Commuting reimbursement car	Employer / Government	Reduces financial barrier to car commuting, enabling more flexible day choice
Commuting reimbursement PT	Employer / Government	Reduces financial barrier to PT commuting, enabling more flexible day choice
Commute route conditions (B3)		
Car travel time reliability	Government	Reduces uncertainty of commuting by car, enabling more flexible day choice
PT frequency	Government	Improves PT accessibility on non-peak days, enabling day spreading
PT travel time reliability	Government	Reduces uncertainty of commuting on non-peak days, enabling more flexible day choice

3.2.4 Data Description and Data Representativeness

Table 3.5 shows the socio-demographic, residential and job-related characteristics of the panel sample at three points in time (2023, 2024 and 2025), with 1,026 respondents in each wave. This table serves as the basis for the sample representativeness assessment. For each variable, a deliberate decision was made as to whether report raw or valid percentages, depending on the nature and extent of missing data. The following paragraphs explain these decisions. Descriptive statistics for the commuting indicators and inactive covariates across the three measurement waves are presented in Appendix C.4.

Socio-demographic characteristics

There are no missing values for age across any of the three waves, so the valid and raw percentages are identical. Only negligible proportions of responses are missing for gender and educational level (gender: 2023 = 0.7%; 2024 = 0.4%; 2025 = 1.3%; educational level: 2023 = 0.6%; 2024 = 0.8%; 2025 = 0.3%). For these variables, valid percentages are reported, as the small number of missing cases does not meaningfully affect the distribution.

Income contains no missing values, and therefore only valid percentages are reported. In addition to the standard income categories (low, intermediate and high), an 'other' category was included as a valid response option for those whose income did not fall within these classifications. This accounted for 14.3% of respondents across all three waves. As said in Section 3.2.2, income data were only collected in the 2025 wave. Given that income is considered a relatively stable socio-economic characteristic over time, the 2025 values are assumed to be representative for all three waves. Section 3.2.2 also mentions the creation of household sizes, which were not measured directly in 2024. Instead, they were imputed based on the values from 2023 and 2025 where possible.

Also household composition contains negligible proportions of missing values (2023 = 1.8%; 2024 = 1.9%; 2025 = 1.5%), so valid percentages are reported, as the small number of missing cases does not meaningfully affect the distribution.

Residential characteristics

The urbanisation level shows negligible missing values across all waves (2023 = 0.2%; 2024 = 0.1%; 2025 = 0.4%), so valid percentages can be reported. The commute distance is reported as a mean value, calculated for each respondent based on their reported four-digit postcodes for their home and work locations. This is done using the Google Maps API to find the shortest travel time during the morning rush hour. Respondents who live and work in the same four-digit postal code area are assigned a distance of 0 km.

Job-related characteristics

The job-related variables have high proportions of missing values due to the design of the LRO questionnaire. These questions were only asked of specific subgroups, as determined by a prior filter question regarding employment status.

The question regarding the sector was asked of respondents in paid employment only, thereby excluding job seekers and individuals who were not employed. Company size was only asked of respondents in salaried employment, explicitly excluding self-employed individuals. This resulted in even higher missing rates. Commuting reimbursement was restricted to respondents in salaried employment, yielding the highest proportion of missing values of all the variables. For all three job-related variables, raw percentages are reported as the missing values reflect structural non-applicability rather than non-response.

Table 3.5 Descriptive statistics of LRO data compared with CBS data

Variable	Category	2023 (N=1,026)	2024 (N=1,026)	2025 (N=1,026)	CBS (NL≥18 yr)
Socio-demographic characteristics					
Age (%)	18-34 years	20.4	19.2	17.3	27.3
	35-49 years	17.9	18.0	18.6	22.3
	50-64 years	40.1	37.5	35.8	25.4
	≥ 65 years	21.6	25.2	28.3	25.1
Gender (%)	Male	53.1	52.9	53.0	49.4
	Female	46.9	47.1	47.0	50.6
Educational level (%)	Low	17.5	18.8	16.6	19.3
	Intermediate	55.9	55.0	56.1	39.2
	High	26.7	26.2	27.3	41.8
Income (%)	Low	14.0	14.0	14.0	
	Intermediate	55.3	55.3	55.3	
	High	16.4	16.4	16.4	
	Other	14.3	14.3	14.3	
Household composition (%)	No children	70.6	70.6	70.5	
	Young children	16.4	17.0	17.5	
	Older children or other	13.0	12.4	12.0	
Household size (mean)	-	3.0	3.3	3.5	
Residential characteristics					
Urbanisation level (%)	(Very) strongly urban	49.7	48.6	48.4	55.6
	Moderately urban	15.4	16.0	16.8	16.8
	Low/non-urban	34.9	35.4	34.7	27.6
Commute distance (mean, km)	-	26.6	25.8	25.0	
Job-related characteristics					
Sector (%)	Agriculture & industry	17.2	18.3	17.8	
	Services	13.5	13.3	12.8	
	Government	5.2	4.6	5.2	
	Education	4.2	4.1	4.2	
	Healthcare	15.5	15.2	14.9	
	Other	18.2	17.5	15.2	
	Missing	26.2	27.0	29.9	
Company size (%)	< 100 employees	19.7	19.0	18.8	
	100-250 employees	9.1	9.6	7.7	
	250-500 employees	6.8	6.3	6.0	
	500-1000 employees	5.9	6.5	6.2	
	>1000 employees	19.7	19.0	21.1	
	Don't know	2.6	2.1	1.8	
	Missing	36.2	37.3	38.4	
Commuting reimbursement (%)	Full	22.3	21.2	22.3	
	Partial	26.4	25.9	25.7	
	None	13.3	13.7	11.8	
	Missing	38.0	39.1	40.2	

Sample representativeness

To assess the representativeness of the panel sample, the sample characteristics of the full longitudinal sample (N = 1,026) are compared with reference population figures from Statistics Netherlands (CBS) for the Dutch adult population aged 18 years and older, as shown in Table 3.5. The CBS figures reflect the 'Gouden Standaard' used by LRO 2025 for sample calibration. Only the available variables are used as a benchmark. However, it should be noted that the CBS figures represent the general Dutch working population, which is broader than the population most relevant to this study: workers who have a realistic possibility to choose their office days. Workers in sectors where physical presence is structurally required have limited scope to vary their commuting days and are therefore less relevant to the research question.

Several systematic deviations from the CBS reference population are observed. In terms of age, the sample underrepresents the 18-34 and 35-49 age groups, while the 50-64 age group is notably overrepresented. Workers in this age group tend to prefer more structured, office-based arrangements compared to younger cohorts. Consequently, this overrepresentation of older workers may lead to an overestimation of stable, office-based profiles and an underestimation of profiles characterised by high flexibility. The sample is also slightly male-dominated compared to CBS figures. The most pronounced deviation concerns educational attainment: intermediate education is substantially overrepresented, while highly educated respondents are considerably underrepresented. Since highly educated workers generally have greater access to an adoption of WFH arrangements, their underrepresentation may lead to an underestimation of fully flexible profiles, limiting the generalisability of the findings to this segment of the Dutch working population. In terms of urbanisation, respondents from (very) strongly urban areas are underrepresented, while those from low/non-urban areas are overrepresented. Since rural workers typically face longer commutes, this may lead to an overestimation of WFH patterns and an underestimation of office presence in the latent profiles. These deviations are discussed further as limitations in Section 5.4.

Although several variables deviate from the CBS reference population, the sample is not statistically weighted for latent class and transition analyses (SQ2 and SQ3). LCA and LTA are model-based approaches that identify latent subgroups based on patterns of observed responses, rather than estimating population-level prevalence rates. The primary aim of these analyses is to reveal the underlying structure of commuting behaviour, rather than producing population-representative estimates of class sizes. Therefore, weighting is less critical than in descriptive analysis. Nevertheless, the composition of the sample may still influence the identified profiles: overrepresented groups, such as workers aged 50-64 and those with intermediate education, will contribute more heavily to the latent class solution. This may affect the nature and relative sizes of the profiles, which is acknowledged as a limitation of the study and is discussed further in Section 5.4.

However, for the descriptive trend analyses (SQ1), the full annual LRO samples are used in combination with the post-stratification weights provided by the LRO for each measurement wave. Post-stratification weighting corrects for systematic differences between the composition of the survey sample and the target population. In this case, the target population is the Dutch working population in each respective year. Without these weights, groups that are over- or underrepresented in the sample could distort the estimated proportions and trends. As the descriptive analyses focus on population-level trends rather than latent structures, weighting is both appropriate and necessary to ensure that the descriptive results more accurately reflect the actual distribution of commuting and working from home behaviour among the Dutch working population.

Confidence intervals (CIs)

To indicate the precision of the estimates reported in the descriptive trend analyses, 95% confidence intervals (CIs) have been calculated for each measurement wave and are displayed in the figures in Section 4.1. A 95% CI represents the range within which the true population value would fall in 95 out of 100 random samples drawn from the same population. The width of the CI depends on the sample size: larger samples produce narrower intervals, reflecting greater precision in the estimates. Including CIs enables more cautious interpretation of changes observed over time. When the CIs of two waves do not overlap, this suggests a genuine shift in the population. When they do overlap, however, the observed difference may be due to sampling variation rather than a true change and should therefore be interpreted with caution.

For proportions, the CI is calculated as:

$$CI = p \pm 1.96 \times \sqrt{\frac{p(1-p)}{n}}$$

Where *p* is the observed proportion and *n* is the weighted sample size for that wave.

For means, the CI is calculated as:

$$CI = \bar{x} \pm 1.96 \times \left(\frac{SD}{\sqrt{n}}\right)$$

Where x̄ is the weighted mean, SD is the standard deviation, and *n* is the weighted sample size.

Chapter Summary

This chapter outlines the methodological framework applied in this study. Two complementary analytical methods were employed: latent class analysis (LCA) to identify distinct weekly commuting profiles and latent transition analysis (LTA) to examine transitions of individuals between these profiles over time. These are both model-based, person-oriented approaches that are well-suited to capturing the heterogeneity and dynamics of commuting behaviour. Both models were estimated using LatentGOLD.

The analyses draw on the three consecutive waves of the Landelijk Reizigersonderzoek (LRO) survey, conducted in 2023, 2024, and 2025. For the descriptive trend analyses (SQ1), the complete working population per wave was used: 8,169 in 2023, 8,330 in 2024, and 8,674 in 2025, in combination with the LRO-provided weighting factors to ensure population representativeness. For the latent class analysis (SQ2) and latent transition analysis (SQ3), a balanced longitudinal panel of 1,026 respondents who participated in all three waves was constructed. After excluding respondents not in paid employment and full-time home workers, a final analytical sample of 612 respondents remained. The latent class and transition analyses were conducted on the unweighted panel, as LCA and LTA are model-based approaches concerned with latent structure rather than population-level prevalence.

Five binary commuting indicators – representing whether an individual commuted on each working day from Monday to Friday – formed the basis of the latent class structure. Two types of covariates were included in the LTA. Exogenous variables – comprising socio-demographic, residential, and job-related characteristics – were included as predictors of initial class membership in 2023, capturing stable baseline differences between individuals. Contextual policy factors – covering employer-level regulations and commute route conditions – were included exclusively as predictors of transitions between profiles, as these conditions are expected to change over time and directly enable or constrain shifts in commuting behaviour.

Several deviations from the CBS reference population were identified, most notably the overrepresentation of workers aged 50-64 and the underrepresentation of highly educated respondents. These deviations may influence the identified profiles and limit the external generalisability of the findings, as further addressed in the limitations section of Chapter 5. With these methodological considerations in mind, the following chapter presents the results of the analyses.

4 Results

This chapter presents the results in three sequential sections that correspond to the research questions. Section 4.1 describes the trends observed in commuting and working from home behaviour across the three measurement waves, as well as the factors associated with these behavioural decisions. Section 4.2 presents the results of the latent class analysis, followed by the results of the latent transition analysis in Section 4.3. The chapter concludes with Section 4.4, which discusses the findings in light of the literature reviewed in Chapter 2.

4.1 Results of Trends in Commuting and Working from Home Behaviour

This section addresses the first sub-question of the study:

SQ1: What are the observed trends in commuting and working from home behaviour, and the factors associated with these behavioural decisions, across the three measurement waves (2023, 2024 and 2025)?

Descriptive analyses were conducted on the survey data collected across the three measurement waves to answer this question. As outlined in Section 3.2.1, these analyses draw on the complete working population per wave (see Table 4.1) rather than the longitudinal subsample of respondents who participated in all three waves. The analyses are based on weighted data using the post-stratification weights provided by the LRO for each measurement wave, as described in Section 3.2.4.

Table 4.1 Number of respondents across waves 2023-2025

	2023	2024	2025
Number of respondents (N)	15,048	12,080	12,605
Working population	8,169	8,330	8,674

The analyses focus on changes in commuting behaviour and the frequency of working from home, as well as the factors associated with those behavioural decisions. Together, they provide a comprehensive overview of how these behaviours and their underlying drivers evolved between 2023 and 2025. Detailed results for commuting behaviour are presented in Appendix D. The corresponding results for working from home behaviour are reported in Appendix E. The findings summarised in the following sections are based on these appendices and highlight the most significant trends relevant to understanding commuting and working from home behaviour between 2023 and 2025.

4.1.1 Observed Trends in Commuting Behaviour

This section presents the observed trends in commuting behaviour across the three measurement waves. As mentioned in Section 4.1, the commuting-related questions were only asked of working respondents.

Commuting behaviour was operationalised using three LRO survey questions. The first question captured the typical arrival time at the respondent's fixed or external work location, as well as the departure time for the return journey home. The second question assessed whether respondents travelled to their fixed or external work location on standard days and times, or whether this varied from week to week. The third question addressed the working hours arrangement most applicable to the respondent. The analyses in this section are based on questions W5c, W5d and W8 of the LRO questionnaire. Full question wording is provided in Appendix B.

Together, these questions enable the characterisation of the timing and regularity of commuting behaviour patterns over time. The detailed results of these analyses are presented in Appendix D. The sections below summarise the key trends.

Arrival commuting behaviour

The analyses of peak arrival times are based on the working population per wave, rather than being restricted to respondents who commute to a fixed or external work location. This approach was chosen in order to reflect the absolute contribution of each day to peak-hour traffic. Reporting percentages relative to commuters only would distort the interpretation, as days with fewer commuters, such as Saturday, would appear disproportionately prominent, regardless of their actual contribution to peak demand. The percentages reported in Figure 4.1 therefore reflect the proportion of the total working population that arrived during the morning peak on a given day.

To examine peak arrival commuting behaviour, respondents were asked to indicate the time at which they typically arrived at their (fixed or external) work location each day of the week. In line with the definition employed in the LRO 2024 analyses, arrivals between 07:00 and 09:00 were categorised as peak arrivals (Ministerie van Infrastructuur en Waterstaat et al., 2025). The percentages in Figure 4.1 reflect the proportion of working respondents who arrived during the morning peak on a given day.

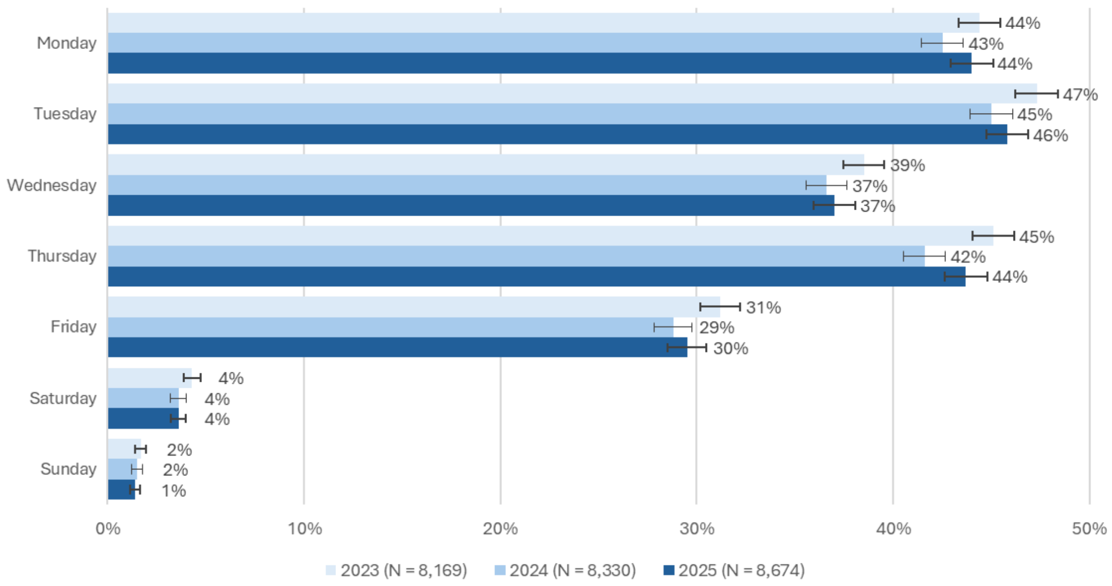

Figure 4.1 Trends in peak arrival commuting times across waves 2023-2025
***Note*. Percentages reflect the population of working respondents per wave who arrived at their fixed or external work location between 07:00 and 09:00 on a given day. Error bars represent 95% confidence intervals.**

As shown in Figure 4.1, peak commuting arrivals are highest on Tuesday and Thursday across all three waves. These days consistently record the highest proportions of peak arrivals, ranging between 42% and 47%. These findings are consistent with those of R. Faber et al. (2023) and Barrero et al. (2023). The ranking of the weekdays remains remarkably stable over time, with Tuesday, Thursday, Monday, Wednesday and Friday appearing in descending order across all three waves. Weekend commuting remains marginal, with Saturday and Sunday accounting for no more than 4% of peak arrivals across all waves. This stability suggests that the days on which people commute during peak arrival times have remained unchanged over the observed period.

A consistent dip is observable across all weekdays in 2024, followed by a partial recovery in 2025. For Tuesdays, Thursdays and Fridays, this decline is statistically significant, as the confidence intervals between 2023 and 2024 do not overlap. While the recovery from 2024 to 2025 is consistent in direction, it is not statistically significant for any weekday. This uniform dip-and-recovery pattern may suggest an increase in WFH in 2024, rather than a particular day-specific effect. This interpretation is consistent with the 2024 LRO findings, which report that the average number of WFH days increased slightly in 2024 compared to 2023, driven in part by improved employer support. Approximately one in five employees reported that either the possibility to work from home (20%) or the associated WFH allowance (21%) had improved in 2024 compared to 2023 (Ministerie van Infrastructuur en Waterstaat et al., 2025).

Departure commuting behaviour

As with peak arrival commuting times, the analyses are based on the working population per wave to reflect each day's absolute contribution to peak departure times. To examine departure commuting behaviour, respondents indicated the time at which they typically left their (fixed or external) work location each day of the week. In line with the LRO 2024 analyses, departures between 16:00 and 18:00 were classified as peak departures (Ministerie van Infrastructuur en Waterstaat et al., 2025). The percentages in Figure 4.2 reflect the proportion of working respondents who departed during the evening peak on a given day.

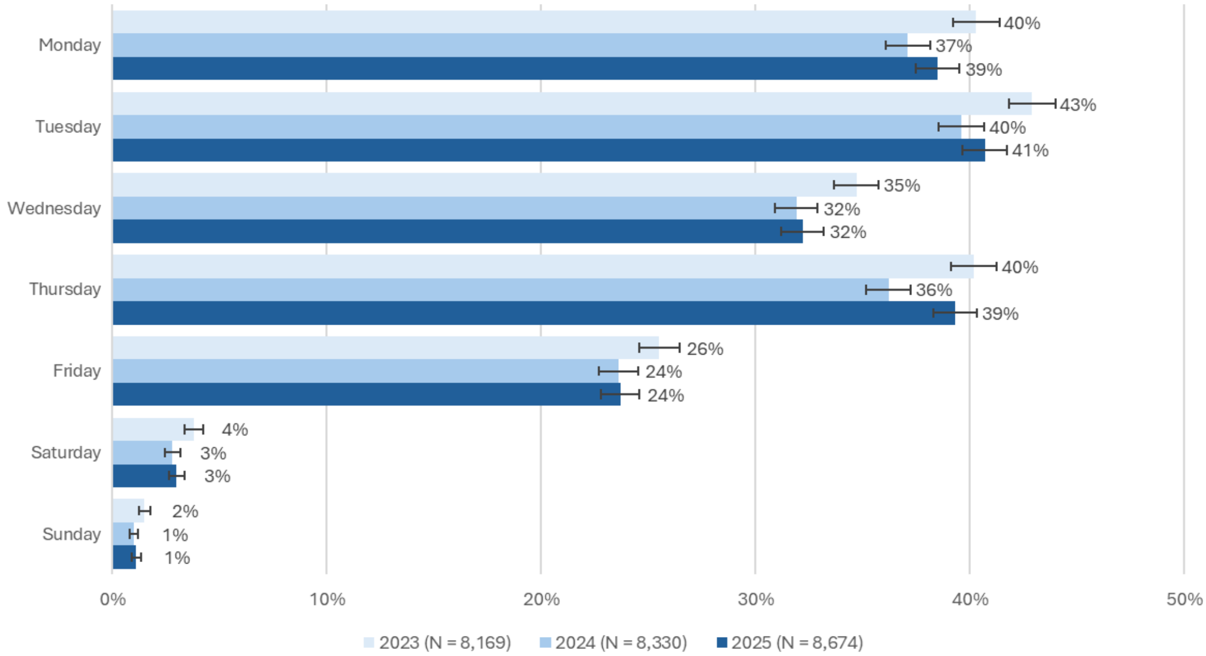

Figure 4.2 Trends in peak departure commuting times across waves 2023-2025
Note. **Percentages reflect the population of working respondents per wave who left their fixed or external work location between 16:00 and 18:00 on a given day. Error bars represent 95% confidence intervals.**

As shown in Figure 4.2, the highest proportions of peak departures are recorded on Tuesday, Monday and Thursday across all waves, ranging from 36% to 43%. However, the differences between these three days are small. Wednesday follows with a notably lower proportion, while Friday consistently records the lowest proportion of all weekdays. Weekend commuting remains marginal across all waves.

The ranking of the weekdays remains stable across all three waves and the dip-and-recovery pattern observed for peak arrivals can also be seen here. The decline from 2023 to 2024 is statistically significant for Monday, Tuesday, Wednesday and Thursday, as their confidence intervals do not overlap in these two years. The recovery from 2024 to 2025 is significant only for Thursday, with the proportion rising from 36% to 39%. For all other weekdays, the recovery is consistent in direction, but not statistically significant. This supports the idea that the 2024 dip reflects a structural rather than day-specific shift.

Notably, peak departure proportions are consistently lower than peak arrival proportions for all days. For instance, Tuesday peaks at 47% for arrivals, but only 43% for departures. This suggests that the evening peak is more dispersed than the morning peak, indicating that working respondents tend to be more flexible when they depart than when they arrive.

Commuting pattern variability

To examine variability in commuting patterns, respondents were asked whether they commute on fixed days and at fixed times, or if their commuting pattern varies from week to week. Unlike the peak arrival and departure analyses, which were based on the working population, the percentages reported in Figure 4.3 are based on respondents who commute to a fixed or external work location. This is because the question only applies to people who actually commute. This results in a smaller sample size than in previous analyses.

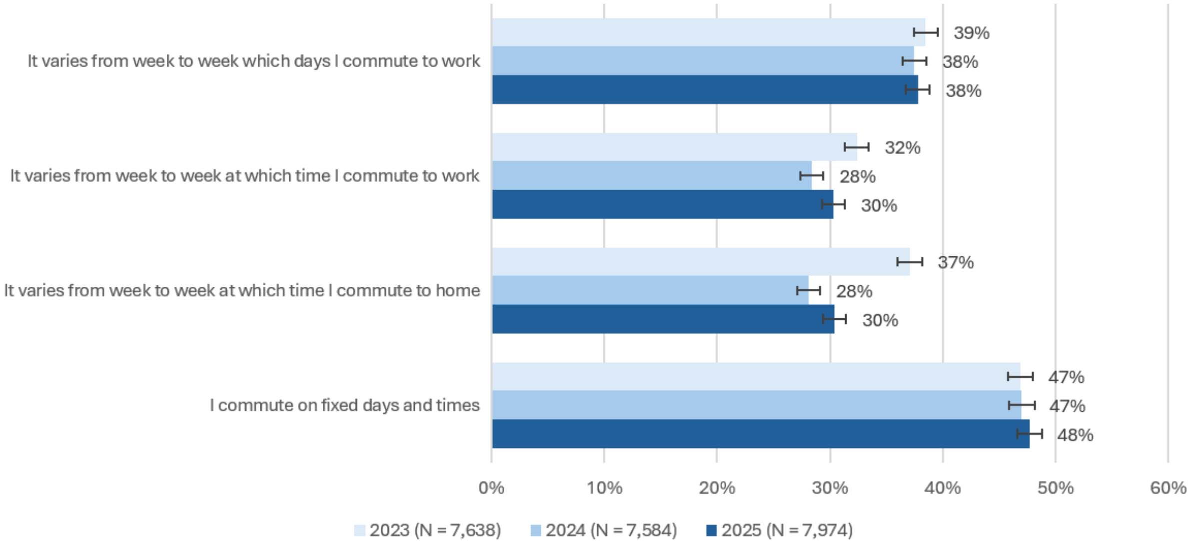

Figure 4.3 Trends in commuting pattern variability across waves 2023-2025
***Note*. Percentages reflect the proportion of commuters per wave: respondents travelling to a fixed or external work location. Full homeworkers are excluded. Multiple responses were permitted. Error bars represent 95% confidence intervals.**

As shown in Figure 4.3, commuting on fixed days and times was the most prevalent pattern across all three waves, reported by around 47% to 48% of commuters. The second most common response was variability in commuting days, reported by 38% to 39% of commuters across all waves, showing no statistically significant change over time, as the confidence intervals overlap between waves. Arrival and departure time variability follows with similar proportions of around 28% to 37%. Both of these patterns show a statistically significant decline from 2023 to 2024. Notably, variability in departure times shows the largest shift from one wave to the next, dropping from 37% in 2023 to 28% in 2024, before recovering to 30% in 2025.

Overall, commuting pattern variability remains largely stable across the three measurement waves. The consistent prevalence of fixed commuting patterns indicates that most commuters organise their commuting pattern around a predictable weekly routine, potentially limiting the potential for redistribution of commuting demand throughout the week.

Working time flexibility

To examine working time flexibility, respondents indicated which working hours arrangement best applied to their situation. The percentages in Figure 4.4 reflect the proportion of working respondents per wave who selected each response category.

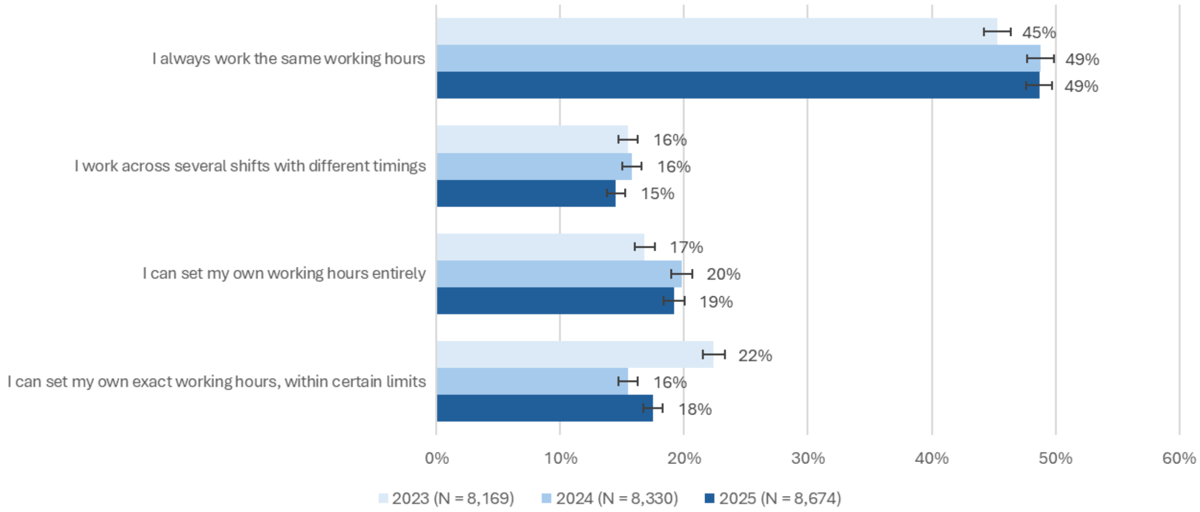

Figure 4.4 Trends in working time flexibility across waves 2023-2025
Note. **Percentages reflect the proportion of working respondents per wave. The question had four response options, with only one answer permitted. Error bars represent 95% confidence intervals.**

As shown in Figure 4.4, the most prevalent arrangement across all three waves is fixed working hours. The proportion of respondents who always worked the same working hours increased significantly, rising from 45% in 2023 to 49% in 2024. This figure remained stable at 49% in 2025, with the confidence intervals not overlapping. Conversely, the proportion of respondents who could set their own hours within certain limits decreased significantly, falling from 22% in 2023 to 16% in 2024 before partially recovering to 18% in 2025. The increase in fixed working hours between 2023 and 2024 appears to correspond with a simultaneous decline in bounded flexibility. This suggests that some employees who previously had limited scheduling discretion may have transitioned to fully fixed arrangements in 2024. As flexibility in working hours is a prerequisite for avoiding peaks, this tightening may help to explain why peak arrivals were concentrated across all three waves. Working across shifts remained stable across all waves. Meanwhile, full autonomy over working hours increased modestly, rising from 17% to 20% between 2023 and 2024 before declining slightly to 19% in 2025.

Overall, these patterns suggest that scheduling flexibility has become increasingly constrained over the observed period, with potential consequences for the redistribution of commuting demand away from peak hours.

4.1.2 Observed Trends in Working from Home Behaviour and Factors

This section presents the observed trends in working from home behaviour and the factors associated with the decision to work from home or not, measured across the three measurement waves. As mentioned in Section 4.1, questions relating to working from home were only asked of working respondents.

Working from home behaviour was operationalised using six LRO survey questions. The first question captured the number of days that respondents worked from home, at their fixed work location or at an external location during the reference week. This was used to derive the total number of days that respondents worked from home per week. The second question assessed respondents' WFH opportunities. The third question addressed the structure of WFH behaviour among those who work from home. The fourth question examined the reasons why respondents worked from home. The fifth question addressed why respondents who could work from home choose not to do so. The sixth question assessed the extent to which various situational factors influence respondents' travel and WFH behaviour. The analyses in this section are based on questions W5, T1, T2, T3, T5.2 and C2 of the LRO questionnaire. Full question wording is provided in Appendix B.

Together, these questions characterise the prevalence, structure and underlying factors of WFH behaviour over time. The detailed results of these analyses are presented in Appendix E. The sections below summarise the key trends.

Mean working from home days

To examine the number of days that respondents worked from home, they were asked to indicate how many days during the reference week they worked from home, from their fixed work location, or from an external location. As described in Section 3.2.1, the LRO measures behaviour during a single reference week, which is assumed to be representative of the respondent's typical working week. The total number of WFH days was calculated as the number of fully WFH days, plus half of the number of days spent partly at home in combination with either a fixed or external work location, as these days represent only a partial contribution to working from home.

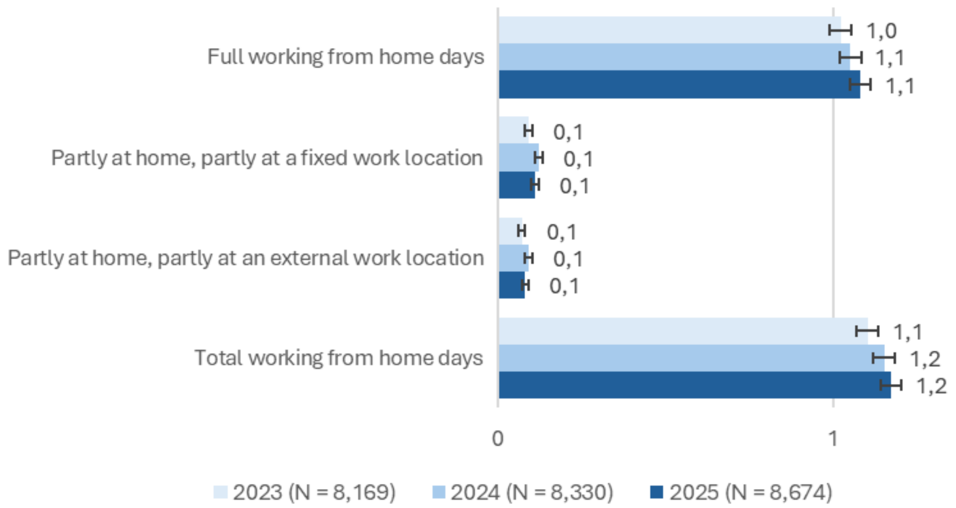

Figure 4.5 Trends in mean WFH days across waves 2023-2025
***Note*. Values reflect mean number of days per week. Partially WFH days (partly at home, partly at a fixed or external work location) are included in the total WFH days calculation. Error bars represent 95% confidence intervals.**

As shown in Figure 4.5, the mean number of full WFH days increased from 1.0 in 2023 to 1.1 in 2024, before remaining stable in 2025. However, the confidence intervals for 2023 and 2024 overlap, suggesting that this increase is not statistically significant. The number of days worked partly from home remained consistently low at 0.1 across all three waves, with no meaningful change over time. Similarly, the mean total number of WFH days increased from 1.1 to 1.2 between 2023 and 2024, and stabilising in 2025. However, the overlapping confidence intervals again indicate that this change is not statistically significant.

Overall, working from home shows a modest upward trend over the observed period, though none of the changes between waves are statistically significant. This gradual rise may reflect the continued normalisation of WFH arrangements following the COVID-19 pandemic. This does not necessarily contradict the recovery in commuting observed in 2025 in Section 4.1.1, as both trends could coexist within the same population: WFH expands among workers who previously never worked from home, while existing commuters simultaneously increase their office attendance after the temporary dip in 2024.

Total working from home days

To examine the frequency of WFH in more detail, the total number of WFH days per week was categorised into six groups: none, one, two, three, four and five or more days. As previously described, the total number of WFH days was calculated by adding the number of fully remote days to half the number of partially remote days, as hybrid days only represent a partial contribution to working from home.

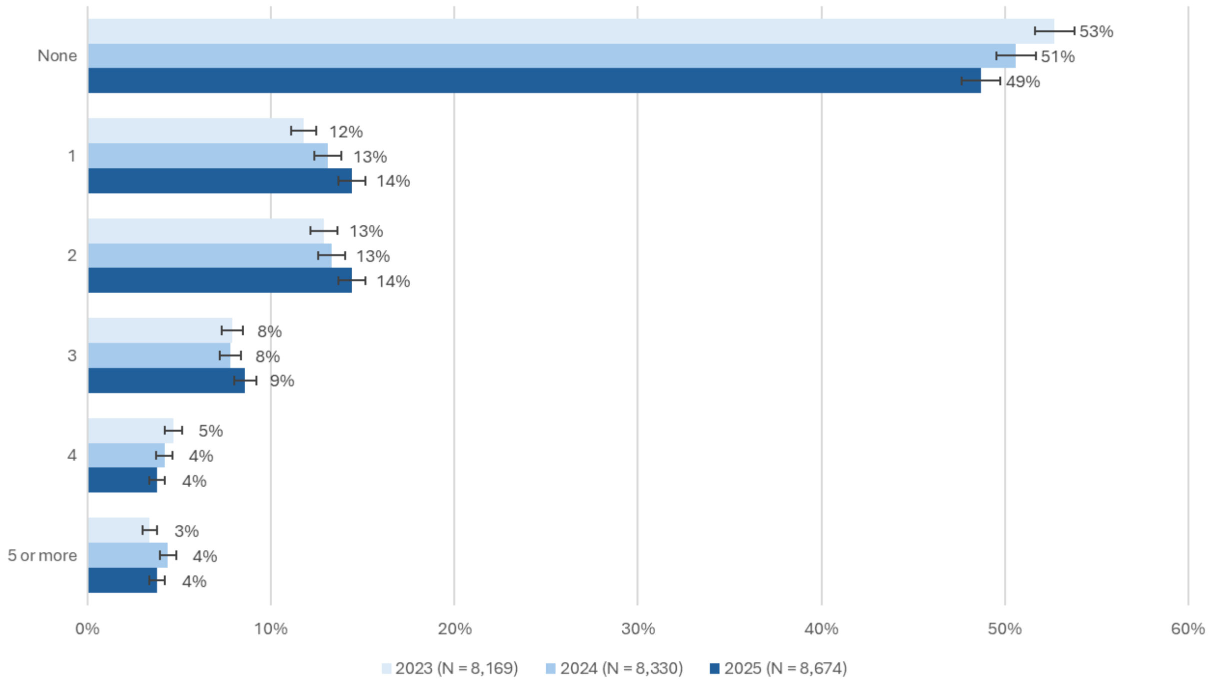

Figure 4.6 Trends in total WFH days per week across waves 2023-2025
***Note*. Percentages reflect the proportion of working respondents per wave. Error bars represent 95% confidence intervals.**

As shown in Figure 4.6, the proportion of respondents who did not work from home at all declined across the waves, from 53% in 2023 to 49% in 2025. While the decline between 2023 and 2024 is not statistically significant, the confidence intervals between 2023 and 2025 do not overlap. This suggests that the overall decline over the three years is statistically significant. There was a modest but statistically significant increase in working from home one or two days per week, with both categories rising from around 12-13% in 2023 to 14% in 2025. The proportion of respondents working from home three or more days per week remained relatively stable across all waves, with no statistically significant changes. Together, these patterns suggest that the growth in WFH is primarily driven by workers shifting from no WFH to one or two days per week, rather than by existing home workers increasing their frequency.

Overall, the distribution of WFH days shifted modestly but consistently across the three measurement waves. These new hybrid workers continue to commute on most of their working days, meaning that the expansion of WFH does not translate directly into a proportional reduction in commuting volume.

Working from home opportunities

To examine working from home opportunities among non-home workers, respondents who indicated zero WFH days were asked which situation best applied to their circumstances. The percentages in Figure 4.7 reflect the proportion of non-home workers per wave.

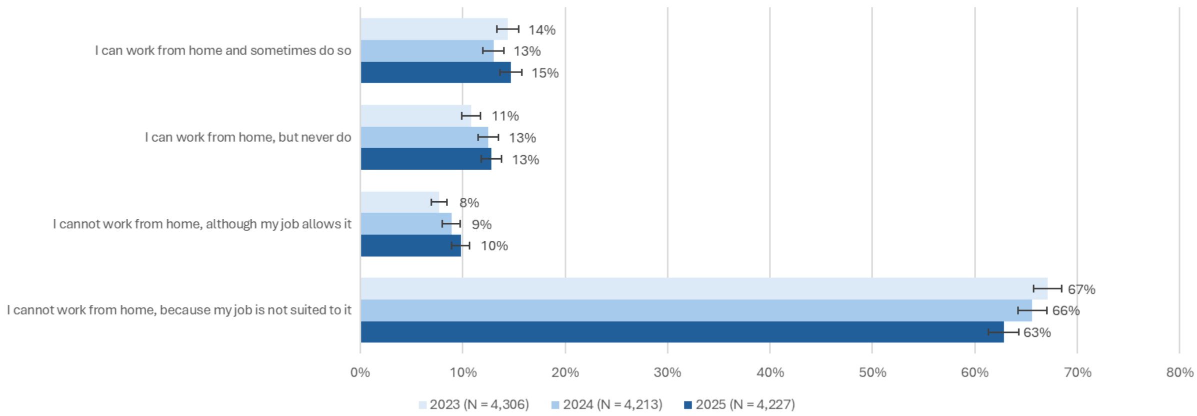

Figure 4.7 Trends in WFH opportunities across waves 2023-2025
***Note.* Percentages reflect proportion of non-home workers per wave. Only one response was permitted. Error bars represent 95% confidence intervals.**

As shown in Figure 4.7, the largest proportion of non-home workers indicated that their job is not suited to work from home, though this proportion declined significantly over time, falling from 67% in 2023 to 63% in 2025. The confidence intervals for these two years do not overlap, suggesting that this decline was statistically significant. The proportion of respondents who can work from home and occasionally do so remained broadly stable. The proportion of respondents who can work from home but never do so increased from 11% to 13% between 2023 and 2024, remaining stable in 2025, though the confidence intervals overlap and this change does not reach statistical significance. The proportion of respondents who cannot work from home despite their job allowing it increased modestly, from 8% to 10%. However, the confidence intervals overlap again, suggesting that this change is not statistically significant.

Figure 4.8 shows the proportion of non-home workers who said their job is not suited to WFH, broken down by sector. The sector breakdown suggests that the decline in job-related impossibility of WFH may be partly explained by a shift in the sectoral composition of non-WFH workers, with a decreasing proportion working in sectors where WFH is structurally infeasible. Notable declines are seen in sectors with high proportions of non-WFH workers, such as hospitality (88% to 80%) and industry (67% to 59%), while increases are seen in knowledge-intensive sectors such as ICT (23% to 29%) and business services (33% to 39%). This pattern suggests that the proportion of respondents working in sectors where WFH is impossible may have decreased, contributing to the overall decline observed in Figure 4.7. However, it should be noted that this sectoral pattern does not conclusively explain the overall decline. Changes in employer arrangements and technological development that enable WFH may have contributed to the broader expansion of the feasibility of WFH.

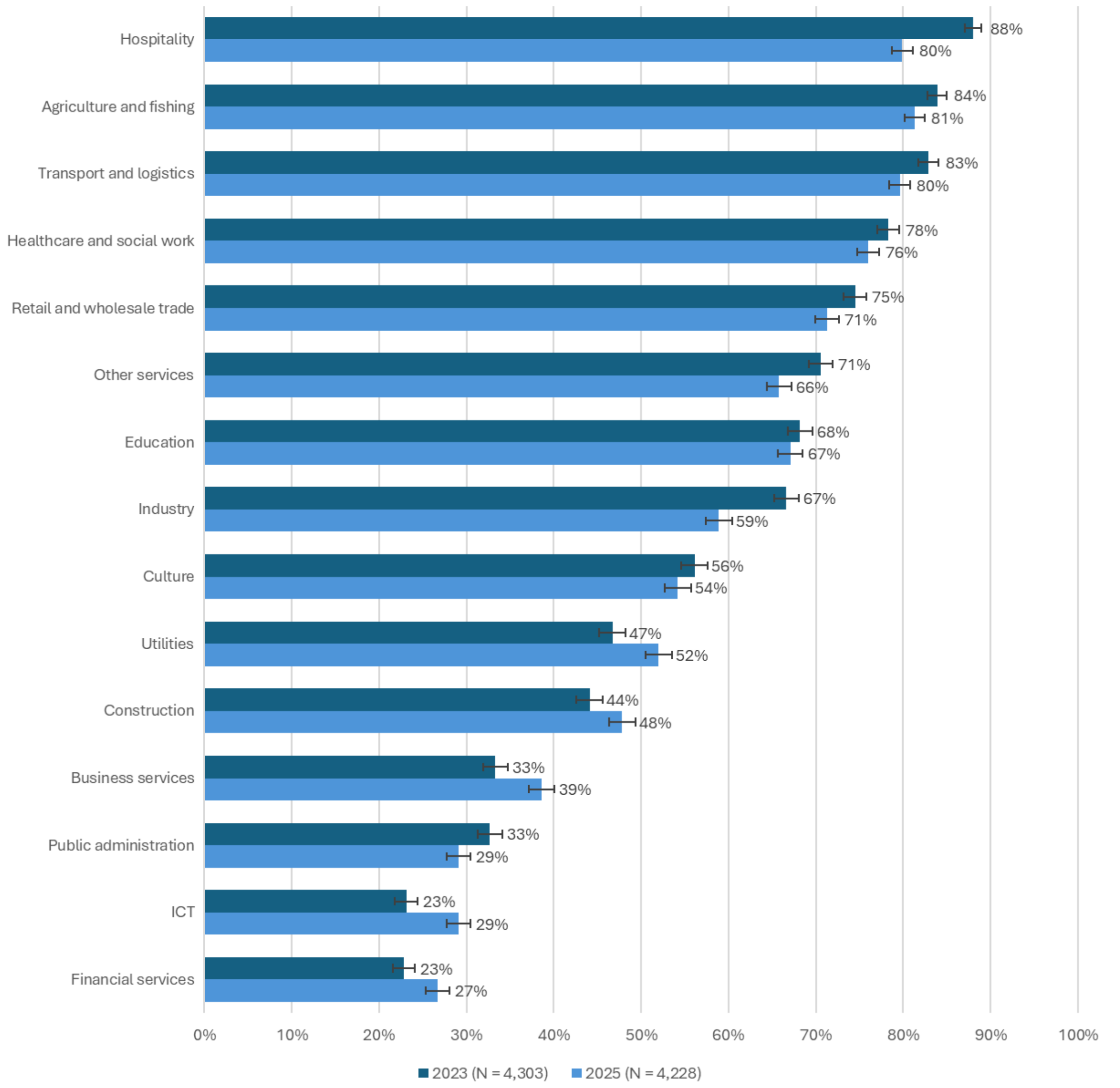

Figure 4.8 Proportion of non-home workers reporting their job is not suited to WFH, by sector (2023 and 2025)
***Note*. Percentages reflect the proportion of non-home workers per sector who indicated their job is not suited to WFH. The sector analysis is based on a slightly smaller sample due to missing values on the sector variable (2023: N = 4,303; 2025: N = 4,228). Error bars represent 95% confidence intervals.**

Working from home structure

To examine the structure of WFH behaviour, respondents who worked from home for at least one day, or who indicated that they could work from home and sometimes do so, were asked to select the option that best described their current WFH pattern. The percentages in Figure 4.9 reflect the proportion of home workers per wave.

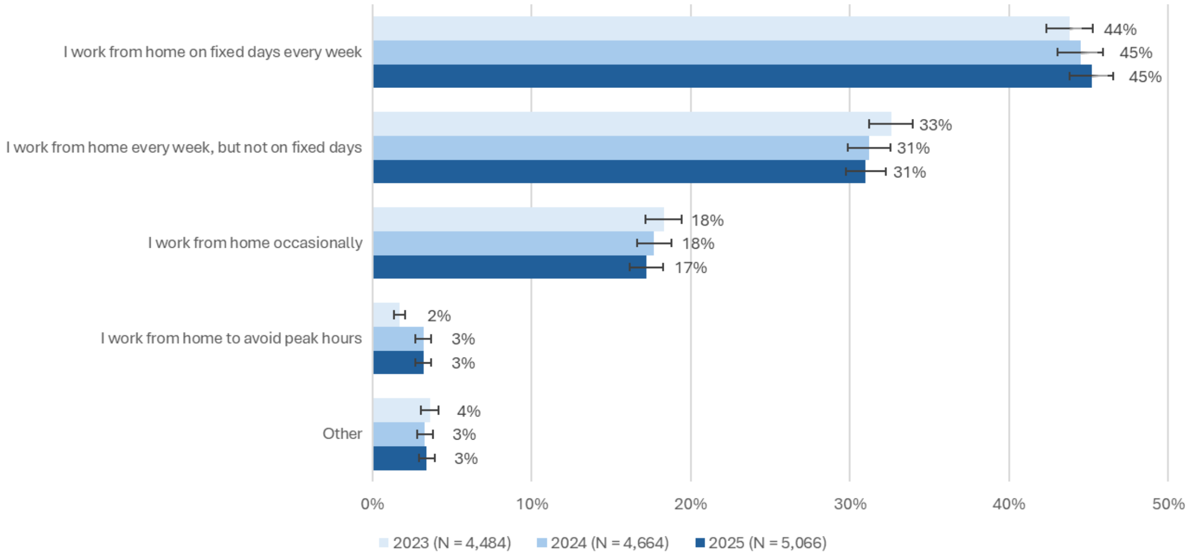

Figure 4.9 Trends in WFH structure across waves 2023-2025
Note. **Percentages reflect the proportion of home workers per wave. Only one response was permitted. Error bars represent 95% confidence intervals. Note that the sum of home workers and non-home workers exceeds the total working population, as respondents who indicated at least one WFH day and also responded their WFH opportunities are counted in both groups.**

As shown in Figure 4.9, the most prevalent pattern is working from home on fixed days every week, which remained stable at around 44-45% across all three waves. Overlapping confidence intervals indicate that there was no statistically significant change. The second most common pattern is working from home every week, but not on fixed days. This declined from 33% in 2023 to 31% in 2024, though the overlapping confidence intervals indicate this change is not statistically significant, remaining stable thereafter. Occasional WFH remained stable at around 17-18% across all waves.

Although neither change is statistically significant, the slight increase in fixed WFH days and the corresponding decline in non-fixed WFH days may suggest that some home workers have shifted from a flexible week-to-week pattern towards a more structured, fixed-day routine.

Notably, the proportion of respondents working from home specifically to avoid peak hours remained consistently low at 2-3% across all three waves, indicating that avoiding peak hours is rarely cited as a primary motivation for working from home.

Overall, the structure of working from home remained largely stable across the three measurement waves, with WFH on fixed days being the most prevalent pattern.

Reasons for working from home

To examine the reasons for working from home, respondents who worked from home for at least occasionally were asked to indicate which reasons applied to their decision to do so. The percentages in Figure 4.10 reflect the proportion of this group per wave.

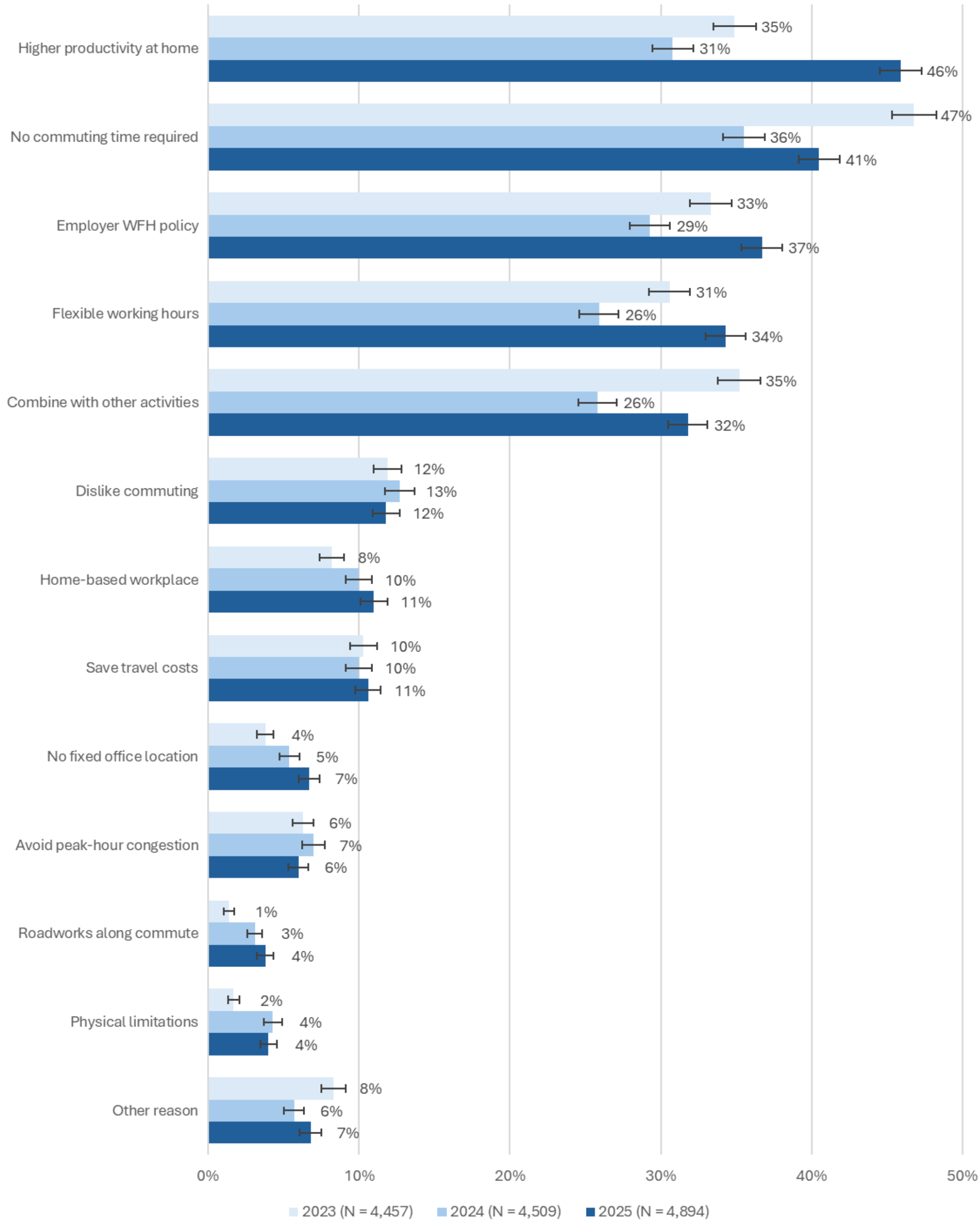

Figure 4.10 Trends in reasons for WFH across waves 2023-2025

Note. **Percentages reflect the proportion of home workers per wave. Multiple responses were permitted. The 2023 and 2024 questionnaires included 17 response options, while the 2025 questionnaire included 13. The four response options available in 2023 and 2024 only are presented separately in Figure 4.11. Error bars represent 95% confidence intervals.**

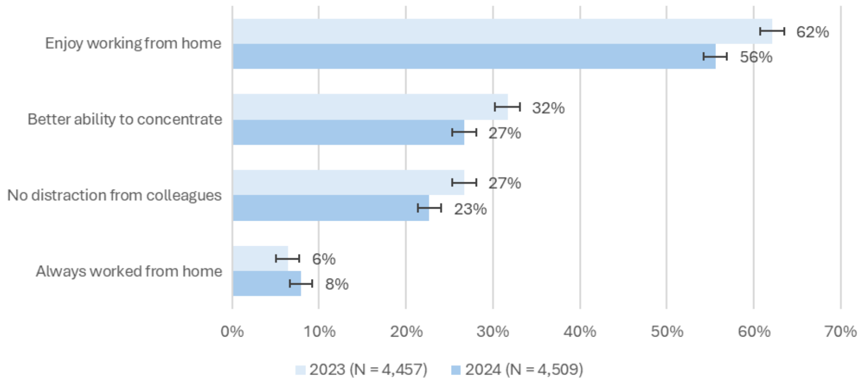

Figure 4.11 Reasons for WFH available in 2023 and 2024 only
***Note*. Multiple responses were permitted. Error bars represent 95% confidence intervals.**

As shown in Figure 4.10, the most frequently cited reasons across all three waves were higher productivity at home, not having to commute, the employer's WFH policy, flexible working hours and being able to combine work with other activities. A consistent pattern emerges, with proportions declining in 2024 before rising more substantially in 2025. However, these increases should be interpreted with caution. In 2025, the number of response options was reduced from 17 to 13, meaning that respondents could no longer select four of the options that had previously been available. This reduction likely inflates the proportions for the remaining categories in 2025, as responses that were previously distributed across more options became concentrated among fewer alternatives. Figure 4.11 presents the four options that were only available in 2023 and 2024. Comparisons between 2023 and 2024 are therefore more reliable, as the response options remained consistent across these waves.

Of the changes between 2023 and 2024, the five most frequently cited reasons all show a statistically significant decline, as the confidence intervals do not overlap between these two years. The most pronounced decline was observed for the combination with other activities, dropping from 35% to 26%. Higher productivity at home showed the largest overall increase across the three waves, rising from 35% in 2023 to 46% in 2025. This may partly reflect the removal of the related options 'better ability to concentrate' and 'no distraction from colleagues' in 2025, as respondents who would previously have selected those options may have shifted towards 'higher productivity at home' as the closest available alternative.

The remaining categories are consistently lower in proportion across all waves. Among these, avoid peak-hour congestion, physical limitations, and dislike commuting are the only reasons that increased between 2023 and 2024 before declining in 2025. However, these increases are small, and the overlapping confidence intervals suggest that they are not statistically significant. Most other lower-proportion categories show no consistent directional pattern across waves, and none of the changes reach statistical significance given the overlapping confidence intervals.

Reasons against working from home

To examine the reasons against working from home, respondents who indicated that they could work from home but never did so were asked to indicate which reasons applied to their decision. The percentages in Figure 4.12 reflect the proportion of this subgroup per wave.

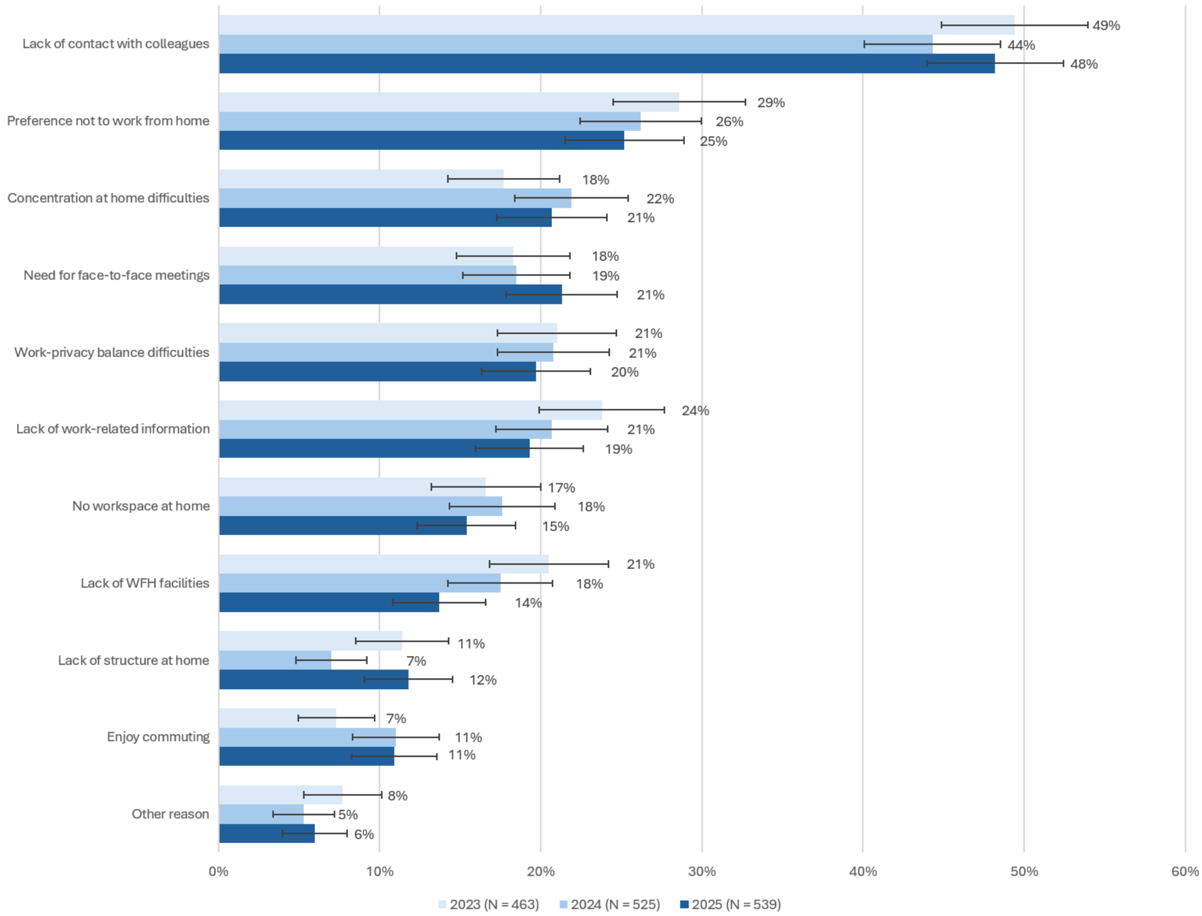

Figure 4.12 Trends in reasons against WFH across waves 2023-2025
Note. **Percentages reflect the proportion of respondents who can work from home but never do so per wave. Multiple responses were permitted, with a maximum of three per respondent. Error bars represent 95% confidence intervals.**

As shown in Figure 4.12, a lack of contact with colleagues was the most frequently cited reason across all three waves, with consistently and substantially higher proportions than all other categories. However, due to the relatively small sample size of this subgroup (approximately 500 per wave), the confidence intervals are wider than in previous analyses, which limits the ability to detect statistically significant changes. The slight decline from 49% in 2023 to 44% in 2024, followed by a recovery to 48% in 2025, are therefore both not statistically significant.

Two broader patterns emerge among the remaining reasons. Several categories show a declining trend over the measurement period. Lack of WFH facilities showed the most pronounced overall decline, dropping from 21% in 2023 to 14% in 2025, though given the wide confidence intervals due to the small sample size, this decline does not reach statistical significance. Preference not to work from home and lack of work-related information also declined, though their confidence intervals overlap and these changes are not statistically significant. Conversely, the need for face-to-face meetings increased consistently, rising from 18% to 21%, and the proportion of people who enjoy commuting increased from 7% to 11%. However, overlapping confidence intervals suggest that these increases are not statistically significant.

Overall, practical barriers to working from home, such as the lack of WFH facilities, limited workspace at home and a lack of work-related information, have shown a declining trend over the observed period. This suggests that the infrastructure for WFH has improved. Meanwhile, social and relational factors, most notably the desire for contact with colleagues and the need for face-to-face meetings, have remained consistently prominent. This shift may indicate that the decision not to work from home is increasingly a matter of personal preference and social motivation rather than practical impossibility. This has implications for how employers might approach WFH policies. However, given the small sample size of this group, these patterns should be interpreted with caution.

Perceived influence of factors on commuting and working from behaviour

To examine the perceived influence of contextual factors on commuting and working from home behaviour, respondents were asked to rate seven factors using a five-point Likert scale, ranging from 1 (no influence) to 5 (strong influence). Figure 4.13 shows the mean scores per wave among working respondents.

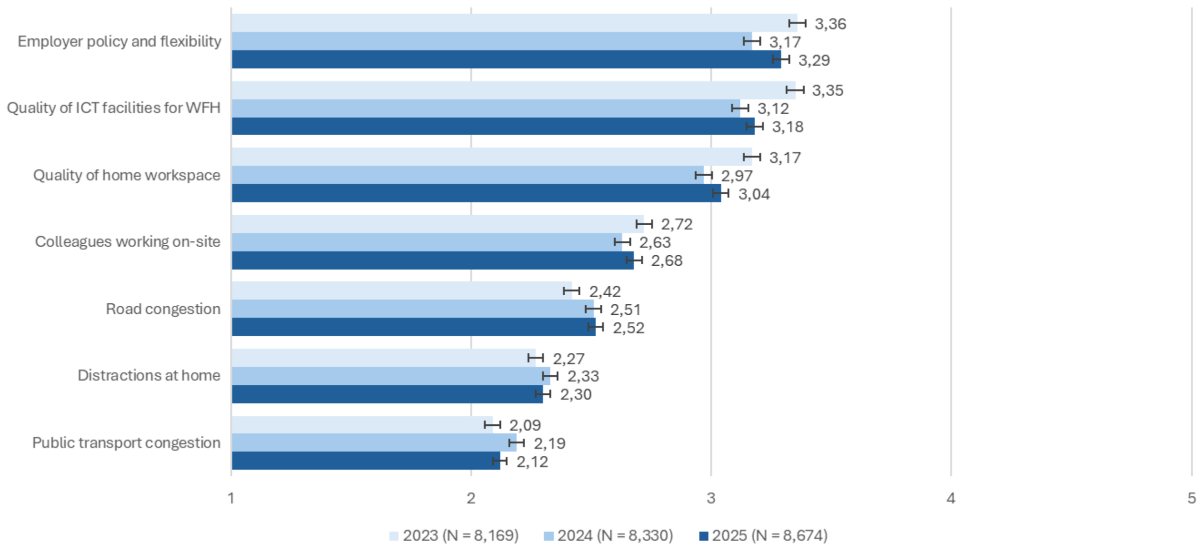

Figure 4.13 Trends in factors on commuting and WFH behaviour across waves 2023-2025
Note. **Values reflect mean scores on a five-point Likert scale (1 = no influence, 5 = strong influence) among working respondents per wave. When interpreting mean scores on Likert scales, it is assumed that the intervals between categories are equal for all respondents. This assumption may not hold in practice, and mean scores should therefore be interpreted with caution. Error bars represent 95% confidence intervals.**

As shown in Figure 4.13, the top three factors – employer policy and flexibility, quality of ICT facilities for WFH, and quality of home workspace – consistently score at or above the midpoint of the scale across all waves, while the remaining four factors fall below it. Notably, all three of the top factors show a statistically significant decline from 2023 to 2024, with the confidence intervals for these two waves not overlapping, followed by a partial recovery in 2025. The decline is most pronounced for the quality of ICT facilities for WFH, dropping from 3.35 to 3.12. The simultaneous decline of all three top factors in 2024 suggests that WFH became a less active consideration for respondents in that year. As more respondents returned to the office more frequently, the practical relevance of factors enabling WFH decreases when office attendance increases. This is consistent with LRO 2024 data, which reports that approximately 12% of working respondents increased their number of commuting days in 2024 (Ministerie van Infrastructuur en Waterstaat et al., 2025). While this may appear to contradict the earlier observed increase in WFH days, both patterns can coexist if some employees worked from home more while others returned to the office more frequently within the same year.

Meanwhile, road and public transport congestion shows a modest but statistically significant increase from 2.42 to 2.51 and 2.09 to 2.19 respectively, between 2023 and 2024, remaining stable thereafter. This increase may reflect the same return-to-office dynamic: as more respondents commuted more frequently in 2024, their exposure to peak-hour traffic increased, making road and public transport congestion more significant factors in their daily travel decisions.

From a policy perspective, the consistently high perceived influence of employer policy and flexibility is noteworthy. This suggests that organisational decisions play a central role in shaping commuting and WFH behaviour. This finding is consistent with the latent transition analysis in Section 4.3, which examines the relationship between changes in contextual policy factors and transitions between commuting profiles.

Key findings: observed trends in commuting behaviour

Commuting behaviour remained largely stable throughout 2023, 2024 and 2025. Peak arrivals were consistently concentrated on Tuesdays and Thursdays, and the full weekday ranking – Tuesday, Thursday, Monday, Wednesday, and Friday – remained unchanged throughout the observed period. The evening peak was more dispersed than the morning peak, suggesting that departure times were more flexible than arrival times. The most notable deviation from this overall stability was a uniform dip in peak commuting across all weekdays in 2024, followed by a partial recovery in 2025. This points to a temporary structural shift, likely related to an increase in WFH, rather than a day-specific effect.

Fixed commuting patterns were the most prevalent arrangement, reported by around 47% to 48% of commuters across all waves. Fixed working hours were the most prevalent arrangement across all three waves and increased in share between 2023 and 2024, coinciding with a decline in bounded flexibility. As scheduling flexibility is a prerequisite for voluntarily avoiding peak times, this tightening, alongside the prevalence of fixed commuting patterns, helps to explain why peak arrivals remained persistently concentrated throughout the observed period, with limited scope for the spontaneous redistribution of commuting demand.

Key findings: observed trends in WFH behaviour

WFH showed a modest but gradual expansion over the observed period. The average number of days spent working from home increased slightly from 1.0 in 2023 to 1.1 in 2024, before stabilising in 2025. Meanwhile, the proportion of non-home workers fell from 53% in 2023 to 49% in 2025. Conversely, there was an increase in one- and two-day WFH patterns. While these year-on-year changes were not statistically significant, the overall decline across the full observation period was, suggesting a gradual but real increase in WFH among the working population.

The structural impossibility of WFH decreased too, falling from 67% to 63% among non-home workers. This was partly driven by a shift in sectoral composition, as well as potentially by improvements in employer arrangements and technology. Among home workers, fixed WFH day patterns remained the most prevalent structure, becoming slightly more prevalent over time. This suggests a gradual shift towards more structured WFH arrangements. Notably, only 2-3% of respondents reported working from home specifically to avoid peak hours, indicating that peak avoidance is rarely a primary motivation for WFH.

The most frequently cited reasons for WFH were higher productivity, avoiding commuting, the employer's WFH policy, flexible working hours and combining work with other activities. Among those who could work from home but chose not to, practical barriers such as the lack of WFH facilities decreased over time. Meanwhile, social motivations, such as the desire for contact with colleagues, remained consistently prominent. This suggests that the decision not to work from home is increasingly a matter of personal preference rather than practical impossibility. Employer policy and flexibility were the most influential factors in shaping commuting and WFH behaviour across all three waves, emphasising the role of organisational decisions in determining travel patterns. Employer policy, in particular, may therefore be a key predictor of transitions between commuting profiles, as examined in the latent class and latent transition analyses, presented in Section 4.2 and Section 4.3, respectively.

4.2 Results of Latent Class Analysis

This section addresses the second sub-question of the study:

SQ2: Which distinct commuting profiles can be identified based on individuals' commuting behaviour per day of the week?

To answer this question, a latent class analysis (LCA) was conducted on the LRO survey data. This analysis was based on the longitudinal subsample of working respondents who participated in all three measurement waves (N = 612), as described in Section 3.2.1.

The results of the LCA are presented in three sequential sections. First, Section 4.2.1 establishes the optimal number of latent classes. Section 4.2.2 then examines consistency across waves, and finally, Section 4.2.3 interprets the commuting profiles.

4.2.1 Model Specification and Estimation

As described in Section 3.1.1, distinct commuting profiles were identified using a latent class analysis conducted separately for each measurement wave. The measurement model was estimated using only the indicators and without covariates to determine the optimal number of latent classes. The indicators used in the model are binary variables that represent whether or not a respondent commuted on each weekday (Monday to Friday), specified as nominal variables.

Models with one to eight latent classes were estimated for each wave using LatentGOLD with maximum likelihood estimation. Table 4.2 presents the model fit statistics for these models. The fit of each model was evaluated using the complementary criteria, as recommended by Magidson & Vermunt (2004).

Table 4.2 Model fit of the latent class analyses

Wave	No. of classes	LL	BIC(LL)	L^2	Reduction in L^2 (%)	Max. BVR	Entropy R^2	Min. class size (%)
2023	1	-1921.722	3875.527	139.469	0.00	21.436	1.000	1.00
	2	-1871.878	3814.341	39.783	0.71	3.411	0.494	0.32
	3	**-1865.106**	**3839.296**	**26.237**	**0.81**	**1.017**	**0.469**	**0.11**
	4	-1860.712	3869.009	17.450	0.87	0.790	0.628	0.08
	5	-1857.642	3901.369	11.309	0.92	0.216	0.607	0.05
	6	-1855.755	3936.096	7.536	0.95	0.052	0.565	0.06
	7	-1853.972	3971.031	3.970	0.97	0.030	0.574	0.05
	8	-1852.623	4006.831	1.271	0.99	0.048	0.546	0.03
2024	1	-1925.536	3883.155	177.908	0.00	37.756	1.000	1.00
	2	-1864.658	3799.901	56.153	0.68	5.521	0.554	0.30
	3	**-1851.673**	**3812.430**	**30.182**	**0.83**	**1.437**	**0.523**	**0.15**
	4	-1847.698	3842.981	22.232	0.88	0.529	0.506	0.14
	5	-1843.371	3872.827	13.578	0.92	0.276	0.562	0.05
	6	-1841.231	3907.048	9.299	0.95	0.081	0.575	0.06
	7	-1838.331	3939.749	3.499	0.98	0.053	0.617	0.03
	8	-1837.021	3975.629	0.879	1.00	0.012	0.609	0.03
2025	1	-1923.006	3878.095	139.023	0.00	14.108	1.000	1.00
	2	-1872.411	3815.406	37.834	0.73	2.201	0.522	0.32
	3	**-1865.910**	**3840.905**	**24.832**	**0.82**	**2.483**	**0.505**	**0.07**
	4	-1861.304	3870.194	15.621	0.89	0.965	0.508	0.12
	5	-1857.265	3900.615	7.542	0.95	0.054	0.555	0.10
	6	-1855.937	3936.460	4.886	0.96	0.086	0.542	0.10
	7	-1854.702	3972.490	2.416	0.98	0.025	0.558	0.04
	8	-1854.451	4010.489	1.915	0.99	0.021	0.518	0.07

Note. LL = Log-likelihood; BIC(LL) = Bayesian Information Criterion (based on log-likelihood); BVR = Bivariate Residual.

The BIC reaches its lowest value at two classes in all three waves. However, the BIC alone is insufficient, as it only penalises model complexity and does not assess residual misfit or classification quality (see Section 3.1.1). The BVR value for the two-class solution exceeds the threshold of 3.84 in 2024, indicating that the local independence assumption is violated. The two-class solution is therefore rejected.

The four-class solution produces higher Entropy R^2 values than the three-class solution in 2023 (0.628 vs. 0.469) and a marginally higher value in 2025 (0.508 vs. 0.505). However, this advantage disappears in 2024, where the Entropy R^2 of the four-class solution falls below that of the three-class solution (0.506 vs. 0.523), indicating inconsistent classification quality across waves. Furthermore, inspection of the four-class indicator profiles revealed that the third and fourth classes show substantial overlap in their commuting probabilities, particularly on Tuesdays, Wednesdays and Thursdays, rendering the two profiles difficult to distinguish in substantive terms. The indicator profiles of the four-class solution are presented in Appendix F for reference. The four-class solution is therefore rejected on grounds of interpretability.

> The three-class solution satisfies all criteria simultaneously: BVR falls below 3.84 across all three waves, the reduction in L^2 shows meaningful improvement over the two-class solution with diminishing returns thereafter. Entropy R^2 values are consistently acceptable, and all class sizes remain at or above the 5% threshold. The three-class solution was therefore retained as the optimal solution.

4.2.2 Measurement Invariance Across Waves

Table 4.3 shows the three-class LCA solution for each of the three measurement waves. Two of the three profiles demonstrate stability across waves in terms of both class size and indicator probabilities. The first two classes (C1 and C2) show stable class sizes and indicator patterns across all three waves. In contrast, the third class (C3) shows a more pronounced shift in its indicator pattern across waves. In 2023, C3 showed elevated commuting probabilities on Thursdays (0.82), Fridays (0.58) and Wednesdays (0.43), moderate probabilities on Tuesdays (0.41), and near-zero probabilities on Mondays (0.06). Between 2023 and 2024, this pattern changed markedly: Tuesday increased from 0.41 to 0.89, while Wednesday and Friday decreased to almost zero (0.07 and 0.04), establishing office attendance primarily on Tuesdays and Thursdays. This pattern persisted in 2025, with Wednesday and Friday probabilities remaining near zero (0.12 and 0.02, respectively).

To determine whether this shift reflects a change in the composition of C3 or behavioural changes among the same individuals, posterior membership probabilities were analysed for the longitudinal panel. Table 4.4 presents the results of this analysis.

Table 4.3 Commuting profiles of the 3-class solution per wave

	Wave 1 (2023)			Wave 2 (2024)			Wave 3 (2025)		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
Class size (%)	56	33	11	50	34	15	59	34	7
Indicators									
Monday	0.68	0.88	0.06	0.67	0.86	0.42	0.57	0.95	0.09
Tuesday	0.68	0.97	0.41	0.56	1.00	0.89	0.58	1.00	0.97
Wednesday	0.55	0.85	**0.43**	0.61	0.85	**0.07**	0.59	0.78	**0.12**
Thursday	0.55	0.97	0.82	0.53	0.99	0.58	0.59	0.96	0.66
Friday	0.30	0.84	**0.58**	0.44	0.79	**0.04**	0.40	0.72	**0.02**

Note. Values represent the probability of commuting on a given day.

Table 4.4 Posterior membership analysis of C3 across waves

	N (2023)	N (2023, 2024)	N (2023, 2025)
C3	80 (100%)	80 (100%)	79 (99%)

The modal posterior class membership method assigns each respondent to the class with the highest estimated membership probability at each wave. As shown in Table 4.4, of the 80 respondents assigned to C3 in 2023, 80 were also assigned to C3 in 2024 and 79 in 2025. By contrast, if the shift had been caused by compositional change, meaning different individuals entering and leaving C3 between waves, one would expect many respondents to switch to a different class over time. However, the near-complete overlap indicates that the same individuals remained in C3 across waves while reorganising their commuting days. This confirms that the shift in indicator probabilities reflects genuine behavioural change within a stable group.

Measurement invariance is the assumption that the same latent classes are consistently measured across time, meaning that the indicator probabilities that define each class remain consistent. Therefore, measurement invariance is a prerequisite for latent transition analysis. If class definitions change across waves, the observed transitions cannot be interpreted as genuine behavioural change. Instead, they may reflect changes in how the profiles are defined (Collins & Lanza, 2010). While strict measurement invariance requires identical indicator probabilities across all waves, in practice, partial invariance, where the majority of profiles remain stable, is considered sufficient for LTA (M. C. de Haas et al., 2018; Kroesen, 2014). Since C1 and C2 show consistent indicator patterns and class sizes across all three waves and C3 membership remains almost completely stable, the partial invariance observed here meets this threshold. Measurement invariance is therefore assumed for the subsequent latent transition analysis.

However, the shift in C3 requires careful interpretation. The posterior membership analysis confirms that the same individuals belong to C3 across all three waves. What changes is not who belongs to the profile, but how those individuals organise their commuting days. Therefore, transitions between profiles reflect genuine behavioural change at an individual level rather than artefacts of shifting profile definitions. However, the instability of C3 is acknowledged as a limitation and will be revisited in the discussion in Section 5.4.

4.2.3 Interpretation of Commuting Profiles

Table 4.5 shows the latent class profiles of the three-class solution. Unlike Table 4.3, which presented wave-specific indicator probabilities to assess measurement invariance, Table 4.5 presents indicator probabilities and covariate distributions estimated across all three waves simultaneously, using the full longitudinal dataset in long format. This table therefore serves as the basis for substantive interpretation.

The profiles capture two distinct forms of heterogeneity. Observed heterogeneity refers to systematic differences between profiles that can be explained by measurable characteristics, such as sector, educational level, or commute distance. Unobserved heterogeneity, on the other hand, refers to unobserved differences underlying the profiles themselves: the behavioural patterns that the covariates only partially explain. This distinction is important because two individuals with identical socio-demographic characteristics may still belong to different commuting profiles. This reflects differences in organisational context, social norms, or habitual routines that are not directly measured. Both dimensions are considered when interpreting the profiles below.

C1: Moderate Commuter (MC, 57%)

The first and largest cluster comprises respondents with a moderate commuting pattern characterised by relatively consistent travel frequencies across all five working days, ranging from 42% on Fridays to 65% on Tuesdays. Friday attendance is notably lower than on other days. Combined with an average of 0.83 days worked from home and 2.73 days spent at a fixed location, this pattern suggests a flexible working arrangement without a preference for specific days.

Respondents in this cluster are predominantly aged between 50 and 64, with a slight female majority. Income and educational levels are predominantly intermediate, and employment is strongly concentrated in the healthcare sector. The residential profile is mixed, with respondents distributed across strongly urban areas (50%) and low/non-urban areas (35%). The mean commute distance is 26.0 km, and partial reimbursement is the most common arrangement. Together, these characteristics suggest a profile of workers with moderate flexibility, operating in sectors where a partial on-site presence is required, but not on specific days.

C2: Intensive Full-Week Commuter (IFW, 30%)

The second cluster represents an almost daily commuting pattern, with high travel probabilities across all five working days. These probabilities range from 83% on Fridays to 97% on Tuesdays. Working from home is minimal, averaging just 0.17 days per week, and respondents spend an average of 4.04 days at a fixed location, indicating a predominantly office-based working pattern.

This cluster is predominantly made up of older men aged between 50 and 64. Employment is strongly concentrated in the agriculture and industry sectors, as well as in small organisations with fewer than 100 employees. Respondents are distributed across both strongly urban and low/non-urban areas. With a mean commute distance of 17.3 km, this cluster has the shortest commute of all clusters, and the proportion of respondents without commuting reimbursement is highest in this cluster. The concentration in agriculture and industry and small organisations suggests that the nature of work in this cluster structurally requires physical presence, as these sectors typically involve tasks that cannot be carried out remotely. Therefore, the IFW profile reflects a sectoral and organisational reality in which remote working is absent from workplace design and employer expectations, rather than an individual choice to commute.

C3: Tuesday and Thursday Commuter (TT, 13%)

The third cluster represents the most selective commuting profile. It is characterised by high travel probabilities on Tuesdays and Thursdays, moderate probabilities on Mondays, low attendance on Wednesdays, and virtually no commuting on Fridays (8%). With the highest average number of days worked from home (M = 1.77) and the lowest number of days spent at a fixed location (M = 2.06) of all the clusters, this pattern strongly indicates a structured hybrid working arrangement involving the deliberate avoidance of specific office days.

The cluster has the highest proportion of young children at home, which may partly explain the preference for working from home. High educational attainment and high income are most prevalent in this cluster, with employment strongly concentrated in the government sector and large organisations with over 1,000 employees. Respondents are predominantly located in urban areas. With a mean commute distance of 42.7 km, which is by far the longest of all the clusters, this profile suggests that reducing the number of commuting days makes longer commutes more manageable. Full commuting reimbursement is most prevalent in this cluster, consistent with employment being concentrated in large public sector organisations. More broadly, the concentration in government and large organisations suggests that public sector employers actively facilitate remote working, which may enable respondents to live further from their workplace. Therefore, the selective attendance pattern of this profile likely reflects not only individual preference, but also organisational routines and implicit team agreements about which days warrant physical presence. Within these contexts, Tuesdays and Thursdays have emerged as the socially and professionally expected office days.

Table 4.5 LCA profiles of the 3-class solution

Class	MC	IFW	TT	Overall	Wald	p-value
Class size (%)	57	30	13	100		
Indicators (%)						
Commuting day						
Monday	60	92	46	68	96.22	< .001
Tuesday	65	97	68	75	30.43	< .001
Wednesday	57	86	33	62	142.03	< .001
Thursday	60	96	65	71	47.44	< .001
Friday	42	83	8	50	169.76	< .001
Active covariates (%)						
Socio-demographic characteristics						
Age					24.99	< .001
18 – 34 years	30	18	25	26		
35 – 49 years	23	26	27	24		
50 – 64 years	38	54	40	43		
65+	9	2	9	7		
Gender					56.17	< .001
Male	43	80	48	55		
Female	57	19	51	45		
Educational level					44.37	< .001
Low	5	22	11	11		
Intermediate	60	65	30	57		
High	35	13	59	32		
Income					19.76	< .001
Low	13	8	0	9		
Intermediate	57	70	44	59		
High	19	14	51	22		
Household composition					12.71	0.013
No children	63	66	52	62		
Young children	23	17	40	23		
Older children or other	13	15	9	13		
Household size					1.23	**0.540**
Mean	3.31	3.38	3.25	3.32		
Residential characteristics						
Urbanisation level					9.81	0.044
(Very) strongly urban	50	48	66	52		
Moderately urban	15	11	22	15		
Low/non-urban	35	41	12	33		
Commute distance					26.06	< .001
Mean, km	26.04	17.34	42.70	25.69		
Job-related characteristics						
Sector					53.84	< .001
Agriculture and industry	20	44	9	25		
Services	18	7	28	16		
Government	3	3	37	7		
Education	6	9	6	7		
Healthcare	35	9	0	22		
Other	20	28	21	23		
Company size					31.69	< .001
< 100 employees	25	40	6	27		
100 – 250 employees	14	16	3	13		
250 – 500 employees	8	9	13	9		

500 – 1000 employees	10	10	4	10		
> 1000 employees	27	15	69	29		
Don't know	4	3	0	3		
Commuting reimbursement					5.94	**0.200**
Full	32	27	46	32		
Partial	39	37	40	39		
None	15	27	9	18		
Inactive covariates (Mean)						
Days at fixed location	2.73	4.04	2.06	3.03		
Days at external location	0.49	0.64	0.41	0.52		
Days at home	0.83	0.17	1.77	0.76		
Total days worked	4.05	4.85	4.24	4.31		

Despite the meaningful differences between the clusters, all three profiles share several characteristics. The most prevalent age group across all clusters is respondents aged 50 to 64, and the majority of respondents in each cluster have no children living at home. These two factors reflect the panel composition rather than profile-specific characteristics. Mean household size is similar across the clusters, ranging from 3.25 to 3.38. Furthermore, while the degree varies notably between profiles, a substantial share of respondents in all three clusters live in strongly urban areas.

Two covariates did not significantly predict cluster membership: household size and commuting reimbursement. As shown in bold in Table 4.5, their p-value is above the 0.05 threshold, indicating that these variables do not significantly differentiate between the three commuting profiles. Nevertheless, these variables are retained in Table 4.5 as they contribute to a more complete descriptive profile of each cluster.

Key Findings: Latent Class Analysis

The latent class analysis revealed three distinct commuting patterns among working respondents who commuted to a fixed or external work location during all three measurement waves (N = 612). Figure 4.14 provides an overview of these profiles, detailing their commuting probabilities and key characteristics.

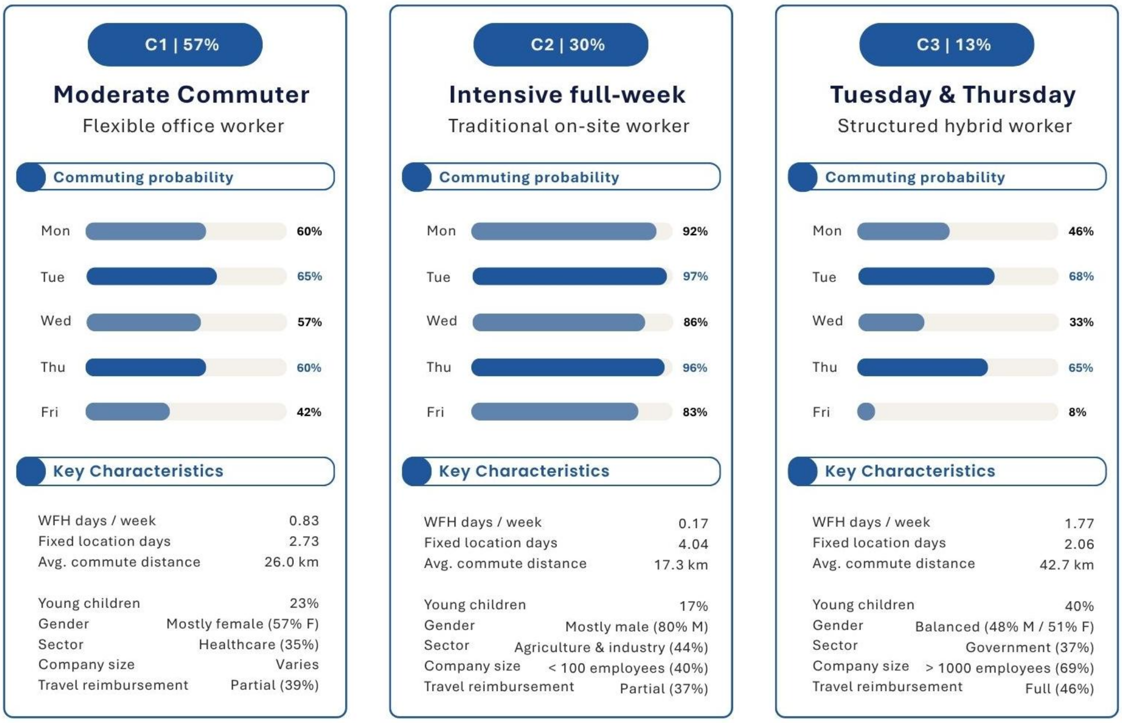

Figure 4.14 Overview of commuting profiles identified by LCA

The largest profile is the ‘Moderate Commuter’ (MC), accounting for 57% of the sample. This profile is characterised by relatively consistent commuting frequencies across all five working days, with notably lower Friday attendance than other days, and an average of 0.83 WFH days per week. The ‘Intensive Full-Week Commuter’ (IFW, 30%) profile involves commuting on nearly all working days at high frequencies, with virtually no WFH days (M = 0.17). The ‘Tuesdays and Thursday Commuter’ (TT, 13%) is the most selective profile, with high commuting probabilities on Tuesdays and Thursdays, virtually no commuting on Fridays, and an average of 1.77 WFH days per week.

From a congestion management perspective, Tuesdays and Thursdays remain the most relevant days for policy as they consistently record the highest commuting volumes across all three waves. The observed peak on these days is the aggregate outcome of all three profiles commuting simultaneously: Tuesday and Thursday probabilities are high across MC (65% and 60%), IFW (97% and 96%), and TT (68% and 65%). The TT profile contributes most directly through deliberate day selection, the IFW profile through its high commuting intensity, and the MC profile through its dominant population share of 57%.

This distinction has direct implications for peak-spreading policy. Transitions away from the TT and IFW profiles, particularly towards the MC profile, are of greatest policy interest, as these would redistribute commuting demand more evenly throughout the week. Whether such transitions occur and which contextual policy factors drive them is examined in the latent transition analysis in Section 4.3.

4.3 Results of Latent Transition Analysis

This section addresses the third sub-question of the study:

> **SQ3: How do individuals transition between commuting profiles over time, and which contextual policy factors are associated with these transitions?**

To answer this question, latent transition analysis (LTA) was conducted on the LRO survey data collected between 2023 and 2025. The analysis used the same longitudinal subsample as the LCA: respondents who were employed in all three measurement waves and commuted to a fixed or external work location (N = 612), as described in Section 3.2.1.

The LTA produced slightly different commuting profiles to the LCA because class membership and transition probabilities were estimated simultaneously. Table 4.6 presents the LTA-profile output. The three LTA states are substantially similar to the LCA profiles: State 1 corresponds to the Moderate Commuter (MC, 50%), State 2 to the Intensive Full-Week Commuter (IFW, 32%), and State 3 to the Selective Commuter (SC, 18%). The SC profile replaces the TT label used in the LCA. Unlike the TT profile, which showed selective commuting primarily on Tuesdays and Thursdays, the SC profile shows high commuting probabilities from Monday to Thursday, with Friday avoidance as its most distinctive characteristic. This difference likely results from the simultaneous estimation of class membership and transition probabilities in the LTA, though the precise mechanism requires further investigation. For the purposes of this study, the SC profile is interpreted as capturing the same group of selective hybrid workers as the TT profile in the LCA, with avoiding Friday as the defining behavioural characteristic.

Table 4.6 LTA commuting profiles

	State 1	State 2	State 3
	Moderate Commuter (MC)	**Intensive Full-Week Commuter (IFW)**	**Selective Commuter (SC)**
Size (%)	50	32	18
Indicators			
Monday	0.47	0.86	0.95
Tuesday	0.59	0.96	0.81
Wednesday	0.39	0.81	0.94
Thursday	0.56	0.91	0.78
Friday	0.31	0.98	0.16

From a policy perspective, not all transitions between profiles are equally relevant. As shown in Section 4.2, the peak on Tuesdays and Thursdays is the aggregate outcome of all three profiles. However, the degree of peak concentration differs substantially. SC commuters deliberately coordinate their attendance on these days, whereas IFW commuters commute intensively across all weekdays, including peak days. By contrast, the MC profile distributes attendance more evenly across the week, commuting at moderate frequencies on any given day. Therefore, a transition from SC or IFW towards MC would not eliminate peak demand, but would reduce its intensity and contribute to a more even distribution of commuting across the week. Transitions from SC to MC and from IFW to MC therefore most directly align with the policy goal of redistributing commuting demand. The LTA therefore focuses on identifying which contextual policy factors are associated with the likelihood of these transitions occurring between measurement waves.

First, Section 4.3.1 presents the observed distribution of changes in contextual policy factors across the sample, providing the necessary descriptive context to interpret the LTA results. Section 4.3.2 then examines which contextual policy factors are associated with transitions between commuting profiles by presenting the Wald statistics and transition probability matrices.

4.3.1 Observed Changes in Contextual Policy Factors

As discussed in Section 3.2.3, the latent transition analysis focuses on factors derived from the LRO questionnaire which measure perceived changes in employer policies and commuting conditions over the past year. These contextual factors are particularly relevant from a policy perspective, as they represent conditions that could be modified to redistribute commuting demand more evenly throughout the week. The variables are based on questions B2 and B3 of the LRO questionnaire and are summarised in Figure 4.15. The selection criteria and the full screening of all 26 candidate variables are discussed in Section 3.2.3 and Appendix C.3, with the full question wording provided in Appendix B. In brief, variables were retained only if they plausibly influence which specific days individuals travel to the office, rather than how they travel. This focus on contextual policy factors is further supported by the descriptive trends reported in Section 4.1. These showed that employer policies and flexibility were consistently rated as the most influential factors in shaping commuting and WFH behaviour across all three waves (see Figure 4.13).

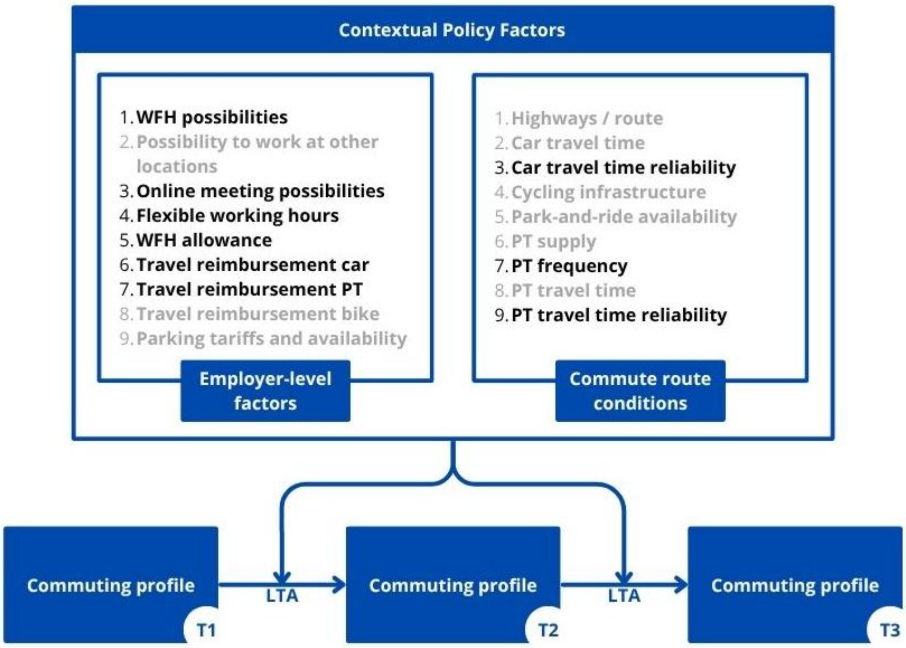

Figure 4.15 Overview of final contextual policy factors included in the LTA
Note. **Bold variables are included in the LTA. Non-bold variables were screened but excluded. See Appendix C.3 for the full screening.**

Table 4.7 shows the descriptive frequencies of the nine contextual policy factors included for 2023. Similar distributions were observed for 2024 and 2025, which are presented in Appendix G. Across nearly all variables, the majority of respondents reported that conditions were perceived to be unchanged compared to the previous year. This limited variation likely reduced the explanatory power of several transport-related covariates.

Table 4.7 Descriptive frequencies of contextual policy factors (2023)

	Improved (%)	Unchanged (%)	Worsened (%)	N (valid)
Employer-level factors				
Possibility to WFH	19.1	75.7	5.2	5425
Possibility to meet online	27.3	69.7	2.9	5743
Flexible working hours	15.3	80.9	3.8	5952
WFH allowance	21.5	74.0	4.5	4921
Travel reimbursement car	21.1	73.6	5.3	5485
Travel reimbursement PT	9.8	86.2	4.0	4685
Commute route conditions				
Car travel time reliability	5.8	72.8	21.4	6279
PT frequency	4.6	77.3	18.1	4914
PT travel time reliability	3.4	75.2	21.4	4840

Note. Values reflect the proportion of respondents who perceived each condition as improved, unchanged, or worsened compared to the previous year. The number of valid observations varies across variables due to missing values and responses indicating 'don't know' or 'not applicable', both of which were excluded from the analysis.

4.3.2 TRANSITION PROBABILITY MATRICES

Table 4.8 and Table 4.9 present the Wald statistics for the two types of variables included in the LTA model. Exogenous variables were included in order to predict initial class membership. Contextual policy factors were included to predict transition probabilities.

Several of the exogenous variables exhibited statistically significant associations with initial class membership, as indicated by the bold entries in Table 4.8. Gender, educational level, household composition, commute distance and sector all significantly predicted individuals' commuting profile at baseline, suggesting that initial profile membership is shaped by these socio-demographic, residential and job-related characteristics. However, age, income level, household size, urbanisation level, number of employees and travel reimbursement did not reach statistical significance. This indicates that these latter characteristics do not systematically differentiate between commuting profiles at the start of the observation period.

None of the nine contextual policy factors had a statistically significant effect on transition probabilities between commuting profiles (see Table 4.9). This is consistent with the descriptive frequencies reported in Table 4.7, which showed that the majority of respondents reported no change in their employer or commute route conditions across all waves, which likely limited the statistical power to detect effects. Nevertheless, following M. C. de Haas et al. (2018), transition matrices were computed using all parameters – both significant and non-significant – to illustrate the potential direction of effects exploratively.

Table 4.8 Significance of exogenous variables in the LTA (initial class membership)

	Wald	df	p-value
Exogenous variables			
Age	11.04	6	0.087
Gender	21.61	2	**< .001**
Educational level	13.39	4	**0.001**
Income level	8.84	4	0.065
Household composition	11.48	4	**0.022**
Household size	2.51	2	0.290
Urbanisation level	4.51	4	0.340
Commute distance	10.23	2	**0.006**
Sector	30.95	10	**0.001**
Number of employees	17.60	10	0.062
Travel reimbursement	4.19	4	0.380

Note. Bold values are statistically significant at $p < 0.05$.

Table 4.9 Significance of contextual policy factors in the LTA (profile transitions)

	Wald	df	p-value
Contextual policy factors			
Employer-level factors			
Possibility to WFH	9.23	6	0.16
Possibility to meet online	8.95	6	0.18
Flexible working hours	5.43	6	0.49
WFH allowance	7.74	6	0.26
Car allowance	9.35	6	0.15
PT allowance	9.01	6	0.17
Commute route conditions			
Car travel time reliability	4.79	6	0.57
PT frequency	5.73	6	0.45
PT travel time reliability	6.78	6	0.34

Table 4.10 shows the transition probability matrices for the nine contextual policy factors included in the LTA model. For each covariate, the matrix shows the probability of transitioning between commuting profiles when respondents perceived that condition as improved, while all other covariates remain at their baseline value. First, the baseline transition probabilities are presented as a reference, representing the situation in which no contextual policy changes were perceived. Each subsequent matrix illustrates the directional pattern associated with a perceived improvement in a specific condition. Particular attention is paid to the policy-relevant transitions from SC to MC and from IFW to MC, as these contribute most directly to the redistribution of commuting demand across the working week.

Table 4.10 Transition probability matrices for different contextual policy factors

Baseline				**Travel reimbursement car**			
	MC	**IFW**	**SC**		**MC**	**IFW**	**SC**
MC	0.9997	0.0003	0.0000	**MC**	0.9984	0.0016	0.0000
IFW	0.0006	0.9831	0.0163	**IFW**	0.0017	0.9495	0.0489
SC	0.0001	0.0001	0.9999	**SC**	0.0000	0.0000	1.0000
Possibility to work from home				**Travel reimbursement PT**			
	MC	**IFW**	**SC**		**MC**	**IFW**	**SC**
MC	0.9999	0.0001	0.0000	**MC**	0.9976	0.0024	0.0000
IFW	0.0007	0.8852	0.1141	**IFW**	0.0001	0.9997	0.0002
SC	0.7076	0.0001	0.2923	**SC**	0.0000	0.0000	1.0000
Possibility to meet online				**Car travel time reliability**			
	MC	**IFW**	**SC**		**MC**	**IFW**	**SC**
MC	0.9661	0.0339	0.0000	**MC**	0.9999	0.0001	0.0000
IFW	0.0573	0.8519	0.0908	**IFW**	0.0004	0.9918	0.0078
SC	0.0000	0.1328	0.8672	**SC**	0.0003	0.0017	0.9981
Flexible working hours				**PT frequency**			
	MC	**IFW**	**SC**		**MC**	**IFW**	**SC**
MC	0.9999	0.0001	0.0000	**MC**	1.0000	0.0000	0.0000
IFW	0.0006	0.9990	0.0004	**IFW**	0.0006	0.8838	0.1156
SC	0.0081	0.0000	0.9919	**SC**	0.9971	0.0000	0.0029
WFH allowance				**PT travel time reliability**			
	MC	**IFW**	**SC**		**MC**	**IFW**	**SC**
MC	0.9989	0.0011	0.0001	**MC**	0.9990	0.0010	0.0000
IFW	0.0025	0.9901	0.0074	**IFW**	0.0047	0.7747	0.2206
SC	0.0142	0.0000	0.9857	**SC**	0.0000	0.0000	1.0000

Note. To compute the transition matrices, all parameters from Table 4.8 and Table 4.9 are used, both the significant and non-significant parameters. MC = Moderate Commuter, IFW = Intensive Full-Week Commuter, SC = Selective Commuter. Colour coding: green = transitions aligned with peak spreading (SC→MC, IFW→MC); orange = secondary transitions increasing commuting intensity (MC→IFW, SC→IFW); red = transitions reinforcing peak-day concentration (IFW→SC).

Overall, the LTA suggests that commuting patterns tend to remain consistent over time. In the baseline scenario, the probability of remaining in the same profile is 99.97% for MC commuters, 98.31% for IFW commuters and 99.99% for SC commuters. Diagonal probabilities consistently approach or equal 1.00 across almost all covariate scenarios, indicating that weekly commuting patterns are deeply ingrained and resistant to change, even when contextual conditions are perceived to be improved.

Nevertheless, the transition matrices reveal directional differences between the covariates that are informative as exploratory patterns, even though none reached statistical significance. The directional patterns are discussed below in relation to policy-relevant transitions from SC to MC and from IFW to MC. The covariates fall into four broad patterns: those associated with peak-spreading towards MC; those with a mixed directional effect; those with negligible policy-relevant transitions; and those that reinforce concentration on peak days. Each pattern is discussed in turn.

Transitions aligned with peak spreading

The two covariates most strongly associated with the policy-relevant transition from SC to MC are perceived improvements in WFH possibilities and PT frequency. The respective transition probabilities are 70.76% and 99.71%. These are by far the largest off-diagonal values observed across all scenarios, suggesting that selective commuters may be more inclined to adopt a more evenly distributed commuting pattern if either of these conditions improves.

For the **possibility to work from home**, this may be because selective commuters currently schedule their office attendance on peak days, as these are the days when workplace visibility and social interaction are most valued. When respondents perceived WFH possibilities as improved, this pressure may diminish, enabling office attendance to be distributed more flexibly. The **PT frequency** result suggests that poor service may currently act as a structural barrier to spreading out commuting, and that a perceived improvement in PT frequency could make it more practically feasible to attend the office on a broader range of days.

However, both measures simultaneously show unfavourable directional patterns for IFW commuters, with transitions from IFW to SC of 11.41% and 11.56%, respectively. Rather than encouraging intensive commuters to adopt a more moderate commuting pattern, these perceived improvements appear to push some of them towards more concentrated attendance on peak days. For the possibility to work from home, this may mean that IFW commuters use the gained flexibility to work from home on less popular office days, while maintaining office attendance on peak days, when social presence is most valued. A similar mechanism may apply to PT frequency: IFW commuters, who already travel almost every weekday, may respond to greater flexibility or more frequent PT services by consolidating their office attendance around the most socially desirable days. This may limit the overall peak-spreading potential of both measures: although the SC to MC transition represents a net gain for peak spreading, it is partially offset by the simultaneous shift of IFW commuters towards more concentrated peak-day attendance.

Transitions partially aligned with peak spreading

The only covariate associated with a meaningful IFW to MC transition is the **possibility to meet online**, at 5.73%. This is the most notable policy-relevant transition for IFW commuters across all scenarios, suggesting that reducing the obligation to commute for meetings may lead to a more even distribution of office days among intensive commuters. This may reflect the fact that Tuesdays and Thursdays are particularly popular days for in-person meetings in the Netherlands and that freeing up these days could enable office attendance to be spread more evenly across the week.

Meanwhile, the possibility to meet online is associated with an SC to IFW transition of 13.28% and an MC to IFW transition of 3.39%. This suggests that, for commuters who already attend the office on a selective or moderate basis, reducing meeting obligations may not encourage a more even spread of office days, but instead shift some towards more intensive commuting. This may be because SC and MC commuters currently partly structure their office days around meeting obligations. When these obligations are reduced, the pressure to be in the office on particular days diminishes, and some commuters may respond by attending more freely throughout the week. Therefore, the net directional effect of this covariate is mixed: while it may benefit IFW commuters from a peak-spreading perspective, it may simultaneously increase commuting intensity among SC and MC commuters.

Transitions with negligible policy-relevant effects

Flexible working hours and **WFH allowances** show negligible transitions in the policy-relevant directions. For flexible working hours, the SC to MC and IFW to MC transition rates are 0.81% and 0.06%, respectively. The WFH allowance shows slightly larger values, with an SC to MC transition of 1.42% and an IFW to MC transition of 0.25%. However, this remains small compared to the structural enablers discussed above. These patterns suggest that financial incentives and scheduling flexibility may have limited potential to encourage employees to redistribute their commuting days. Without a day-specific incentive structure, these measures appear to have limited potential for reducing peak commuting demand.

Travel reimbursement for PT also shows negligible transitions in the policy-relevant directions, with an IFW to MC transition of only 0.01% and no SC to MC movement. Interestingly, however, it is associated with a small MC to IFW transition of 0.24%, suggesting a marginally counterproductive directional pattern. Rather than redistributing commuting demand, perceived improvement in PT reimbursement may encourage moderate commuters to commute more frequently.

Transitions reinforcing peak concentration

PT travel time reliability is associated with the largest IFW to SC transition across all scenarios, at 22.06%. This suggests that, when respondents perceived PT reliability as improved, a substantial proportion of intensive commuters may tend towards more concentrated attendance on peak days rather than spreading their office days more evenly. The mechanism behind this pattern is not entirely clear, but it may reflect that improved PT reliability reduces the practical barriers to commuting selectively, enabling IFW commuters to consolidate their office attendance around the most socially desirable days rather than commuting on all weekdays. The social pull of Tuesdays and Thursdays may then reinforce this consolidation. From a peak-spreading perspective, this directional pattern is potentially counterproductive.

Travel reimbursement for cars is associated with a transition from IFW to SC of 4.89%, with no meaningful movement from SC to MC or IFW to MC. This suggests that a perceived improvement in car reimbursement may not redistribute commuting demand, but rather reinforce day-concentrated patterns among intensive commuters. **Car travel time reliability** shows a similar, though smaller, pattern: it is associated with an IFW to SC transition of 0.78% and an SC to IFW transition of 0.17%. While these values are small, they are consistent with the broader directional pattern whereby perceived improvements in infrastructure tend to reinforce concentration on peak days rather than encouraging redistribution.

These findings are discussed further in Chapter 5, considering their implications for employers and policymakers seeking to reduce peak commuting demand, and reflecting on how they relate to the theoretical framework and existing literature introduced in Chapter 2.

Key Findings: Latent Transition Analysis

Weekly commuting profiles were found to be highly stable over time, with baseline probabilities of remaining in the same profile of 99.97% for MC commuters, 98.31% for IFW commuters, and 99.99% for SC commuters. This suggests that commuting patterns are deeply ingrained and resistant to change, even when contextual conditions are perceived as improved. Figure 4.16 illustrates the observed profile transitions across the three measurement waves, confirming that the vast majority of individuals remained in the same profile over time.

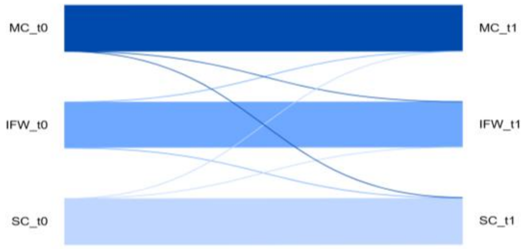

Figure 4.16 Baseline commuting profile transitions across three measurement waves (2023-2025)
***Note.* Each flow represents the proportion of individuals transitioning between or remaining within commuting profiles across consecutive waves. The width of each flow is proportional to the share of individuals following that transition path.**

None of the nine contextual policy factors were statistically significant predictors of profile transitions. As these factors reflect perceived rather than objectively measured changes, all directional patterns should be interpreted as exploratory indications rather than confirmed effects. Nevertheless, these patterns reveal informative differences between covariates. Perceived improvements in WFH possibilities and PT frequency showed the strongest directional association with the policy-relevant transition from SC to MC, with respective probabilities of 70.76% and 99.71%. However, both measures simultaneously showed a directional shift of IFW commuters towards SC, thereby limiting their overall peak-spreading potential. The possibility to meet online was the only covariate with a meaningful directional IFW to MC transition (5.73%), though its net effect was mixed due to simultaneous increases in commuting intensity among SC and MC commuters.

Financial incentives and scheduling flexibility, including WFH allowances, flexible working hours, and PT reimbursement, showed negligible policy-relevant transitions, while perceived improvements in infrastructure were primarily associated with reinforcing peak-day concentration among IFW commuters.

	S1 to S2	S1 to S3	S2 to S1	S2 to S3	S3 to S1	S3 to S2
Covariate	**MC to IFW**	**MC to SC**	**IFW to MC**	**IFW to SC**	**SC to MC**	**SC to IFW**
Possibility to work from home	0,00	0,00	0,00	0,11	0,71	0,00
Possibility to meet online	0,03	0,00	0,06	0,09	0,00	0,13
Flexible working hours	0,00	0,00	0,00	0,00	0,01	0,00
WFH allowance	0,00	0,00	0,00	0,01	0,01	0,00
Travel reimbursement car	0,00	0,00	0,00	0,05	0,00	0,00
Travel reimbursement PT	0,00	0,00	0,00	0,00	0,00	0,00
Car travel time reliability	0,00	0,00	0,00	0,01	0,00	0,00
PT frequency	0,00	0,00	0,00	0,12	1,00	0,00
PT travel time reliability	0,00	0,00	0,00	0,22	0,00	0,00

Figure 4.17 Transition probabilities by contextual policy factor
***Note.* Values represent transition probabilities under the perceived improved condition for each covariate, with all other covariates held at baseline. Values of 0.00 reflect probabilities below 0.005.**

Together, these exploratory findings suggest that reducing peak commuting demand may require targeted, day-specific interventions rather than generic improvements in flexibility, reimbursement or infrastructure.

4.4 Discussion of the Results

The results from Section 4.1 to Section 4.3 suggest an overarching conclusion: the weekly commuting profiles among the Dutch working population are highly stable, distinctly structured, and largely resistant to change, even when contextual conditions are perceived as improved. This section reflects on these findings in light of existing literature.

Stability of weekly commuting patterns

The near-complete stability of commuting profiles is the most striking result of this study. Diagonal transition probabilities approach or equal 1.00 across all covariate scenarios, indicating that the vast majority of individuals remain in the same profile across consecutive measurement waves. However, existing longitudinal studies have demonstrated that commuting behaviour can change in response to strong external triggers such as workplace attendance requirements, pandemic restrictions, shifting attitudes towards working from home, and sustained changes in residential and modal choices (Kroesen et al., 2022; Magriço et al., 2024; Pedreira Junior & Pitombo, 2024; Xie & Liao, 2025). While the current results do not contradict this, they suggest that, by 2023, the Dutch working population had established weekly routines that remained remarkably stable, even as contextual conditions continued to change.

The trends reported in Section 4.1 are consistent with this finding. Despite a modest increase in WFH prevalence between 2023 and 2025, the weekday ranking of peak arrivals (Tuesday, Thursday, Monday, Wednesday and Friday) remained entirely unchanged across all three measurement waves. This indicates that an increase in WFH prevalence does not necessarily lead to a permanent change in weekly commuting patterns. This is consistent with the findings of M. de Haas (2023) and Barrero et al. (2023), who observed a similar concentration on Tuesdays and Thursdays in the Netherlands and the United States, respectively.

What is genuinely new is that this stability is demonstrated at the level of the day-specific structure of the working week rather than at the level of WFH frequency. All the studies reviewed in Chapter 2 operationalise WFH as a frequency-based variable, and none of them can detect shifts in commuting days between specific weekdays over time. Therefore, existing longitudinal approaches are unable to detect the stability of the weekly structure, even though it is precisely this structure that determines the distribution of peak demand across the week.

Profile structure and day-specific heterogeneity

The three commuting profiles identified in the latent class analysis are consistent with the documented heterogeneity in the literature on WFH, while adding a day-specific dimension. The socio-demographic composition of the MC, IFW and TT profiles aligns closely with the predictions from the literature on determinants. Beyond individual characteristics, these profiles also reflect broader organisational and sectoral structures, as discussed in Section 4.2.3.

The TT profile most clearly reflects the characteristics associated with deliberate hybrid working. Mid-career employees with young children in large organisations are most likely to adopt structured hybrid working arrangements (Criscuolo et al., 2021; Dunatchik et al., 2021; Ory & Mokhtarian, 2006). The longer average commute distances observed in this profile further reinforce this pattern, as greater distances increase the appeal of avoiding the daily commute (Moeckel, 2017). Conversely, workers in sectors requiring physical presence have limited WFH feasibility (Elldér, 2019), which explains the concentration of IFW commuters in agriculture and industry. The overrepresentation of IFW commuters in lower-urbanised areas is consistent with this, as these sectors tend to be located outside urban centres. Although full commuting reimbursement is most prevalent in the TT profile, these commuters nonetheless adopt a selective hybrid working pattern. This suggests that financial incentives alone are insufficient to determine the day-specific structure of commuting, when other factors also come into play (Reiffer et al., 2023).

Previous studies have shown that the effect of WFH on travel behaviour varies systematically across population groups, depending on factors such as educational level and travel purpose (Kroesen et al., 2023), or individual level of local accessibility (Victoriano-Habit & El-Geneidy, 2024). The TT and IFW profiles extend this heterogeneity to a day-specific dimension: while prior research has shown that these groups differ in how much they commute, this study reveals that they also differ in the days on which they commute.

The instability of the TT profile across waves is particularly notable. A posterior membership analysis revealed that, between 2023 and 2024, the same individuals reorganised their commuting from Wednesdays and Fridays towards Tuesdays and Thursdays, without any change in class composition. This type of behavioural reorganisation within profiles is invisible to frequency-based approaches, since the total number of commuting days remained constant while the pattern specific to each day shifted. This builds on the descriptive evidence of M. de Haas (2023) and Barrero et al. (2023) regarding the concentration on Tuesdays and Thursdays, demonstrating that this convergence is an ongoing dynamic process rather than a static cross-sectional pattern.

Contextual policy factors: heterogeneous and profile-dependent effects

The LTA results are the study's most significant findings from a theoretical perspective. Contrary to the expectation of uniform peak spreading, the transition matrices reveal that the same perceived contextual improvement may produce fundamentally different effects depending on an individual's commuting profile. This profile-dependent pattern is consistent with the modification framework: WFH reshapes mobility rather than simply reducing it (Andreev et al., 2010). While there is aggregate evidence that WFH is associated with reductions in commuting time and distance (R. Faber et al., 2023; R. M. Faber et al., 2023; Rüger et al., 2024), Böhnen & Kuhnimhof (2024) and Elldér (2020) have documented rebound effects at residential and non-work travel levels, whereby the gained flexibility is used for other mobility adjustments rather than simply reducing demand. The transition patterns found here represent the day-specific analogue of this rebound: rather than spreading attendance uniformly, the same perceived contextual improvements can simultaneously redistribute commuting among one profile group while reinforcing peak concentration among another. This is consistent with Xie & Liao (2025), who demonstrated that WFH and commuting behaviour constitute a mutually reinforcing dynamic system in which day-specific patterns are embedded in social norms, organisational scheduling, and individual habits.

The persistence of peak-day concentration across almost all scenarios is consistent with the Theory of Planned Behaviour (Ajzen, 1991). When colleagues concentrate their office attendance on specific days, the subjective norm reinforces presence on those days, making transitions unlikely even when contextual conditions are perceived as improved. This is empirically supported by the trends in Section 4.1, in which a lack of contact with colleagues was consistently cited as the main reason for not working from home. As argued by Schoenduwe et al. (2015) and Gärling & Axhausen (2003), behavioural change requires a sufficiently disruptive trigger, and generic improvements in flexibility, reimbursement, or infrastructure do not appear to constitute such a trigger in this dataset. Furthermore, Magriço et al. (2024) demonstrated that organisational constraints only redirect behaviour when applied in a specific direction.

Against this background, the covariates that show policy-relevant directional effects are particularly noteworthy. Structural enablers, such as perceived improvements in the possibility to work from home and PT frequency, are most strongly associated with peak-spreading transitions among SC commuters. This suggests that reducing structural barriers to attending the office on non-peak days could encourage this group to adopt a more moderate attendance pattern. For IFW commuters, the possibility to meet online shows the most relevant directional transition, as it directly weakens the incentive to go to the office on days when there are many meetings. This is consistent with R. Faber et al. (2023), who found that teleconferencing was specifically associated with reductions in travel across all modes. However, both sets of findings have important limitations: structural enablers reinforce peak concentration among IFW commuters, and the possibility of online meetings has mixed effects, increasing commuting intensity among SC and MC commuters. This suggests that even the most promising interventions cannot be isolated from broader behavioural responses across profile groups.

5 CONCLUSION AND DISCUSSION

This chapter presents the conclusions and discussion of the study. Section 5.1 addresses the research questions and presents the main findings. Section 5.2 discusses how the findings contribute to existing scientific literature. Section 5.3 outlines the policy implications and recommendations for employers and policymakers. Section 5.4 reflects on the study's limitations and suggests areas for future research. Section 5.5 concludes with personal reflections and final remarks.

5.1 CONCLUSION

This study examined how the weekly structure of commuting behaviour evolves over time at an individual level and which contextual policy factors are associated with transitions between distinct commuting profiles. The following sections address each sub-question before turning to the main research question.

> **SQ1: What are the observed trends in commuting and working from home behaviour, and the factors associated with these behavioural decisions, across the three measurement waves (2023, 2024 and 2025)?**

Commuting behaviour remained largely stable across all three measurement waves. Peak arrivals were consistently highest on Tuesdays and Thursdays, and the ranking of weekdays in order of peak arrival (Tuesday, Thursday, Monday, Wednesday and Friday) remained unchanged throughout the observation period. The evening peak was more dispersed than the morning peak, suggesting greater flexibility in departure times than arrival times. The most notable deviation from this overall stability was a uniform dip in peak commuting across all weekdays in 2024, followed by a partial recovery in 2025. This points to a temporary structural shift, likely related to an increase in working from home rather than a day-specific effect.

This stability in peak patterns is reinforced by limited changes in commuting variability and working time flexibility. Fixed commuting patterns were the most prevalent arrangement, reported by almost 50% of commuters across all three waves. Working time flexibility showed a comparable trend: the proportion of respondents with fixed working hours increased significantly, while bounded flexibility declined over the same period. As flexibility in working hours is essential for avoiding peak times, this reduction in flexibility helps to explain why peak arrivals remained concentrated across all three waves.

WFH showed a modest but gradual expansion over the observed period. The proportion of non-home workers declined from 53% in 2023 to 49% in 2025, while patterns involving one or two days of WFH increased slightly. Fixed WFH day patterns remained the most prevalent structure among home workers and became slightly more common over time. Notably, only 2-3% of home workers cited peak avoidance as a primary motivation for WFH across all three waves. This suggests that WFH is primarily driven by personal and organisational preferences rather than congestion-related motives. Social motivations, particularly the desire for contact with colleagues, remained the most prominent reason for not working from home among those who were able to do so but chose not to.

Employer policy and flexibility were consistently rated as the most influential factors shaping commuting and WFH behaviour across all three waves. This is a finding particularly relevant for the latent transition analysis, as it suggests that employer-level conditions matter most to workers when making commuting and WFH decisions.

Taken together, these trends suggest that the population has settled into stable weekly routines. While WFH is expanding, this has not disrupted the day-specific structure of peak demand. This raises the question of whether distinct commuting profiles can be identified beneath this apparent stability.

SQ2: Which distinct commuting profiles can be identified based on individuals' commuting behaviour per day of the week?

These commuting behaviours were analysed using latent class analysis, which revealed three distinct weekly commuting profiles among employed respondents who commuted to a fixed or external workplace during the observation period (N = 612). The three-class solution was selected as the optimal fit based on a combination of statistical and interpretability criteria, as detailed in Section 4.2.1.

The largest profile, the Moderate Commuter (MC, 57%), travels on all five working days at moderate frequencies, with notably lower attendance on Fridays. On average, they work from home 0.83 days per week and commute an average distance of 26.0 km. Employment is concentrated in healthcare, and residences are spread across strongly urban and low-urbanised areas. This pattern suggests flexible working arrangements without a strong preference for specific office days. The Intensive Full-Week Commuter (IFW, 30%) commutes almost daily, with minimal WFH (M = 0.17), and the shortest mean commute distance of all profiles (17.3 km). Employment is concentrated in agriculture and industry and small organisations, sectors where physical presence is structurally required. The highest share of respondents without commuting reimbursement is found in this profile, consistent with the concentration in small organisations, which are less likely to offer travel reimbursement as part of their employment conditions. The Tuesday and Thursday Commuter (TT, 13%) is characterised by selective commuting on Tuesdays and Thursdays, the highest average number of WFH days (M = 1.77), and the longest mean commute distance (42.7 km). Employment is concentrated in the government sector and large organisations. This profile has the highest prevalence of full commuting reimbursement and of having young children at home. This suggests that public sector employers actively facilitate remote working, and that family obligations reinforce the preference for selective office attendance.

Despite these differences, all three profiles share characteristics reflecting the panel composition rather than profile-specific patterns. For example, respondents aged 50 to 64 are the most prevalent age group across all profiles, and the majority of respondents in each profile have no children living at home.

From a policy perspective, it is worth noting that the peak on Tuesdays and Thursdays is not solely driven by the TT profile: all three profiles show an increased probability of commuting on these days. This means that peak demand is the aggregate outcome of distinct, yet simultaneous, commuting patterns across the entire working population.

Two of the three profiles showed stability in terms of both class size and indicator probabilities across all three measurement waves. However, the TT profile exhibited a notable shift in commuting days, moving from Wednesdays and Fridays in 2023 to Tuesdays and Thursdays in 2024 and 2025. A posterior membership analysis showed that almost all individuals assigned to this profile in 2023 remained in the same profile in subsequent waves, confirming that this shift reflected genuine behavioural reorganisation within a stable group, rather than a change in composition. This satisfies the partial measurement invariance required for latent transition analysis. Furthermore, it shows that the internal weekly structure of commuting can change even when profile membership remains stable, a dynamic that is invisible to frequency-based approaches as total commuting days remained constant while the day-specific pattern changed.

SQ3: How do individuals transition between commuting profiles over time, and which contextual policy factors are associated with these transitions?

Having identified three distinct profiles, the latent transition analysis was used to examine whether individuals moved between them over time and which contextual policy factors were associated with such transitions. Despite the structural differences between the profiles, weekly commuting patterns proved highly resistant to change. Diagonal transition probabilities approached or equalled 1.00 across all scenarios, indicating that the vast majority of individuals remained in the same profile across consecutive measurement waves. However, none of the nine contextual policy factors, which covered employer-level factors and commute route conditions, were statistically significant predictors of profile transitions. As these factors reflect perceived rather than objectively measured changes, the directional patterns discussed below should be interpreted as exploratory indications rather than confirmed effects.

Nevertheless, the directional patterns in the transition matrices were informative. The covariates fell into four broad patterns. Firstly, perceived improvements in WFH possibilities and PT frequency showed the strongest directional association with the policy-relevant SC (Selective Commuter, equivalent to the TT profile in the LCA) to MC transition. The transition probabilities were 70.76% and 99.71% respectively, suggesting that selective commuters may be more inclined to adopt a more evenly distributed commuting pattern if either of these conditions improve. However, both measures simultaneously showed a directional shift of IFW commuters towards SC, with respective transition probabilities of 11.41% and 11.56%, partially offsetting their overall peak-spreading potential. Secondly, the possibility to meet online was the only covariate with a meaningful directional IFW to MC transition (5.73%), though its net effect was mixed as it simultaneously produced transitions towards more intensive commuting among SC and MC commuters. Thirdly, financial incentives and scheduling flexibility, including WFH allowances, flexible working hours and PT reimbursement, showed negligible policy-relevant transitions. This may suggest that these measures have limited potential to redistribute commuting demand without a day-specific incentive structure. Fourthly, infrastructure improvements, including perceived improvements in the reliability of car and PT travel times and car reimbursement, were primarily associated with reinforcing peak-day concentration among IFW commuters. The largest effect was a 22.06% IFW to SC transition under perceived improvement in public transport travel time reliability.

Together, these exploratory findings suggest that generic improvements in contextual conditions may have limited redistributive potential in this dataset. Reducing peak concentration may therefore require more targeted, day-specific interventions that directly reduce the incentive to go to the office on peak days.

> **Main RQ: How does the weekly structure of commuting behaviour evolve over time at the individual level, and which contextual policy factors are associated with transitions between distinct commuting profiles?**

Taken together, the findings from SQ1 to SQ3 paint a consistent picture: the weekly commuting behaviour of the Dutch working population is stable and distinctly organised, with little response to perceived contextual change. Three distinct commuting profiles can be identified: the Moderate Commuter (MC), the Intensive Full-Week Commuter (IFW) and the Tuesday and Thursday Commuter (TT). Each profile is characterised by a specific combination of commuting days, frequency of working from home, commute distance, and socio-demographic composition. These profiles remained stable throughout the observation period, and transitions between them were rare. Where change did occur, it manifested as a reorganisation of commuting days within a profile rather than movement between profiles: between 2023 and 2024, members of the TT profile shifted from Wednesdays and Fridays towards Tuesdays and Thursdays, without any change in profile composition. This dynamic would be invisible to frequency-based approaches, since total commuting days remained constant while the internal weekly structure shifted towards an even greater concentration on peak days. These findings highlight a key methodological insight: by conceptualising WFH as a weekly structure rather than a frequency, this study reveals day-specific dynamics that would remain invisible to conventional approaches.

The contextual policy factors examined were not statistically significant predictors of profile transitions. Nevertheless, the exploratory directional patterns in the transition matrices revealed meaningful differences between covariates. The same perceived contextual improvement may produce opposing effects depending on an individual's commuting profile: structural enablers, such as the possibility to work from home and PT frequency, showed the strongest directional association with peak-spreading transitions among SC commuters. Yet, simultaneously, they reinforced peak concentration among IFW commuters. Financial incentives and scheduling flexibility had negligible directional effects across all profiles, while perceived improvements in infrastructure were primarily associated with reinforcing peak-day concentration. The possibility to meet online was the only covariate with a relevant directional effect for IFW commuters, though its overall effect was mixed due to simultaneous increases in commuting intensity among other profile groups.

Therefore, the findings suggest that generic improvements to working conditions or infrastructure alone may have limited redistributive potential. More targeted interventions directed at specific days, profile groups, and the organisational conditions that sustain peak-day attendance may be needed. The policy implications of these findings are elaborated in Section 5.3.

5.2 Scientific Contributions

This study makes three interrelated scientific contributions to the literature on working from home and commuting behaviour.

A new operationalisation of WFH as a weekly structure

The first and most fundamental contribution is conceptual. All of the longitudinal studies reviewed in Chapter 2 treat WFH as a frequency-based variable, measuring how many days or hours individuals work from home per week. This study overcomes this limitation by introducing a new operationalisation of WFH as a weekly structure: the specific combination of office and WFH days across the five working days of the week. This distinction is important from an analytical perspective: two individuals working from home twice per week could have a very different impact on peak demand depending on which days they choose to commute. By capturing not only how often, but also on which days individuals work from home, this approach fills a fundamental gap in the current measurement framework, providing a more precise empirical foundation for examining the relationship between working from home and peak congestion.

Empirical evidence of heterogeneity in weekly commuting structure

The second contribution addresses the gap in population differentiation. While existing studies acknowledge that individuals respond differently to working from home, these differences have been analysed in terms of effect size rather than in terms of qualitatively distinct weekly patterns. This study uses latent class analysis on longitudinal survey data to demonstrate that the working population can be grouped into three distinct commuting profiles based on the day-specific structure of their weekly routines. This extends existing heterogeneity research to the level of day-specific weekly organisation, showing that the observed concentration of office attendance on Tuesdays and Thursdays is not a uniform, population-level pattern, but rather the aggregate outcome of distinct weekly routines among different population groups. This provides an empirical basis for identifying the population segments that contribute most to peak demand on specific days, as well as those most likely to respond to redistributive interventions.

Longitudinal evidence on the stability of weekly commuting structure

The third contribution addresses the gap in longitudinal dynamics. While existing studies have examined changes in working from home intensity or mobility outcomes over time, none have investigated whether individuals transition between day-specific commuting structures. This study fills that gap in three ways. Firstly, it provides empirical evidence of the stability of day-specific commuting structures over time, demonstrating that weekly routines remain consistent even when contextual conditions are perceived as improved. Secondly, it demonstrates that within-profile reorganisation – shifts in the days on which individuals commute, without changing profile membership – is a form of behavioural change that is invisible to frequency-based approaches. Thirdly, it reveals that perceived contextual improvements may produce profile-dependent effects, simultaneously redistributing demand among some groups while reinforcing peak concentration among others. This extends the modification framework of Andreev et al. (2010) to the day-specific level, challenging the implicit assumption in Dutch mobility policy that WFH-enabling measures will uniformly contribute to peak spreading.

Together, these findings establish the day-specific structure of commuting as a distinct, policy-relevant dimension of mobility dynamics that frequency-based approaches cannot capture.

5.3 Policy Implications and Recommendations

This section discusses the policy implications and recommendations arising from the findings of this study. Section 5.3.1 considers the wider relevance of the findings for Dutch mobility policy, particularly in relation to the Aanpak Spitsspreiden en Mijden 2025-2027 programme. Section 5.3.2 then translates these implications into specific recommendations for employers, national policymakers and the wider mobility system.

5.3.1 Policy Implications

The findings of this study are directly relevant to Dutch mobility policy, particularly the Aanpak Spitsspreiden en Mijden 2025-2027 programme, introduced in Section 1.1. This programme aims to reduce travel during peak hours by 10% on the ten busiest road and rail corridors within ten years and tend to shift 8% of train journeys from Monday, Tuesday, and Thursday to Wednesday and Friday (Ministerie van Infrastructuur en Waterstaat, 2025). However, the results of this study suggest that achieving these goals through generic flexibility-enhancing measures alone may have limited redistributive potential, and that a more targeted approach may be needed.

Three key implications emerge. Firstly, the high stability of weekly commuting profiles indicates that commuting routines are deeply entrenched and resistant to change, even when contextual conditions are perceived as improved. This has direct consequences for the achievability of the programme's ambitions: the exploratory directional patterns in this study suggest that the day-specific structure of commuting may not respond sufficiently to generic improvements in working conditions or infrastructure, making more targeted interventions necessary.

Secondly, the exploratory directional patterns in the transition matrices suggest that generic improvements in employer flexibility, such as WFH allowances, flexible working hours and travel reimbursements, may have negligible effects on the redistribution of peak demand. This is particularly evident among TT commuters, who already structure their office attendance around Tuesdays and Thursdays. Rather than spreading office attendance across the week, the directional patterns suggest that individuals may use gained flexibility to consolidate their presence on socially desirable days. This implies that the programme's current emphasis on increasing individual flexibility without specifying the days on which this flexibility is exercised may not result in the behavioural change required to achieve its goals.

Thirdly, the profile of the working population shows that not all commuters are equally open to interventions that spread peak demand. The programme itself recognises that its target group consists of travellers who have a reasonable alternative to peak-hour travel. The findings of this study enable this target group to be defined more precisely. As shown in Section 4.2, the peak on Tuesdays and Thursdays is the aggregate outcome of all three profiles. However, it is the TT profile – highly educated employees in large public sector organisations, with long commute distances and a relatively high proportion of young children at home – that contributes most directly to peak demand on Tuesdays and Thursdays and simultaneously has the greatest structural capacity to redistribute office attendance. In contrast, IFW commuters, who are predominantly employed in sectors where physical presence is required, have limited scope to work from home and are therefore largely beyond the scope of WFH-based peak-spreading measures. Therefore, focusing policy efforts on the TT profile is not only more promising from a peak-spreading perspective, but also more realistic in terms of behavioural feasibility. Since commuting profiles reflect organisational routines and collective scheduling norms rather than purely individual choices, however, governments may have limited direct influence over individual behaviour. Interventions directed at employers and organisations, who shape the conditions under which these patterns emerge and persist, are therefore likely to be more effective than measures aimed at individuals alone.

The following section translates these implications into concrete recommendations for policymakers and employers.

5.3.2 Policy Recommendations

The central message of the following recommendations is that peak-spreading policies may benefit from shifting towards a day-specific approach. The exploratory directional patterns in this study suggest that generic improvements in employer-level factors and infrastructure may have limited redistributive potential and, in some cases, may even reinforce peak concentration. The difference between more and less effective interventions may lie not in the scale of the improvement, but in whether it directly reduces the obligation or incentive to be present on Tuesdays and Thursdays specifically. These recommendations should be understood as evidence-informed directions rather than definitive prescriptions, given the exploratory nature of the underlying findings.

For employers: make WFH structurally possible on peak days

The exploratory directional patterns suggest that the possibility to work from home showed the strongest association with peak-spreading transitions among SC commuters. Employers may therefore consider prioritising making WFH genuinely feasible specifically on Tuesdays and Thursdays, not by offering financial compensation for WFH in general, but by removing practical and organisational barriers to working from home on the days that drive peak concentration. This may include explicit team agreements that Tuesdays and Thursdays are also valid WFH days, or managers visibly working from home on these days to reduce the implicit norm of physical presence. The directional patterns suggest that WFH allowance showed negligible redistributive effects, while the actual possibility to work from home showed the strongest directional association with SC to MC transition of all the examined covariates.

Alongside this, online meeting policies targeted specifically on Tuesdays and Thursdays may be worth considering. The possibility to hold online meetings was the only factor associated with a meaningful directional transition among IFW commuters towards a more moderate pattern, suggesting it may directly weaken the incentive to commute on specific days that drive peak congestion.

As the desire for contact with colleagues was consistently cited as the main reason for not working from home, employers may also consider addressing collective scheduling norms directly. Team-level agreements to stagger office days, designate shared remote working days or move social activities such as team drinks from Thursdays to Fridays could reduce the social pull of peak days. This represents a fundamental shift in approach, from expanding individual flexibility to reorganising collective scheduling practices, and it is precisely this shift that the Aanpak Spitsspreiden en Mijden programme may consider promoting in its engagement with employers.

For national policymakers: redesign fiscal instruments and target the right group

The TT profile, which describes highly educated employees in large public sector organisations who have a long commute and young children at home, appears to contribute most directly to peak demand and may have the greatest potential to redistribute office attendance. Policymakers may therefore consider explicitly targeting this group, rather than applying uniform measures across the working population.

The Wednesday dip in office attendance among TT commuters may partly reflect the traditional Wednesday half-day school schedule in the Netherlands, which could reinforce the preference for working from home on that day among parents in this group. Staggering school schedules across regions, rather than concentrating them on Wednesday afternoons, could reduce this effect. However, addressing this would require coordination beyond the mobility domain.

Where fiscal instruments are used, a day-specific design may be more effective than generic measures. WFH allowances could offer higher compensation for working from home on Tuesdays and Thursdays, or provide financial incentives for commuting on Mondays, Wednesdays or Fridays. The directional patterns suggest that generic car reimbursement without a day-specific component may reinforce peak-day concentration among IFW commuters rather than redistributing demand, though this finding is exploratory and should not be treated as conclusive. It is also worth considering whether day-specific financial incentives are practically feasible and enforceable within existing employment frameworks, as implementation may require coordination between employers, government and fiscal authorities.

For IFW commuters, WFH-based interventions are largely infeasible due to the physical presence requirements of their sectors. Staggered working hours or shift adjustments that redistribute arrival times rather than office days may be more appropriate for this group.

For policymakers and PT authorities: invest in PT frequency and day-specific fare incentives

Of all the examined covariates, a perceived improvement in PT frequency showed the strongest directional association with SC to MC transitions, with a transition probability of 99.71%. This suggests that insufficient PT capacity may act as a structural barrier for SC commuters, making non-peak days less attractive as office days. Therefore, improving overall PT frequency could indirectly contribute to redistributing commuting demand by making a broader range of days equally feasible for office attendance. This applies not only to rail services, but also to regional bus and other public transport modes, as barriers to non-peak day attendance may exist across the entire PT network. Public transport authorities and NS could complement infrastructure investment by exploring day-specific fare incentives, such as reduced ticket prices on non-peak days, to provide an additional financial incentive to shift away from travelling on Tuesdays and Thursdays. However, given the exploratory nature of this finding, further research is needed before drawing firm conclusions about the magnitude of this effect.

For the system level: extend monitoring to capture day-specific WFH behaviour

Current monitoring frameworks, including the LRO, track how often individuals work from home but not on which days they do so. Although the LRO captures the days on which individuals commute, it does not capture the days on which individuals work from home. This means that the day-specific structure of WFH behaviour cannot be derived directly from existing data. Extending the survey with information about the specific days on which individuals worked from home would provide a more comprehensive overview of weekly commuting and WFH patterns, and would significantly enhance the programme's capacity to monitor the effectiveness of interventions in achieving day-specific redistribution rather than merely increasing overall WFH prevalence.

5.4 Limitations and Future Research

This section reflects on the limitations of this study and identifies directions for future research.

5.4.1 Limitations

When interpreting the findings of this study, several limitations relating to the data and sample, the methodology, and the conceptual framework should be considered.

Data and sample

The LRO measures behaviour during a single reference week in late October or early November each year. This timing may introduce seasonal bias: shorter daylight hours, autumn weather conditions, and the absence of school holidays during this period may all influence commuting and WFH decisions in ways that differ from other times of the year. In particular, the reference week may overestimate fixed commuting patterns and underestimate flexibility, as summer and holiday periods tend to produce more varied behaviour. This limits the generalisability of the identified profiles and transition probabilities to other seasons.

As outlined in Section 3.2.4, the sample exhibits several systematic deviations from the CBS reference population. Notably, there is an overrepresentation of workers aged 50-64, as well as an underrepresentation of highly educated respondents and those from (very) strongly urban areas. These deviations are particularly relevant for this study, as the most policy-relevant population consists of workers who have a realistic possibility to choose their office days, such as knowledge workers in hybrid arrangements, rather than the Dutch working population in general. Since highly educated hybrid workers are underrepresented while workers in sectors requiring physical presence are overrepresented, the TT profile's prevalence may be underestimated and the IFW profile overrepresented relative to their actual shares among workers who can realistically redistribute their office days.

Another limitation is the exclusion of fully remote workers. Individuals who worked entirely from home during the reference week are excluded from the LCA and LTA, as they have no commuting pattern to profile. These workers tend to be more highly educated, concentrated in IT and professional services, and more likely to live in urban areas, which are all groups that are already underrepresented in the sample. Therefore, the findings relate specifically to the hybrid working population and cannot be generalised to individuals who have fully substituted commuting with WFH.

Restricting the analysis to respondents who participated in all three waves introduces an additional risk of attrition bias. Respondents who completed all three waves may differ systematically from those who dropped out, for example with regard to commuting intensity or WFH behaviour. This could affect the generalisability of the identified profiles and transition probabilities (Olde Kalter et al., 2020). Panel attrition also resulted in a relatively small analytical sample with a limited number of observed transitions between profiles.

Methodological limitations

As outlined in Section 3.1.3, both LCA and the LTA have several inherent limitations that are relevant to interpreting the findings of this study. Due to the probabilistic nature of class assignment, the exact composition of the three identified profiles (MC, IFW and TT) is uncertain, and individuals near the boundaries of profiles may have been misclassified (Weller et al., 2020). The three-profile solution likewise reflects modelling decisions regarding indicator selection and the number of classes, and should be understood as a possible representation of the underlying structure, rather than a definitive classification. Similarly, the qualitative labels assigned to the profiles necessarily simplify the behavioural complexity within each group (Weller et al., 2020).

Assuming measurement invariance across waves is another limitation, particularly for the TT profile. Between 2023 and 2024, the same individuals reorganised their commuting days from Wednesdays and Fridays towards Tuesdays and Thursdays, resulting in a shift in the indicator probabilities that define this profile. Although a posterior membership analysis confirmed that this reflects genuine behavioural reorganisation within a stable group rather than compositional change, the altered indicator pattern means that the TT profile is not being compared on identical terms across all three waves. The assumption of partial invariance, while considered sufficient for LTA in the literature, therefore introduces uncertainty specifically in the transition estimated involving the TT profile. This should be kept in mind when interpreting the LTA results for this group.

The small analytical sample size (N = 612) and limited number of observed transitions between profiles constrained the statistical power of the LTA. None of the nine contextual policy factors reached statistical significance, which may be partly due to this limited power rather than reflecting a true absence of effects. Therefore, the findings should be interpreted as directional patterns rather than statistically robust estimates. Furthermore, the sample was not weighted in the LCA and LTA analyses, meaning that the systematic deviations from the reference population described above are not corrected for in the profile identification or transition estimates.

Conceptual limitations

The contextual policy factors are measured as respondents' perceived changes in conditions rather than objective, externally verified policy changes. This means that the transition matrices reflect associations between perceived improvements and profile transitions, rather than the effects of actual policy interventions. It is therefore possible that the same objective change in conditions is perceived differently across individuals, introducing measurement error that may further reduce the statistical power of the LTA. Furthermore, the associations between the covariates and the transitions cannot be interpreted as causal effects. Although covariate selection is theory-driven, it is constrained by data availability, meaning that other relevant factors may have been overlooked, including unobserved variables that influence both commuting behaviour and the included covariates. Consequently, the directional patterns observed in the transition matrices should not be used to predict the precise magnitude of behavioural change that specific measures would produce. The recommendations in Section 5.3 should therefore be understood as evidence-informed directions rather than definitive prescriptions.

5.4.2 Future Research

Several directions for future research emerge from the limitations and findings of this study. Firstly, the small analytical sample size and the limited number of observed transitions necessitate replication using larger longitudinal datasets, which would provide greater statistical power for detecting whether associations between contextual policy factors and commuting profile transitions are statistically significant.

Secondly, the analytical framework could be extended to include fully remote workers by adding a question to the LRO about which specific days individuals worked from home. This would provide a fuller picture of the day-specific structure of WFH behaviour across the entire working population and address the exclusion of this group, which was identified as a limitation of the current study.

Thirdly, the within-profile reorganisation of the TT profile between 2023 and 2024 suggests that behavioural change can occur within a single measurement interval. Extending the observation period beyond three waves would allow a more robust assessment of whether such shifts are temporary adjustments or reflect structural changes in commuting behaviour over time. It would also help to clarify the methodological question of why the TT profile in the LCA and the SC profile in the LTA show different indicator patterns, which currently warrants further investigation.

Fourthly, the exploratory directional patterns observed in the transition matrices suggest hypotheses that could be tested using experimental or quasi-experimental designs. In particular, the profile-dependent effects of perceived improvements in the possibility to work from home and public transport frequency warrant further investigation to better understand the mechanisms underlying these opposing responses.

Fifthly, future research could address the measurement of contextual policy factors by linking individual-level survey data to objective policy indicators, such as registered changes in employers' WFH policies or

PT timetables, rather than relying on perceived changes. This would enable a more rigorous causal assessment of the effects of specific policy measures on commuting profile transitions.

Finally, qualitative research among TT commuters could provide a deeper understanding of the social and organisational factors that influence attendance on Tuesdays and Thursdays. This could help to identify the types of day-specific intervention that are most likely to be perceived as feasible and acceptable by this group.

5.5 Personal Reflection and Final Remarks

This section takes a step back from the findings to reflect on the research process. It concludes by offering a broader perspective on what this study means for mobility policy.

5.5.1 Personal Reflection

When I started this research project, I expected the most challenging aspect to be the methods. In practice, however, I found that the decisions were the real challenge. In research like this, there is rarely a single correct answer – what matters is that choices are clearly justified. Yet that does not make the decisions any easier, especially when you want to get the most out of your data. Every choice regarding variable selection, covariate inclusion or respondent definition was a difficult one. I know this study is not perfect, but every decision made along the way has been carefully considered and clearly accounted for.

Working with methods I had never used before added another layer of uncertainty. It was hard to estimate how long certain analyses would take or how sensitive the results would be to different modelling choices. Looking back, I am satisfied with my approach of running analyses iteratively and then refining and integrating the results into a coherent whole.

What surprised me most was how stable commuting profiles were across waves. Even though I had considered this beforehand and discussed with family and friends what might cause someone to change their weekly routine, the extent to which patterns persisted was striking. This resonated with my own experience at Goudappel: as almost no one came to the office on Wednesdays, I gradually stopped going in on these days too, while Tuesdays and Thursdays remained busy and social. Office attendance is largely self-reinforcing, which makes it difficult for policy to shift.

I was also struck by how clearly the three commuting profiles emerged from the LCA. The distinctiveness of the MC, IFW and TT profiles was greater than I had anticipated, which I believe to be one of the most valuable contributions of this study. It demonstrates that general WFH statistics can mask meaningful differences in how people organise their working week.

This research has deepened my interest in the analysis of travel behaviour. What I find most compelling is that it starts from what people actually do rather than predetermined policy targets. If behaviour does not connect to policy, policy will not work. This may sound obvious, but it is a perspective that is easily lost in practice, one that I hope to keep in mind.

5.5.2 Final Remarks

The central finding of this study is that hybrid workers organise their working week in fundamentally different ways, and that the concentration of commuting on Tuesdays and Thursdays is driven by selective hybrid workers whose patterns are deeply embedded in social and organisational routines. This concentration is not a coincidence; it reflects the accumulated weight of habit, social coordination and employer expectations, all of which are difficult to change through infrastructure investment or financial incentives alone. Understanding which groups of workers drive this concentration, and why they maintain their patterns, is a necessary first step towards designing effective interventions.

This does not mean that policy is powerless. Every marginal shift in commuting behaviour contributes to a more evenly distributed demand across the week. However, effective peak spreading requires working with, rather than against, behaviour. Start by analysing what people actually do. Understand the system they are embedded in. Then design policies that connect to these realities, and be realistic about how much change any single measure can produce.

The findings of this study are intended to provide a useful empirical foundation for the Dutch Ministry of Infrastructure and Water Management and other stakeholders involved in mobility policy. The profiles identified here offer a more detailed picture of the commuting population than aggregate statistics can provide. The directional patterns in the transition matrices, however exploratory, suggest where targeted interventions could be most effective. The work is far from finished, but the direction is clear: behaviour first, policy second.

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Appendices

Appendix A – Literature Review Search Strategy

In accordance with the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021), a structured literature review was conducted to identify the knowledge gap underlying Chapter 1. Figure A.1 on the next page shows the complete flowchart of the review process.

Scopus was used as the primary database. The search focused on working from home, commuting and travel behaviour, and longitudinal analyses, yielding 36 records. Prior to screening, three records were excluded based on their document type (reviews and data papers), ensuring that only journal articles were retained. This resulted in 33 records being screened.

During the screening process, the records were manually filtered to include only studies published between 2016 and 2026, and to exclude those classified under the subject area Medicine. All remaining records were sought for retrieval, resulting in 31 reports being assessed for eligibility.

The full texts of the 31 retrieved reports were assessed for eligibility based on predefined exclusion criteria. The focus was on analytical relevance of commuting and travel behaviour, the presence of individual-level longitudinal or within-person analysis, the conceptual treatment of working from home, attention to behavioural heterogeneity, and the inclusion of a structural rather than purely short-term pandemic perspective. Following this assessment, 20 reports were excluded, leaving 11 studies included in the literature review.

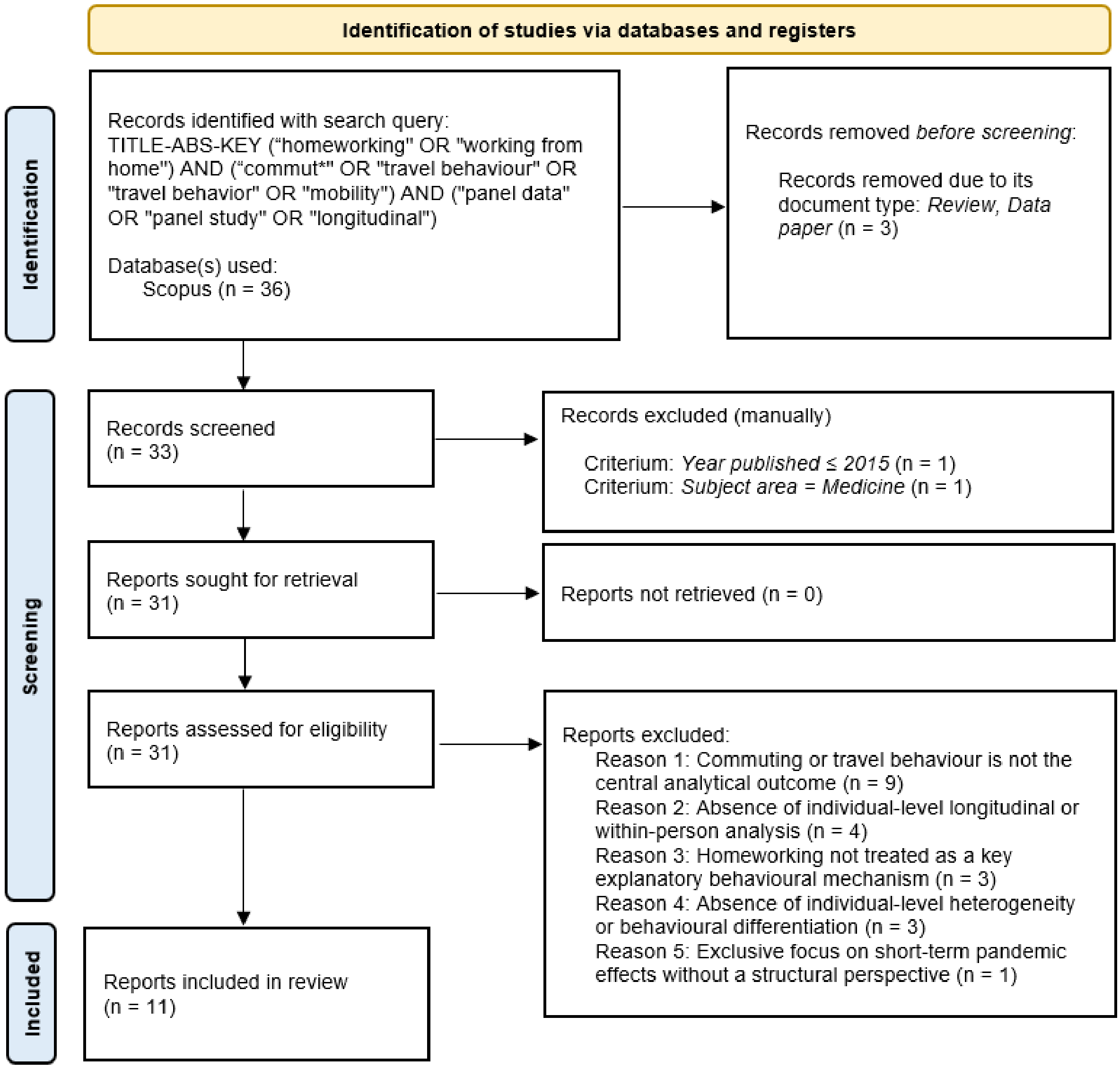

Figure A.1 Literature identification and screening flowchart according to PRISMA (2021).

A.1 – Literature Synthesis

This thesis is based on a structured literature review that examines working from home behaviour in relation to travel and commuting contexts. Following the search and screening procedure outlined in Appendix A, eleven academic studies were selected for inclusion. These studies provide the empirical and methodological basis for the academic relevance of this thesis. Table A.1 provides an overview of the included studies, specifying their authors, publication year and title.

To enable a systematic synthesis of the literature, Table A.2 classifies the selected studies according to four analytical dimensions that are central to this research: (1) the operationalisation of WFH, (2) the use of a longitudinal perspective on WFH behaviour, (3) the explicit treatment of behavioural heterogeneity, and (4) the application of dynamic analytical approaches to capture behavioural change over time. These dimensions were selected because they reflect the dominant methodological choices in the literature and directly relate to the conceptual focus of this thesis.

The classification in Table A.2 reveals distinct patterns in the existing literature. All of the included studies adopt a longitudinal perspective and operationalise WFH as either a frequency-based measure or a binary indicator, with none capturing how WFH is distributed across specific weekdays. A smaller subset addresses behavioural heterogeneity by examining how different population groups respond to WFH, while a similarly small subset applies dynamic modelling approaches that explicitly capture behavioural change over time. This overview shows that, although longitudinal data are widely used, the operationalisation of WFH as a weekly structure and the simultaneous integration of heterogeneity and dynamics remain absent from the existing literature.

Table A.2 therefore provides an analytical bridge between the descriptive literature review in Appendix A and the critical discussion of previous research and scientific knowledge gaps in Chapter 1. By structuring the literature in this way, the synthesis clarifies how the reviewed studies relate to one another and where substantive gaps remain.

Table A.1 Overview of the selected literature

No.	Authors	Year	Title
1	Xie & Liao	2025	Dynamic relationships between working from home, commute distance, mode preference, and car use: A six-year longitudinal study
2	R. M. Faber et al.	2023	The relations between working from home and travel behaviour: a panel analysis
3	Böhnen & Kuhnimhof	2024	Working from home and commuter travel in germany – panel data analysis of long-term effects
4	Rüger et al.	2024	To what extent does working from home lead to savings in commuting time? A panel analysis using the Australian HILDA Survey
5	Victoriano-Habit & El-Geneidy	2024	Studying the Interrelationship between Telecommuting during COVID-19, residential local accessibility, and active travel: a panel study in Montréal, Canada
6	Magriço et al.	2024	A longitudinal survey on the effect of the Covid-19 pandemic on long-term rail commuting
7	Pedreira Junior & Pitombo	2024	Unveiling substitution patterns of work trips by teleworking and their associations with physical and virtual accessibility in the Brazilian COVID-19 crisis
8	Kroesen et al.	2023	Revealing latent trajectories of (intended) train travel during and after COVID-19
9	R. Faber et al.	2023	Estimating post-pandemic effects of working from home and teleconferencing on travel behaviour
10	Kroesen et al.	2022	Exploring attitude-behaviour dynamics during COVID-19: How fear of infection and working from home influence train use and the attitude toward this mode
11	M. de Haas et al.	2020	How COVID-19 and the Dutch ‘intelligent lockdown’ change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands

Table A.2 Thematic classification of the reviewed literature

No.	Authors	Year	Operationalisation of WFH	Longitudinal perspective on WFH behaviour	Heterogeneity in WFH behaviour	Dynamic analysis of changes in WFH
1	Xie & Liao	2025	Frequency-based	✓		✓
2	R. M. Faber et al.	2023	Frequency-based	✓		
3	Böhnen & Kuhnimhof	2024	Binary indicator	✓		
4	Rüger et al.	2024	Frequency-based	✓		
5	Victoriano-Habit & El-Geneidy	2024	Frequency-based	✓	✓	
6	Magriço et al.	2024	Frequency-based	✓		✓
7	Pedreira Junior & Pitombo	2024	Frequency-based	✓	✓	
8	Kroesen et al.	2023	Frequency-based	✓	✓	
9	R. Faber et al.	2023	Frequency-based	✓		
10	Kroesen et al.	2022	Frequency-based	✓		✓
11	M. de Haas et al.	2020	Frequency-based	✓		

Appendix B – Questionnaire LRO 2025

The full LRO report is publicly available at: https://open.overheid.nl/documenten/c52594a7-9d7f-4d45-8d1f-0ba4ff19bd68/file

1. Basisvragenlijst

1.1 Introductie

Van harte welkom bij de online vragenlijst van het Landelijk Reizigersonderzoek

Met deze vragenlijst van het Ministerie van Infrastructuur en Waterstaat willen we het reisgedrag in Nederland in kaart brengen.

De vragenlijst invullen duurt ongeveer 15 minuten. De resultaten worden geheel anoniem verwerkt. We willen je vragen de vragenlijst in één keer in te vullen. Navigeren kun je alleen met de 'vorige' en 'volgende' knoppen in de vragenlijst, dus niet met de browser buttons.

Alvast hartelijk dank voor je medewerking!

Dit onderzoek wordt uitgevoerd door Goudappel en Ipsos I&O in opdracht van het Ministerie van Infrastructuur en Waterstaat.
Wij werken volgens de richtlijnen voor informatiebeveiliging en marktonderzoek (ISO 27001 en ISO 20252).

Jouw gegevens worden vertrouwelijk behandeld en verwerkt.
Voor meer informatie verwijzen wij je door naar het privacy statement [Link] van het ministerie

1.2 Woon- en werksituatie

We beginnen de vragenlijst met een aantal vragen over jouw woon- en werksituatie

W0 Heb je in het afgelopen jaar de volgende gebeurtenissen meegemaakt?
Meerdere antwoorden mogelijk

1. Begonnen met een nieuwe baan (ⓘeerste baan of baan bij een andere werkgever)
2. Verhuisd naar een ander adres
3. Geboorte van een kind (of opnemen adoptiekind en/of pleegkind binnen het gezin)
4. Geen van bovenstaande gebeurtenissen

W1 Welke situatie is op dit moment op jou van toepassing?
Indien meerdere antwoorden van toepassing zijn, kies dan het antwoord dat geldt voor de meeste uren per week

1. Baan in loondienst (fulltime/parttime)
2. Zelfstandig ondernemer zonder personeel (bv. zzp/freelancer)
3. Zelfstandig ondernemer met personeel
4. Werkzoekend
5. Niet werkzoekend (bv. schoolgaand/studerend/gepensioneerd/arbeidsongeschikt etc.)

Alleen stellen indien W1= 1, 2, of 3 (werkende)

W2 In welke branche/ sector ben je werkzaam?

1. Landbouw en visserij
2. Industrie
3. Bouwnijverheid
4. Nutsbedrijven
5. Handel
6. Horeca
7. Vervoer
8. ICT
9. Financiële dienstverlening
10. Zakelijke dienstverlening
11. Openbaar bestuur
12. Onderwijs
13. Gezondheid- en welzijnszorg
14. Cultuur
15. Overige dienstverlening

W3 Wat zijn de 4 cijfers van de postcode van jouw woonadres?
[XXXX] hele getallen 1000-9999

Alleen stellen indien W0 = 2 (Verhuisd naar een ander adres)

V2 Wat zijn de 4 cijfers van je oude postcode waar je in oktober 2024 woonde?
Postcode oude woonadres: [XXXX] hele getallen 1000-9999
Ik woonde toen in het buitenland

1.4 Woon- werkverkeer (A)

Blok woon-werkverkeer (A) alleen stellen indien W1 = 1, 2 of 3

De volgende vragen gaan over hoe vaak je thuiswerkt en op locatie en hoe je reist.

W4 Hoeveel dagen werkte je vorige week?

Als je vorige week vakantie had, neem dan de meest recente representatieve week waarin je wel werkzaam was. Met representatief bedoelen we dat je niet op vakantie was of door andere omstandigheden een uitzonderlijk reispatroon had.

1. 1 dag in de week
2. 2 dagen in de week
3. 3 dagen in de week
4. 4 dagen in de week
5. 5 dagen in de week
6. 6 dagen in de week
7. 7 dagen in de week

W5 Hoeveel dagen hiervan werkte je thuis, op jouw vaste werklocatie of op een externe locatie?

1. [x] dagen thuis
x 1 thuis (H2b)
2. [x] dagen op mijn vaste werklocatie
x 1 vast (H2a)
3. [x] dagen externe locatie
x 1 extern (H2c)
4. [x] dagen gedeeltelijk thuis en gedeeltelijk op vaste werklocatie
x 1 thuis (H2b) & x 1 vast (H2a)
5. [x] dagen gedeeltelijk thuis en gedeeltelijk externe locatie
x 1 thuis (H2b) & x 1 extern (H2c)
6. [x] dagen gedeeltelijk vaste werklocatie en gedeeltelijk externe locatie
x 1 vast (H2a) & x 1 extern (H2c)
7.

Controle: som van W5 dient gelijkt te zijn aan antwoord op W4.

Toelichting vaste werklocatie: "De locatie waar je het meest werkt."

Toelichting externe locatie: "Een hele dag op locatie, anders dan je huisadres of je vaste werklocatie (denk aan een detachering, een flexwerklocatie, of een bouwplaats)."

Berekenen H2a, H2b, H2c en H2d:

H2a = aantal dagen vaste werklocatie

H2b = aantal dagen thuis

H2c = aantal dagen externe werklocatie

H2d = totaal aantal werkdagen = W4

Bepaling variabele [H2-VastOfExtern] en [H3-VastOfExtern]:

H2a > 0	*[H2-VastOfExtern]=vaste werklocatie & [H3-VastOfExtern]=externe werklocatie*

H2a = 0 & H2c > 0	*[H2-VastOfExtern]=externe werklocatie & [H3-VastOfExtern]=vaste werklocatie*
H2a = 0 & H2c = 0	*=thuiswerker (ter controle: h2b=W4)*

Indien H2a = 0 & H2c = 0 (dus thuiswerker) skip naar W8.

W5b **Op welke dagen reisde je afgelopen week (of laatste werkweek) naar jouw [H2-VastOfExtern]?**
Meerdere antwoorden mogelijk

1. Maandag
2. Dinsdag
3. Woensdag
4. Donderdag
5. Vrijdag
6. Zaterdag
7. Zondag

Alleen tonen indien H2-VastOfExtern = vaste werklocatie
Controle: som aangevinkte antwoorden = {H2a}. als niet Foutmelding: "Je hebt eerder aangegeven dat je {H2a} dagen per week naar jouw vaste werkadres gaat. Zorg ervoor dat de som van de antwoorden in deze vraag daarmee in overeenstemming is."

Alleen tonen indien H2-VastOfExtern = externe werklocatie
Controle: som aangevinkte antwoorden = {H2c} Foutmelding: "Je hebt eerder aangegeven dat je {H2c} dagen per week naar een extern werkadres gaat. Zorg ervoor dat de som van de antwoorden in deze vraag daarmee in overeenstemming is."

W5c **Hoe laat kwam je aan op jouw [H2-VastOfExtern]? En hoe laat reisde je terug naar huis?** *Vul eerst het uur in en vervolgens het kwartierblok waar binnen je aankomt of vertrekt.*
Kom je 's avonds aan en vertrek je de volgende ochtend weer? Vul dat in bij dezelfde dag. Dus kom je maandagavond om 22.00u aan en vertrek je dinsdagochtend om 06.00u, dan vul je bij maandag aankomst 22.00u en vertrek 06.00u in.

Alleen dagen laten zien die bij W5b. zijn aangevinkt

	Aankomst op [H2-VastOfExtern]	Vertrek vanaf [H2-VastOfExtern]
A. Maandag	[uitklapmenu]	[uitklapmenu]
B. Dinsdag	[uitklapmenu]	[uitklapmenu]
C. Woensdag	[uitklapmenu]	[uitklapmenu]
D. Donderdag	[uitklapmenu]	[uitklapmenu]
E. Vrijdag	[uitklapmenu]	[uitklapmenu]
F. Zaterdag	[uitklapmenu]	[uitklapmenu]
G. Zondag	[uitklapmenu]	[uitklapmenu]

W5d **Reis je standaard op deze dagen en tijden naar jouw [H2-VastOfExtern] en terug naar huis of varieert dit per week?**

Meerdere antwoorden mogelijk

1. Het verschilt per week op welke **dagen** ik naar mijn [H2-VastOfExtern] reis
2. Het verschilt per week op welke **tijden** ik naar mijn [H2-VastOfExtern] reis
3. Het verschilt per week op welke **tijden** ik vanaf mijn [H2-VastOfExtern] terug naar huis reis
4. Ik reis standaard op deze dagen en tijden *[uitsluitend]*

W6 **Met welk vervoermiddel reisde je vorige week (of laatste werkweek) naar jouw [H2-VastOfExtern]?**

Ga uit van het vervoermiddel waarmee je de grootste afstand aflegt.

Vervoermiddel	Aantal dagen per week
A. Auto (als bestuurder) Alleen tonen indien A1=1.	[..]
B. Auto (als passagier)	[..]
C. Motor	[..]
D. Trein	[..]
E. Bus	[..]
F. Tram ofmetro	[..]
G. Taxi/ deeltaxi/ taxibusje	[..]
H. Brom/ snorfiets, scooter, brommobiel	[..]
I. Fiets	[..]
J. E-bike/ speed-pedelec	[..]
K. Lopend	[..]
L. Anders, namelijk ...	[..]

Alleen tonen indien H2-VastOfExtern = vaste werklocatie

Controle: som A t/m L = {H2a}. als niet Foutmelding: "Je hebt eerder aangegeven dat je {H2a} dagen per week naar jouw vaste werkadres gaat. Zorg ervoor dat de som van de antwoorden in deze vraag daarmee in overeenstemming is."

Alleen tonen indien H2-VastOfExtern = externe werklocatie

Controle: som A t/m L = {H2c} Foutmelding: "Je hebt eerder aangegeven dat je {H2c} dagen per week naar een extern werkadres gaat. Zorg ervoor dat de som van de antwoorden in deze vraag daarmee in overeenstemming is."

Alleen indien: W6=D

W7.1 **Hoe reis je van en naar het treinstation?**

Ga uit van het vervoermiddel waarmee je de grootste afstand aflegt.

1. Van woonlocatie naar het treinstation <dropdown menu>
2. Van het treinstation naar de werklocatie <dropdown menu>

Alleen indien: W6=E

W7.2 **Hoe reis je van en naar de bushalte?**

Ga uit van het vervoermiddel waarmee je de grootste afstand aflegt.

1.	Van woonlocatie naar de bushalte	<dropdown menu>
2.	Van de bushalte naar de werklocatie	<dropdown menu>

Alleen indien: W6=F

W7.3 Hoe reis je van en naar de tram of metro?

Ga uit van het vervoermiddel waarmee je de grootste afstand aflegt.

1.	Van woonlocatie naar de tram-/metrohalte	<dropdown menu>
2.	Van de tram-/metrohalte naar de werklocatie	<dropdown menu>

<dropdown menu voor W7.1, W7.2 en W7.3>

A. Met mijn eigen auto
B. Met een deelauto
C. Met de auto als passagier (carpoolen)
D. Met de bus *[alleen bij W7.1 en W7.3 tonen]*
E. Met de tram of metro *[alleen bij W7.1 en W7.2 tonen]*
F. Met de bromfiets/scooter
G. Met een deelscooter
H. Met mijn eigen fiets
I. Met een deelfiets (zoals de OV-fiets, FlickBike, Glimble-fiets, Donkey-fiets)
J. Met de e-bike (elektrische fiets)
K. Speed pedelec
L. Lopend
M. Anders, namelijk … [open invulveld]

W8 Welke werktijden zijn voor jou het meest van toepassing?

1. Ik werk altijd op dezelfde werktijden
2. Ik werk met meerdere diensten waarvan de tijden verschillen (bv. ochtend/middag dienst of middag/ avond/ nacht dienst)
3. Ik kan mijn werktijden volledig zelf bepalen
4. Ik kan mijn exacte werktijden zelf bepalen, binnen bepaalde marges (bv. wel altijd beginnen tussen 8:00 en 10:00 uur)

Alleen stellen indien geen thuiswerker.

W9 Vul hier de postcode in van de [H2-VastOfExtern] waar je werkt (let op: niet de postcode van de postbus). Als je deze niet weet of wanneer je op meerdere locaties werkte, vul dan de plaatsnaam in waar je het vaakst werkt.

Cijfers postcode: *[XXXX] hele getallen 1000-9999*

Plaats: … [open invulveld]

(postcode of plaatsnaam mag dus leeg blijven, maar minstens 1 van beide moet wel worden ingevuld). Postcodecontrole door Ipsos I&O en plaatnamenlijst voorgeprogrammeerd.

Alleen stellen indien thuiswerker.

W9b Vul hier de postcode in van je vaste werklocatie waar je werkt als je niet thuis zou werken (let op: niet de postcode van de postbus). Als je deze niet weet of wanneer je op meerdere locaties zou werken, vul dan de plaatsnaam in waar je het vaakst zou werken.

Toelichting vaste werklocatie: "De locatie waar je het meest werkt."

Cijfers postcode: *[XXXX] hele getallen 1000-9999*

Plaats: ... [open invulveld]

1. Ik heb geen vaste werklocatie buitenshuis

(postcode of plaatsnaam mag dus leeg blijven, maar minstens 1 van beide moet wel worden ingevuld). Postcode controle door Ipsos I&O en plaatnamenlijst voorgeprogrammeerd.

1.5 Woon- werkverkeer (B)

Alleen stellen indien W1= 1 of 3 (werkende, niet zijnde ZZP-er)

W10Hoeveel mensen werken er bij de organisatie waar je werkzaam bent?

1. Minder dan 100 werknemers
2. 100-250 werknemers
3. 250-500 werknemers
4. 500-1000 werknemers
5. Meer dan 1000 werknemers
6. Weet ik niet

Alleen stellen indien W1 = 1 (loondienst)

W11 Worden jouw reiskosten voor woon-werkverkeer volledig, gedeeltelijk of niet vergoed?

1. Volledig
2. Gedeeltelijk
3. Niet

De volgende paar vragen gaan over jouw werksituatie en reisgedrag naar werk in oktober 2024.

Alleen stellen indien H2a>0 of H2c >0 (geen thuiswerker).

V3 Welke werksituatie was vorig jaar (oktober 2024) op jou van toepassing?

1. Ik werkte toen op dezelfde ***[H2-VastOfExtern]***
2. Ik werkte toen op een andere ***[H2-VastOfExtern]***, maar in hetzelfde postcodegebied
3. Ik werkte toen op een andere ***[H2-VastOfExtern]***, in een ander postcodegebied
4. Ik werkte toen op een ***H3-VastOfExtern]***.
5. Ik werkte toen (vooral) thuis
6. Ik werkte toen niet

Alleen stellen indien W1= 4, 5

V4 Wat was een jaar geleden (oktober 2024) je arbeidspositie?

Indien meerdere antwoorden van toepassing zijn, kies dan het antwoord dat gold voor de meeste uren per week

1. Baan in loondienst (fulltime/parttime)
2. Zelfstandig ondernemer zonder personeel (bv. zzp/freelancer)
3. Zelfstandig ondernemer met personeel

1.10 Thuiswerken

Dit hele blok alleen stellen indien W1 = 1, 2 of 3

De volgende vragen gaan over jouw mogelijkheden en ervaringen met betrekking tot thuiswerken.

Alleen stellen indien W5 "thuis" en "gedeeltelijk thuis" nul dagen ingevuld (H2b = 0, niet thuiswerken)

T1 Wat is voor jou van toepassing met betrekking tot thuiswerken?

1. Ik mag (een deel) thuis of buiten de werklocatie werken en doe dit ook wel eens
2. Ik mag (een deel) thuis of buiten de werklocatie werken maar doe dit nooit
3. Ik heb geen mogelijkheid om thuis te werken, al zou mijn werk zich hier wel voor lenen
4. Ik heb geen mogelijkheid om thuis te werken, mijn werk leent zich hier niet voor

Alleen stellen indien W5 "thuis" of "gedeeltelijk thuis" bij minstens 1 dag (H2b > 0, thuiswerker) OF T1 = 1

T2 Welke situatie is het meest van toepassing op de manier waarop je op dit moment thuis werkt?

1. Ik werk elke week dezelfde vaste dag(en) thuis [niet tonen indien T1=1]
2. Ik werk elke week op één of meerdere dagen thuis, maar niet op vaste dagen
3. Ik werk incidenteel een dagdeel of een dag thuis
4. Ik werk als het zo uitkomt een paar uur thuis om de spits te mijden
5. Anders, namelijk ... [open invulveld]

Alleen stellen indien W5 "thuis" of "gedeeltelijk thuis" bij minstens 1 dag aangevinkt (H2b > 0, thuiswerker) OF T1=1 en T2=1,2,3,4

T3 Wat is de reden dat je (gedeeltelijk) thuiswerkt?

Meerdere antwoorden mogelijk.

1. Vanwege het thuiswerkbeleid van mijn werkgever
2. Ik vind het niet fijn om te reizen
3. Vanwege fysieke beperkingen kan ik niet naar mijn werklocatie reizen
4. Thuis werk ik beter (productiever, minder afleiding, beter concentreren)
5. Ik heb geen vast kantoorpand (meer)
6. Vanwege werkzaamheden op mijn route
7. Geen reistijd
8. Buiten de spits kunnen reizen [T2 is niet 4]
9. Besparing reiskosten
10. Ik heb mijn kantoor/bedrijf aan huis
11. Zelf je werktijd in kunnen delen
12. Combinatie met andere activiteiten (gezin, klusjes in huis, sport, etc.)
13. Anders, namelijk ... [open invulveld]

Alleen stellen indien T1 = 2 (werkt nooit thuis, maar zou wel kunnen)

T5.2 Wat zijn voor jou de belangrijkste redenen waarom je nooit thuis werkt, terwijl dat wel zou kunnen?

Kies minimaal 1 en maximaal 3 opties

1. Ik heb niet de nodige faciliteiten/ spullen om thuis te werken
2. Ik heb geen eigen (aparte) werkplek

3. Ik vind de werk-privé balans moeilijk
4. Ik mis dan het contact met collega's
5. Ik kan me thuis niet concentreren
6. Ik mis informatie over het werk
7. Ik vind het fijn om te reizen naar werk
8. Ik heb thuis te weinig structuur
9. Mijn werk vraagt om fysieke afspraken (face-to-face)
10. Ik wil niet thuiswerken
11. Anders, namelijk … [open invulveld]

C2. In hoeverre zijn onderstaande situaties van invloed op jouw reis- en thuiswerkgedrag?

[Geen invloed – weinig invloed – neutraal – beetje invloed – Veel invloed]

1. Het hebben van een goede werkplek thuis
2. Goede ICT-voorzieningen voor thuiswerken (bijv. online werkomgeving)
3. Beleid en flexibiliteit van mijn werkgever
4. De aanwezige afleiding thuis (van bijv. kinderen)
5. Of mijn collega's naar kantoor gaan
6. De drukte op de weg
7. De drukte in het OV

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1.13 Regelingen

Alleen stellen indien W1 = 1

B1 **Van welke reiskostenvergoeding(en) of regelingen voor je woon-werkverkeer maak je gebruik?**

Meerdere antwoorden mogelijk

1. Kilometervergoeding alleen voor de auto
2. Kilometervergoeding alleen voor de fiets/ e-bike
3. Kilometervergoeding alleen voor OV
4. Kilometervergoeding onafhankelijk van vervoermiddel
5. Leaseauto
6. Mobiliteitsbudget
7. Persoonlijke mobiliteitskaart
8. Aanschafvergoeding fiets/ e-bike
9. Leaseregeling fiets/ e-bike
10. OV-abonnement
11. Thuiswerkvergoeding
12. Anders, namelijk … [open invulveld]
13. Geen van deze regelingen *[uitsluitend]*

Alleen stellen indien W1 = 1, 2 of 3

B2 **Hebben er sinds oktober 2024 veranderingen plaatsgevonden in de regelingen die worden aangeboden vanuit jouw werkgever/ opdrachtgever?**

		Sterk verbeterd	Verbeterd	Ongewijzigd	Verslechterd	Sterk verslechterd	Weet niet/ n.v.t.
1.	Mogelijkheid om thuis te werken						
2.	Mogelijkheid om op andere locaties te werken						
3.	Mogelijkheid om online te vergaderen						
4.	Flexibele werktijden						
5.	Thuiswerkvergoeding						
6.	Reiskostenvergoeding auto						
7.	Reiskostenvergoeding fiets/ e-bike						
8.	Reiskostenvergoeding OV						
9.	Aanschafvergoeding fiets/ e-bike						
10.	Leaseregeling fiets/ ebike						
11.	De parkeertarieven						

12.	De beschikbaarheid van parkeerplaatsen auto						
13.	De beschikbaarheid van parkeerplaatsen fiets						
14.	Beschikbaarheid van laadpalen auto						
15.	Beschikbaarheid van laadplekken e-bike/ speed-pedelec						

Alleen stellen indien W1 = 1, 2 of 3

B3 Hebben er sinds oktober 2024 veranderingen plaatsgevonden op of rond je woon-werk route?

		Sterk verbeterd	Verbeterd	Ongewijzigd	Verslechterd	Sterk verslechterd	Weet niet/ n.v.t.
1.	Autowegen / route						
2.	Autoreistijd						
3.	Betrouwbaarheid autoreistijd						
4.	Fietspaden/route						
5.	Fietsreistijd						
6.	Fietsenstalling station						
7.	P+R						
8.	Aanbod OV mogelijkheden						
9.	Frequentie OV						
10.	OV reistijd						
11.	Betrouwbaarheid OV reistijd						

Toelichting bij Frequentie OV: "Hoe vaak per uur je een bus, trein, tram of metro kunt nemen"

1.14 Algemeen

Ten slotte volgen nog enkele achtergrondvragen.

Alleen stellen aan respondenten buiten het Ipsos I&O panel, want van panelleden is dit bekend.

A2 Wat is je leeftijd?

[xx] jaar

Alleen stellen aan respondenten buiten het Ipsos I&O panel, want van panelleden is dit bekend.

A3 Wat is je geslacht?

1. Man
2. Vrouw
3. Ik identificeer mij als [open invulveld]
4. Wil ik niet zeggen

Uitvragen aan alle respondenten, i.v.m. afwijkende vraagstelling panel.

A4 Wat is de hoogste opleiding die je hebt voltooid?

1. Geen onderwijs
2. Lager onderwijs/ basisonderwijs
3. Lager of middelbaar algemeen voortgezet onderwijs (LAVO, V(G)LO, MULO, MAVO)
4. Hoger algemeen voortgezet onderwijs (HAVO, VWO, HBS, MMS, lyceum, gymnasium)
5. Lager beroepsonderwijs (ambachts/huishoudschool, LTS, VBO, LHNO, LEAO, V(M)BO)
6. Middelbaar beroepsonderwijs (UTS, MTS, (K)MBO, MEAO, INAS, ROC, leerlingwezen)
7. Hoger beroeps- of wetenschappelijk onderwijs (HTS, HEAO, hogeschool, universiteit)
8. Anders, namelijk … [open invulveld]

Alleen stellen aan respondenten buiten het Ipsos I&O panel, want van panelleden is dit bekend.

A5 In welke categorie valt het totale bruto jaarinkomen van jouw huishouden??

1. minimum (minder dan € 16.000)
2. beneden modaal (€ 16.000 tot € 33.500)
3. bijna modaal (€ 33.500 tot € 41.500)
4. modaal (€ 41.500 tot € 49.500)
5. tussen 1 en 2 keer modaal (€ 49.500 tot € 83.000)
6. twee keer modaal (€ 83.000 tot € 99.000)
7. meer dan 2 keer modaal (€ 99.000 of meer)
8. weet ik niet / wil ik niet zeggen

Uitvragen aan alle respondenten, i.v.m. afwijkende vraagstelling panel.

A6 **Wat is de samenstelling van jouw huishouden?**

Meerdere antwoorden mogelijk

1. Ik woon alleen *[uitsluitend]*
2. Ik woon samen met partner zonder kinderen *[uitsluitend]*
3. Ik woon met/zonder partner en minstens één kind van 12 jaar of jonger
4. Ik woon met/zonder partner en minstens één kind tussen 13 en 17 jaar
5. Ik woon met/zonder partner en kind(eren) vanaf 18 jaar en ouder
6. Ik woon met andere mensen samen (bijv. met familie, in studentenhuis, woongroep, etc.)
7. Wil ik niet zeggen
8. Anders, namelijk … [open invulveld]

Alleen stellen indien A6= 3,4,5,6 -> NIET als A6=7.

Alleen stellen aan respondenten buiten het Ipsos I&O panel, want van panelleden is dit bekend.

A6.2 **Met hoeveel mensen woon je in huis?**

Vul het aantal mensen in waarmee jij de voordeur deelt, inclusief jezelf.

[x] open invulveld

Uitvragen aan alle respondenten

A7 **Heb je een OV-chipkaart of gebruik je OVpay?**

Meerdere antwoorden mogelijk

1. Ja, ik heb een OV-chipkaart voor privé gebruik
2. Ja, ik heb een OV-chipkaart voor zakelijk gebruik
3. Ja, ik gebruik OVpay (via betaalpas of telefoon)
4. Nee, ik reis niet met het OV

A9 **In hoeverre volg jij technologische trends en producten?**

1. Ik ben altijd op de hoogte en probeer nieuwe producten meteen
2. Ik hou de trends in de gaten en overweeg deze na positieve feedback
3. Ik volg trends, maar wacht met aanschaf tot er veel gebruikers zijn
4. Ik ben niet echt geïnteresseerd in technologie

A8 **Als je nog opmerkingen over deze vragenlijst hebt, kun je deze hier invullen:**

……… [open invulveld]

geen opmerkingen

Je antwoorden zijn verzonden!

Hartelijk dank voor de tijd die je hebt genomen om deze vragenlijst in te vullen. Jouw input is zeer waardevol voor ons.

APPENDIX C – DATA PREPARATION

APPENDIX C.1 – VARIABLE HARMONISATION

The following harmonisation steps were carried out to ensure the variables were operationalised consistently across the three LRO datasets.

Reasons for working from home. The question comprised 17 response options in 2023 and 2024, whereas the 2025 dataset included only 13. To maintain longitudinal consistency, only the 13 items present in all three datasets were retained. The four reasons for WFH discontinued in 2025 were excluded from the analysis: 'I enjoy working from home', 'I always worked from home', 'No distraction from colleagues', and 'Better ability to concentrate'.

Reasons not to work from home. In 2024 and 2025, respondents could select up to three reasons from a list of eleven options within a single question. In 2023, respondents were asked to answer the same question three times, selecting one option each time from the same list. As the underlying response options were identical across all three datasets, the 2023 responses were recoded to match the 2024-2025 format.

Household income. Income was only recorded in the 2025 dataset. As income is measured in categorical groups rather than exact values, it was assumed that an individual's income category remained stable across the three years. The 2025 income category was therefore applied to the 2023 and 2024 datasets.

Household size. Despite being included in the LRO questionnaire, household size was absent from the 2024 dataset. Where the reported household size in 2023 was identical to that in 2025, the same value was assigned to 2024. In all other cases, the 2024 value was treated as missing.

Work location variables. The variables indicating the number of days spent at a fixed location, at home or at an external location, as well as the total number of working days, were absent from the 2023 dataset. These were calculated by summing the relevant day-level responses for 2023, using the same method applied to the 2024 and 2025 datasets.

APPENDIX C.2 – VARIABLE SIMPLIFICATION AND CATEGORY REDUCTION

Table C.1 Detailed overview of original and recoded categories per variable

Variable	Original Code	Original Category	Recoded Code	Recoded Category
Age	-	Continuous (years)	(1)	18 – 34
			(2)	35 – 49
			(3)	50 – 64
			(4)	65 +
Gender	(1)	Man	(1)	Male
	(2)	Vrouw	(2)	Female
	(3) (4)	Ik identificeer mij als Wil ik niet zeggen	(99)	Missing
Educational level	(1) (2) (3)	Geen onderwijs Lager onderwijs / basisonderwijs Lager of middelbaar algemeen voortgezet onderwijs (LAVO, V(G)LO, MULO, MAVO)	(1)	Low
	(4) (5) (6)	Hoger algemeen voortgezet onderwijs (HAVO, VWO, HBS, MMS, lyceum, gymnasium) Lager beroepsonderwijs (ambachts/huishoudschool, LTS, VBO, LHNO, LEAO, V(M)BO) Middelbaar beroepsonderwijs (UTS, MTS, (K)MNO, MEAO, INAS, ROC, leerlingwezen)	(2)	Intermediate
	(7)	Hoger beroeps- of wetenschappelijk onderwijs (HTS, HEAO, hogeschool, universiteit)	(3)	High
	(8)	Anders, namelijk...	(99)	Missing
Income	(1) (2)	Minimum (minder dan € 16.000) Beneden modaal (€ 16.000 tot € 33.500)	(1)	Low
	(3) (4) (5)	Bijna modaal (€ 33.500 tot € 41.500) Modaal (€ 41.500 tot € 49.500) Tussen 1 en 2 keer modaal (€ 49.500 tot € 83.000)	(2)	Intermediate
	(6) (7)	Twee keer modaal (€ 83.000 tot € 99.000) Meer dan 2 keer modaal (€ 99.000 of meer)	(3)	High
	(8)	Weet ik niet / wil ik niet zeggen	(99)	Missing

Household composition	(1)	Ik woon alleen	(1)	No children
	(2)	Ik woon samen met partner zonder kinderen		
	(3)	Ik woon met/zonder partner en minstens één kind van 12 jaar of jonger	(2)	Young children (≤ 17 years)
	(4)	Ik woon met/zonder partner en minstens één kind tussen 13 en 17 jaar		
	(5)	Ik woon met/zonder partner en kind(eren) vanaf 18 jaar en ouder	(3)	Older children or other
	(6)	Ik woon met andere mensen (bijv. met familie, in studentenhuis, woongroep, etc.)		
	(7)	Wil ik niet zeggen	(99)	Missing
	(8)	Anders, namelijk ...		
Sector	(1)	Landbouw en visserij	(1)	Agriculture and industry
	(2)	Industrie		
	(3)	Bouwnijverheid		
	(4)	Nutsbedrijven		
	(5)	Handel		
	(6)	Horeca	(2)	Services
	(8)	ICT		
	(9)	Financiële dienstverlening		
	(10)	Zakelijke dienstverlening		
	(11)	Openbaar bestuur	(3)	Government
	(12)	Onderwijs	(4)	Education
	(13)	Gezondheid- en welzijnszorg	(5)	Healthcare
	(14)	Cultuur	(6)	Other
	(15)	Overige dienstverlening		
	(7)	Vervoer		
Changes to regulations	(1)	Sterk verbeterd	(1)	Improved
	(2)	Verbeterd		
	(3)	Ongewijzigd	(2)	Unchanged
	(4)	Verslechterd	(3)	Worsened
	(5)	Sterk verslechterd		
	(6)	Weet niet / n.v.t.	(99)	Missing
Changes to commute	(1)	Sterk verbeterd	(1)	Improved
	(2)	Verbeterd		
	(3)	Ongewijzigd	(2)	Unchanged
	(4)	Verslechterd	(3)	Worsened
	(5)	Sterk verslechterd		
	(6)	Weet niet / n.v.t.	(99)	Missing
Urbanisation level	(1)	Zeer sterk stedelijk	(1)	(Very) strongly urban
	(2)	Sterk stedelijk		
	(3)	Matig stedelijk	(2)	Moderately urban
	(4)	Weinig stedelijk	(3)	Low/non-urban
	(5)	Niet stedelijk		
	(99)	Missing	(99)	Missing

Appendix C.3 – Contextual Policy Factors Selection

Table C.2 Overview of included and excluded contextual policy covariates in LTA

	Contextual Policy Factor	Actor	Included	Reason for inclusion or exclusion
Employer-level factors (B2)				
1	Possibility to WFH	Employer	✓	Directly enables reduction in commuting days
2	Possibility to work at other locations	Employer	×	Conceptual overlap with possibility to WFH, both capture locational flexibility
3	Possibility to meet online	Employer	✓	Reduces obligation to commute for meetings
4	Flexible working hours	Employer	✓	Enables commuting on non-peak days
5	WFH allowance	Employer	✓	Financial incentive to increase WFH days
6	Commuting reimbursement car	Employer / Government	✓	Reduces financial barrier to car commuting, enabling more flexible day choice
7	Commuting reimbursement bike/e-bike	Employer	×	May shift mode choice, but not the day-specific structure of office attendance
8	Commuting reimbursement PT	Employer / Government	✓	Reduces financial barrier to PT commuting, enabling more flexible day choice
9	Purchase allowance bike/e-bike	Employer	×	May shift mode choice, but not the day-specific structure of office attendance
10	Lease scheme bike/e-bike	Employer	×	May shift mode choice, but not the day-specific structure of office attendance
11	Parking tariffs (car)	Employer / Government	×	May shift mode choice, but not travel day; peak days remain unchanged
12	Availability of car parking	Employer	×	May shift mode choice, but not travel day; peak days remain unchanged
13	Availability of bicycle parking	Employer	×	May shift mode choice, but not the day-specific structure of office attendance
14	Availability of EV charging	Employer / Government	×	May shift mode choice, but not travel day; peak days remain unchanged
15	Availability of e-bike charging	Employer	×	May shift mode choice, but not the day-specific structure of office attendance
Commute route conditions (B3)				
1	Motorway / route conditions	Government	×	May shift mode choice, but not travel day; peak days remain unchanged
2	Car travel time	Government	×	Determined by geography; not directly actionable through policy in the short term
3	Car travel time reliability	Government	✓	Reduces uncertainty of commuting by car, enabling more flexible day choice
4	Cycle path / route conditions	Government	×	May shift mode choice, but not the day-specific structure of office attendance
5	Cycle travel time	Government	×	May shift mode choice, but not the day-specific structure of office attendance
6	Bicycle storage at station	Government	×	May shift mode choice, but not the day-specific structure of office attendance
7	Park-and-ride availability	Government	×	May shift mode choice, but not travel day; peak days remain unchanged
8	PT supply	Government	×	Conceptual overlap with PT frequency
9	PT frequency	Government	✓	Improves PT accessibility on non-peak days, enabling day spreading
10	PT travel time	Government	×	Determined by geography; not directly actionable through policy in short term
11	PT travel time reliability	Government	✓	Reduces uncertainty of commuting on non-peak days, enabling more flexible day choice

APPENDIX C.4 – DESCRIPTIVE STATISTICS FOR INDICATORS AND INACTIVE COVARIATES

Table C.3 Daily commuting rates across measurement waves (2023-2025)

	2023	2024	2025
Commuting on Monday	65.4	67.6	65.9
Commuting on Tuesday	73.0	74.0	73.8
Commuting on Wednesday	62.7	60.6	61.4
Commuting on Thursday	69.3	66.8	71.1
Commuting on Friday	50.1	48.5	47.2
N (valid)	703	695	671
N (excluded)	323 (31.5%)	331 (32.3%)	355 (34.6%)

Note. Excluded respondents are the ones working exclusively from home during the reference week.

Table C.4 Work location and working days across measurement waves (2023-2025)

Variable		2023	2024	2025
Days at fixed work location	Mean (SD)	2.73 (1.79)	2.75 (1.76)	2.73 (1.75)
Days at external work location	Mean (SD)	0.50 (1.16)	0.48 (1.18)	0.47 (1.17)
Days at home	Mean (SD)	1.03 (1.48)	1.01 (1.46)	1.01 (1.46)
Total working days	Mean (SD)	4.26 (1.12)	4.24 (1.08)	4.21 (1.11)
N (valid)		757	749	719

Note. Mixed days (i.e. days on which respondents worked partly at home and partly at a fixed or external location) are allocated as 0.5 to each respective location type to avoid double-counting.

Appendix D – Trends in Commuting Behaviour

Table D.1 Trends in commuting times across weekdays

Commuting day	Commuting times	Response	2023 (%) (N = 8,169)	2024 (%) (N = 8,330)	2025 (%) (N = 8,674)
Monday	Peak arrival	No	16.9	17.4	16.5
		Yes	44.4	42.5	44.0
	Peak departure	No	21.0	22.7	22.0
		Yes	40.3	37.1	38.5
		Missing	38.7	40.2	39.5
Tuesday	Peak arrival	No	18.2	19.2	19.6
		Yes	47.3	45.0	45.8
	Peak departure	No	22.6	24.6	24.8
		Yes	42.9	39.6	40.7
		Missing	34.5	35.8	34.6
Wednesday	Peak arrival	No	17.4	17.6	17.8
		Yes	38.5	36.6	37.0
	Peak departure	No	21.2	22.3	22.6
		Yes	34.7	31.9	32.2
		Missing	44.1	45.7	45.2
Thursday	Peak arrival	No	18.8	18.9	19.6
		Yes	45.1	41.6	43.7
	Peak departure	No	23.7	24.2	24.0
		Yes	40.2	36.2	39.3
		Missing	36.1	39.5	36.6
Friday	Peak arrival	No	15.0	15.3	14.9
		Yes	31.2	28.8	29.5
	Peak departure	No	20.7	20.6	20.7
		Yes	25.5	23.6	23.7
		Missing	53.8	55.8	55.6
Saturday	Peak arrival	No	7.4	6.6	6.5
		Yes	4.3	3.6	3.6
	Peak departure	No	7.9	7.4	7.0
		Yes	3.8	2.8	3.0
		Missing	88.3	89.7	90.0
Sunday	Peak arrival	No	5.0	4.3	4.1
		Yes	1.7	1.5	1.4
	Peak departure	No	5.1	4.8	4.4
		Yes	1.5	1.0	1.1
		Missing	93.3	94.3	94.5

Note. Peak arrival is defined as 07:00-09:00 and peak departure as 16:00-18:00 (Ministerie van Infrastructuur en Waterstaat et al., 2025).

Table D.2 Trends in commuting patterns

	Response	2023 (%) (N = 7,638)	2024 (%) (N = 7,584)	2025 (%) (N = 7,974)
Commuting patterns				
It varies from week to week which days I commute to work	No	61.5	62.5	62.2
	Yes	38.5	37.5	37.8
It varies from week to week at which time I commute to work	No	67.6	71.6	69.7
	Yes	32.4	28.4	30.3
It varies from week to week at which time I commute to home	No	62.9	71.9	69.6
	Yes	37.1	28.1	30.4
I commute on fixed days and times	No	53.1	53.0	52.3
	Yes	46.9	47.0	47.7

Table D.3 Trends in working time flexibility

	2023 (%) (N = 8,169)	2024 (%) (N = 8,330)	2025 (%) (N = 8,674)
Working time flexibility			
I always work the same working hours	45.3	48.8	48.7
I work across several shifts with different timings	15.5	15.8	14.5
I can set my own working hours entirely	16.8	19.8	19.2
I can set my own exact working hours, within certain limits	22.4	15.5	17.5

APPENDIX E – TRENDS IN WFH BEHAVIOUR

Table E.1 Trends in mean WFH days across waves 2023-2025

	2023 (N = 8,169)		2024 (N =8,330)		2025 (N = 8,674)	
	Mean	SD	Mean	SD	Mean	SD
WFH Days						
Full WFH days	1.02	1.434	1.05	1.498	1.08	1.451
Partly at home, partly at a fixed work location	0.09	0.477	0.12	0.544	0.11	0.525
Partly at home, partly at an external work location	0.07	0.412	0.09	0.513	0.08	0.469
Total WFH days	1.10	1.463	1.15	1.517	1.17	1.473

Note. Mixed days (partly at home, partly at a fixed or external work location) were weighted by 0.5 when calculating total WFH days, consistent with the LRO methodology in 2024.

Table E.2 Trends in total WFH days per week across waves 2023-2025

	2023 (%) (N = 8,169)	2024 (%) (N = 8,330)	2025 (%) (N = 8,674)
Total WFH Days			
None	52.7	50.6	48.7
1	11.8	13.1	14.4
2	12.9	13.3	14.4
3	7.9	7.8	8.6
4	4.7	4.2	3.8
5 or more	3.4	4.4	3.8
Missing	6.7	6.7	6.2

Note. Missing values represent respondents for whom the amount of working days was not recorded.

Table E.3 Trends in WFH opportunities across waves 2023-2025

	2023 (%) (N = 4,306)	2024 (%) (N = 4,213)	2025 (%) (N = 4,227)
WFH Opportunities			
I can WFH and sometimes do so	14.4	13.0	14.7
I can WFH, but never do so	10.8	12.5	12.8
I cannot WFH, although my job allows it	7.7	8.9	9.8
I cannot WFH, because my job Is not suited to it	67.1	65.6	62.8

Table E.4 Proportion of non-home workers reporting their job is not suited to WFH, by sector, across waves 2023-2025

Sector	2023 (%)	N	2024 (%)	N	2025 (%)	N
Agriculture and fishing	83.9	87	74.7	95	81.3	80
Industry	66.6	521	63.5	496	58.9	491
Construction	44.1	161	53.0	202	47.8	207
Utilities	46.7	15	61.3	31	52.0	25
Retail and wholesale trade	74.5	663	73.8	504	71.3	522
Hospitality	88.0	341	75.5	253	79.9	259
Transport and logistics	82.9	369	85.2	331	79.6	289
ICT	23.1	134	27.3	150	29.1	134
Financial services	22.8	145	25.3	150	26.7	172
Business services	33.3	318	38.3	269	38.6	306
Public administration	32.7	49	28.9	83	29.1	79
Education	68.2	255	68.3	290	67.1	295
Healthcare and social work	78.3	765	77.9	876	73.0	847
Culture	56.1	41	54.3	46	54.2	48
Other services	70.6	439	68.1	439	65.8	474
Total	67.2	4,303	65.6	4,215	62.8	4,228

Note. Interpret utilities with caution due to small sample size.

Table E.5 Trends in WFH structure

	2023 (%) (N = 4,484)	2024 (%) (N = 4,664)	2025 (%) (N = 5,066)
WFH Structure			
I work from home on fixed days every week	43.8	44.5	45.2
I work from home every week, but not on fixed days	32.6	31.2	31.0
I work from home occasionally	18.3	17.7	17.2
I work from home to avoid peak hours	1.7	3.2	3.2
Other	3.6	3.3	3.4

Table E.6 Trends in reasons for WFH

	Response	2023 (%) (N = 4,457)	2024 (%) (N = 4,509)	2025 (%) (N = 4,894)
Reasons for WFH				
Employer WFH policy	No	66.7	70.7	63.3
	Yes	33.3	29.3	36.7
Dislike commuting	No	88.1	87.3	88.2
	Yes	11.9	12.7	11.8
Physical limitations	No	98.3	95.7	96.0
	Yes	1.7	4.3	4.0
Higher productivity at home	No	65.1	69.2	54.1
	Yes	34.9	30.8	45.9
No fixed office location	No	96.2	94.6	93.3
	Yes	3.8	5.4	6.7
Roadworks along commute	No	98.6	96.9	96.2
	Yes	1.4	3.1	3.8
No commuting time required	No	53.2	64.5	59.5
	Yes	46.8	35.5	40.5
Avoid peak-hour congestion	No	93.7	93.0	94.0
	Yes	6.3	7.0	6.0
Save travel costs	No	89.7	90.0	89.4
	Yes	10.3	10.0	10.6
Home-based workplace	No	91.8	90.0	89.0
	Yes	8.2	10.0	11.0
Flexible working hours	No	69.4	74.1	65.7
	Yes	30.6	25.9	34.3
Combine with other activities	No	64.8	74.2	68.2
	Yes	35.2	25.8	31.8
Other reason	No	91.7	94.3	93.2
	Yes	8.3	5.7	6.8
Enjoy working from home	No	37.9	44.4	-
	Yes	62.1	55.6	-
Always worked from home	No	93.6	92.1	-
	Yes	6.4	7.9	-
No distraction from colleagues	No	73.3	77.3	-
	Yes	26.7	22.7	-
Better ability to concentrate	No	68.3	73.3	-
	Yes	31.7	26.7	-

Table E.7 Trends in reasons against WFH

	Response	2023 (%) (N = 463)	2024 (%) (N = 525)	2025 (%) (N = 539)
Reasons against WFH				
Lack of WFH facilities	No	79.5	82.5	86.3
	Yes	20.5	17.5	13.7
No workspace at home	No	83.4	82.4	84.6
	Yes	16.6	17.6	15.4
Work-privacy balance difficulties	No	79.0	79.2	80.3
	Yes	21.0	20.8	19.7
Lack of contact with colleagues	No	50.6	55.7	51.8
	Yes	49.4	44.3	48.2
Concentration at home difficulties	No	82.3	78.1	79.3
	Yes	17.7	21.9	20.7
Lack of work-related information	No	76.2	79.3	80.7
	Yes	23.8	20.7	19.3
Enjoy commuting	No	92.7	89.0	89.1
	Yes	7.3	11.0	10.9
Lack of structure at home	No	88.6	93.0	88.2
	Yes	11.4	7.0	11.8
Need for face-to-face meetings	No	81.7	81.5	78.7
	Yes	18.3	18.5	21.3
Preference not to work from home	No	71.4	73.8	74.8
	Yes	28.6	26.2	25.2
Other reason	No	92.3	94.7	94.0
	Yes	7.7	5.3	6.0

Table E.8 Trends in perceived influence of factors on commuting and WFH behaviour

	2023 (N = 8,169)		2024 (N = 8,330)		2025 (N = 8,674)	
Factors influencing travel and WFH behaviour						
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Quality of home workspace	3.17	1.591	2.97	1.563	3.04	1.568
Quality of ICT facilities for WFH	3.35	1.627	3.12	1.600	3.18	1.605
Employer policy and flexibility	3.36	1.605	3.17	1.578	3.29	1.587
Distractions at home	2.27	1.438	2.33	1.433	2.30	1.417
Colleagues working on-site	2.72	1.495	2.63	1.469	2.68	1.482
Road congestion	2.42	1.495	2.51	1.487	2.52	1.482
Public transport congestion	2.09	1.422	2.19	1.437	2.12	1.402

Note. Responses were rated on a five-point Likert scale (1 = no influence to 5 = strong influence). Values represent mean scores and standard deviations.

Appendix F – Latent Class Analysis

Table F.1 Commuting profiles of the 4-class solution per wave

	Wave 1 (2023)				Wave 2 (2024)				Wave 3 (2025)			
	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4
Class size (%)	42	41	9	8	34	31	22	14	38	26	23	12
Indicators												
Monday	0.64	0.85	0.06	0.61	0.84	0.93	0.47	0.13	0.96	0.35	0.89	0.05
Tuesday	0.69	0.94	0.35	0.44	1.00	0.73	0.35	0.87	1.00	0.52	0.55	0.88
Wednesday	0.54	0.81	0.49	0.43	0.86	0.50	0.67	0.15	0.76	0.65	0.54	0.30
Thursday	0.59	0.93	0.97	0.08	0.99	0.53	0.51	0.62	0.92	0.58	0.60	0.64
Friday	0.04	0.87	0.71	0.89	0.82	0.29	0.57	0.06	0.72	0.65	0.15	0.03

APPENDIX G – LATENT TRANSITION ANALYSIS

Table G.1 Descriptive frequencies of contextual policy factors (2024)

	Improved (%)	Unchanged (%)	Worsened (%)	N (valid)
Employer-level factors				
Possibility to WFH	19.5	72.9	7.7	5817
Possibility to meet online	24.4	69.5	6.1	6144
Flexible working hours	18.2	74.6	7.3	6359
WFH allowance	20.9	72.4	6.7	5457
Travel reimbursement car	23.0	70.2	6.7	6052
Travel reimbursement PT	14.8	78.1	7.0	5239
Commute route conditions				
Car travel time reliability	11.5	70.1	18.4	6812
PT frequency	12.1	72.1	15.8	5399
PT travel time reliability	10.3	68.3	21.4	5342

Note. Values reflect the proportion of respondents who perceived each condition as improved, unchanged, or worsened compared to the previous year. The number of valid observations varies across variables due to missing values and responses indicating 'don't know' or 'not applicable', both of which were excluded from the analysis.

Table G.2 Descriptive frequencies of contextual policy factors (2025)

	Improved (%)	Unchanged (%)	Worsened (%)	N (valid)
Employer-level factors				
Possibility to WFH	15.4	76.7	7.9	6230
Possibility to meet online	20.1	74.0	5.9	6520
Flexible working hours	15.7	77.7	6.6	6862
WFH allowance	16.8	76.8	6.4	5859
Travel reimbursement car	17.7	76.4	6.0	6431
Travel reimbursement PT	12.6	81.4	5.9	5627
Commute route conditions				
Car travel time reliability	10.1	70.9	19.0	7076
PT frequency	11.2	76.5	12.3	5646
PT travel time reliability	9.0	73.3	17.7	5620

Note. Values reflect the proportion of respondents who perceived each condition as improved, unchanged, or worsened compared to the previous year. The number of valid observations varies across variables due to missing values and responses indicating 'don't know' or 'not applicable', both of which were excluded from the analysis.

APPENDIX H – LAYMAN'S SUMMARY

TU Delft

June 2026

Why do so many people commute on Tuesdays and Thursdays? And how could we change it?

This summary presents the key findings of a Master's thesis research conducted at Delft University of Technology. The study examines the weekly patterns of commuting behaviour among Dutch workers, analysing why peak congestion on Tuesdays and Thursdays is so persistent and how it can be addressed through policy.

The problem

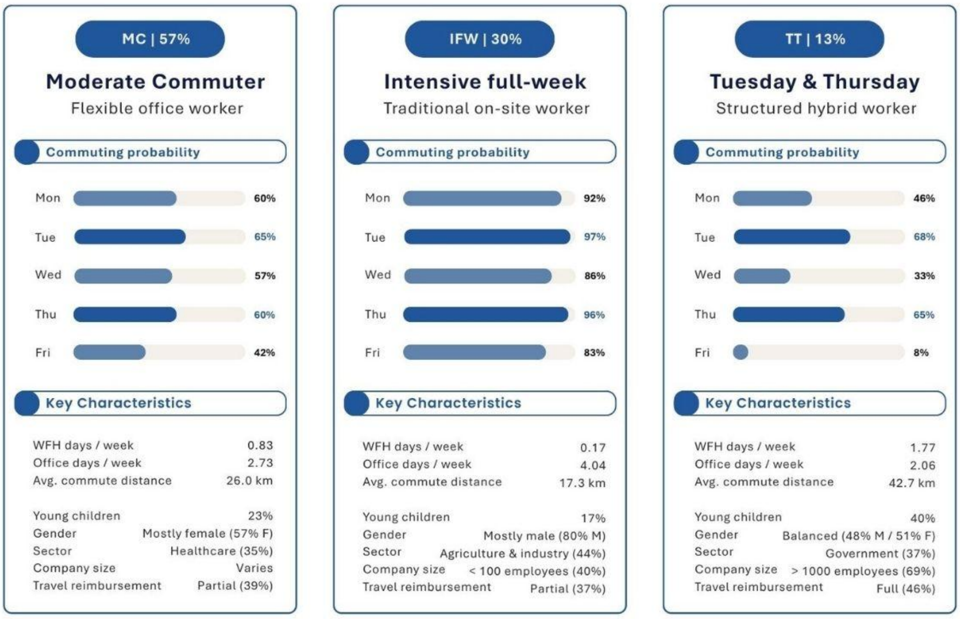
Every Tuesday and Thursday, Dutch roads and public transport are filled with commuters heading to the office. These two days have become the busiest office days in the Netherlands, while Mondays, Wednesdays and Fridays are noticeably quieter. This concentration puts enormous pressure on the road and public transport network, not because more people are working, but because they are all travelling on the same days. Spreading this demand more evenly across the week is one of the main goals of Dutch mobility policy, as part of the Aanpak Spreiden en Mijden 2025-2027 programme.

What we did not yet know

Researchers have long studied *how often* people work from home, but not *on which specific days* they do so. That distinction turns out to matter enormously. Someone who works from home on Mondays and Fridays contributes very differently to peak congestion than someone who works from home on Tuesdays and Thursdays. Without this day-specific information, it is impossible to understand who is causing peak pressure and how to steer them away from it.

What this study found

Using data from 612 Dutch workers across three years (2023-2025), drawn from the Landelijk Reizigersonderzoek - a national travel survey commissioned by the Dutch Ministry of Infrastructure and Water Management - three distinct weekly commuting profiles were identified:



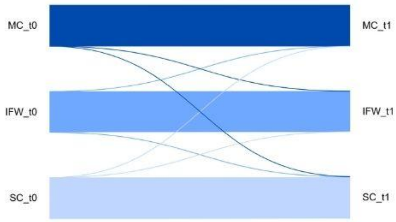
Master Thesis E.L.Schepers | Dynamics and Heterogeneity in Working From Home Behaviour | Summary

The Key Finding

> Once people have settled into a commuting routine, they almost never change it. Across all three years and all nine policy factors examined, the vast majority of commuters stayed in exactly the same profile. Weekly commuting patterns are deeply ingrained habits.

Three policy factors stand out as exceptions. When improvements in **working from home possibilities** or **public transport frequency** are perceived, selective commuters show a meaningful tendency to shift towards a more spread-out pattern. A third mechanism applies to intensive daily commuters: when **online meeting possibilities are perceived to improve**, some reduce their commuting intensity and move towards the moderate profile. This makes sense, since Tuesdays and Thursdays are particularly popular days for in-person meetings. Remove that obligation and the concentration begins to loosen.

Profiles stability
2023→ 2025



Almost all commuters remain in the same profile across all three waves. Thin streams indicate the rare exceptions.

Contextual policy factor	MC to IFW	MC to SC	IFW to MC	IFW to SC	SC to MC	SC to IFW
Possibility to work from home	0,00	0,00	0,00	0,11	**0,71**	0,00
Possibility to meet online	0,03	0,00	**0,06**	0,09	0,00	0,13
Flexible working hours	0,00	0,00	0,00	0,00	0,01	0,00
WFH allowance	0,00	0,00	0,00	0,01	0,01	0,00
Travel reimbursement car	0,00	0,00	0,00	0,05	0,00	0,00
Travel reimbursement PT	0,00	0,00	0,00	0,00	0,00	0,00
Car travel time reliability	0,00	0,00	0,00	0,01	0,00	0,00
PT frequency	0,00	0,00	0,00	0,12	**1,00**	0,00
PT travel time reliability	0,00	0,00	0,00	0,22	0,00	0,00

MC = Moderate Commuter, IFW = Intensive Full-Week Commuter, SC = Selective Commuter. Values represent transition probabilities under the perceived improved condition for each covariate, with all other covariates held at baseline. Values of 0.00 reflect probabilities below 0.005.

What this means for policy

Generic improvements to working conditions or infrastructure are unlikely to substantially redistribute peak commuting demand on their own. The findings suggest that effective peak spreading may require targeted, day-specific interventions directed at the groups that contribute most to Tuesday and Thursday concentration. The selective commuter profile appears to have the greatest potential to redistribute office attendance. The findings suggest the following evidence-informed directions for policy:

Employers
- Consider making WFH genuinely feasible on Tuesdays and Thursdays specifically, through team agreements rather than financial allowances alone
- Explore online meeting policies targeted at peak days to reduce the need for in-person presence

National policymakers
- Consider day-specific fiscal instruments, such as higher WFH allowances or lower PT fares on peak days, rather than generic measures
- Consider targeting interventions at highly educated public sector employees in large organisations with long commutes and young children, as this group appears to contribute most to peak congestion

PT authorities
- Improving overall PT frequency may make non-peak days more attractive as office days for selective commuters

About this research

This study was conducted as part of a Master's thesis in Complex Systems Engineering and Management at Delft University of Technology. The analysis draws on panel data from 612 working respondents who participated in all three measurement waves (2023, 2024 and 2025) of the Landelijk Reizigersonderzoek. The methods applied are Latent Class Analysis (LCA) and Latent Transition Analysis (LTA), conducted in LatentGOLD. Given the exploratory nature of the LTA findings, the recommendations in this study should be understood as evidence-informed directions rather than definitive prescriptions.

Appendix I – AI Statement

This thesis was developed with the support of generative artificial intelligence, specifically Claude (Anthropic), which was used as an assistive tool throughout the research and writing process. AI was only used for supportive, non-decisive activities, and did not replace the author's analytical judgement, methodological choices or responsibility for the thesis's content.

AI tools supported the research and writing process in the following ways. Firstly, they were used as a source of inspiration for chapter titles, section heading, and figure and table names. AI also assisted in drafting, revising and refining text for clarity, structure and academic tone, including rephrasing passages to enhance their academic register. AI was also used as a brainstorming partner to reflect on the structure, coherence, and positioning of arguments across chapters.

During the analytical phase, AI tools supported critical reflection on model specification choices in LatentGOLD, including the interpretation of the commuting profiles (LCA), the transition probability matrices (LTA) and the formulation of cautious, exploratory language around non-significant LTA findings. These reflections served as preparatory input for the author's own analytical decisions, which were made and verified independently.

At no point were AI tools used to generate original empirical data, perform statistical or methodological analyses, or draw substantive conclusions. The author is responsible for all interpretations, analytical decisions, and conclusions presented in this thesis.