

Article

Work Discomfort and Inequalities in Access to Remote Work: Evidence from a Post-Communist CEE Labour Market

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Abstract

The expansion of remote work has transformed labour market conditions across the developed world, yet access to home-based work remains unequally distributed along occupational, sectoral, regional, and organisational lines. Post-pandemic evidence on the persistence of these inequalities is particularly scarce in Central and Eastern European economies, where historically low remote work prevalence, manufacturing-intensive industrial structures, and pronounced regional disparities create a distinctive structural context. Drawing on primary survey data collected from 390 employees in Slovakia in 2025, this study pursues two interrelated empirical goals: to identify the factors predicting a mismatch between the structural feasibility of working from home and its actual availability to employees, and to examine the determinants of experienced work discomfort. Binary logistic regression, multiple linear regression, and a battery of group difference tests were employed across the two analytical strands. The results reveal a pronounced capital–periphery gradient in remote work access, with employees outside the capital city facing dramatically higher odds of mismatch, and identify organisational support as the most practically actionable determinant of work discomfort. Notably, experiencing a mismatch between remote work feasibility and access was not associated with higher discomfort, a finding that challenges assumptions common in the Western European literature and points to the moderating role of contextual expectations in post-communist labour markets. The findings offer directly applicable evidence for employers seeking to reduce work-related strain through targeted support measures, and for policymakers designing regulatory frameworks to promote equitable access to flexible work arrangements across regions and sectors.

Keywords: remote work discomfort; home office access inequality; logistic regression; Central and Eastern Europe; labour market stratification



Academic Editors: Zdenka Gyurák
Babeľová, Natália Vraňáková and
Augustín Stareček

Received: 2 May 2026

Revised: 15 June 2026

Accepted: 17 June 2026

Published: 20 June 2026

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1. Introduction

The transformation of work through digital technologies has fundamentally altered where and how labour is performed. Prior to the COVID-19 pandemic, working outside the traditional office environment remained a marginal phenomenon in most economies, and what was clear was that remote work was neither universally available nor uniformly experienced. The COVID-19 pandemic fundamentally disrupted this equilibrium. Lock-downs and public health restrictions forced employers and employees across sectors and countries to transition to home-based work at an unprecedented scale and speed. This sudden shift accelerated investment in digital infrastructure, prompted the rapid redesign

of work processes, and triggered a wave of new organisational policies supporting remote work. The proportion of employees working from home in 2020 increased dramatically compared to any previous point in the preceding decade [1]. As this transition unfolded, it raised urgent academic and practical questions about what it means to work from home in the long term—for individual well-being, organisational performance, and broader labour market equality [2].

The scholarly consensus that has since emerged is ambivalent. Working from home offers demonstrable advantages: it eliminates commuting time, increases scheduling flexibility, and can improve the balance between professional and personal life. These factors are associated with higher job satisfaction and, under favourable conditions, enhanced productivity [3]. Yet the same body of evidence documents substantial costs. Extended home-based work blurs the boundary between work and private life, erodes the sense of belonging to a team, and fosters social isolation. The resulting strain is associated with longer working hours, heightened stress, and elevated risk of burnout [4]. Therefore, the literature consistently characterises remote work as a “double-edged sword”, as it entails both benefits and challenges with significant consequences for employee well-being [5]. The negative effects are particularly pronounced in the domains of mental and physical health, and they are not distributed equally across employees. The concept of work discomfort, understood as a composite experience of physical, psychological, and organisational strain, is therefore used in this study as a key construct for evaluating the quality of remote work conditions.

Critically, the ability to work from home is not equally available, and a structural mismatch between the theoretical potential for home-based work and its actual availability in practice constitutes a meaningful dimension of labour market inequality—one that has persisted and arguably deepened in the post-pandemic period. These determinants provide the theoretical basis for examining how access to remote work and experienced discomfort are shaped by individual, organisational, and regional conditions.

Slovakia presents a particularly instructive case for studying these dynamics. From a comparative perspective, Slovakia has historically ranked among the European countries with the lowest rates of remote work [2]. Before the pandemic, the home office was used by approximately 5% of the workforce. Even at the height of the 2020 disruption, this ratio rose to only around 12%, which was still below the European average [6]. Moreover, the country’s industrial structure, heavily oriented towards automotive manufacturing and on-site production, constrains the structural potential for remote work. OECD estimates suggest that approximately 29% of Slovak jobs are suitable for home-based work, compared to an OECD average of 34% [7]. This potential is unequally distributed across the national territory. While over 40% of jobs in the Bratislava metropolitan region are compatible with remote work, this share falls to approximately 25% in less developed regions [8]. Deficits in digital infrastructure, digital skills, and organisational capacity outside major urban centres have further limited actual implementation [7]. As Kapitsinis [9] argues, without targeted policy addressing the digital divide and strengthening human capital in peripheral regions, the potential of remote work will remain unevenly realised.

Despite this growing body of evidence, several important gaps remain. First, most research on inequalities in remote work has been conducted in Western European, North American, or East Asian contexts. Post-communist Central and Eastern European (CEE) economies remain substantially underrepresented in the literature, yet their structural features make them theoretically important test cases where the inequalities predicted by resource-based and spatial theories of remote work access may operate with particular intensity. Second, and most critically, existing studies almost universally examine either the distribution of access to remote work or its effects on worker well-being in isolation.

No prior study has jointly modelled the structural predictors of access inequality and experienced work discomfort as a single empirical framework and a single sample, making it impossible to examine whether and how these two dimensions of remote work inequality intersect. Third, the overwhelming majority of existing evidence was collected during the pandemic emergency period, when remote work arrangements were imposed rather than chosen. Evidence on the persistence, or transformation, of structural inequalities in the post-pandemic period, when organisations are making deliberate rather than emergency decisions about flexible work, remains critically limited. This study addresses all three gaps simultaneously, and in doing so produces a fourth contribution that is itself empirically novel: the finding that structural denial of feasible remote work does not translate into measurably higher discomfort in a post-communist labour market context—a result that directly challenges assumptions derived from Western European evidence and opens a new line of theoretical inquiry.

Although this study is grounded in the Slovak context, its implications extend considerably further. Slovakia can be understood as a representative case of a wider category of small, open, manufacturing-intensive economies embedded within integrated regional labour markets—a type found not only across CEE (e.g., Hungary, the Czech Republic, Romania, Bulgaria) but also in parts of Southern and Northern Europe. The structural forces shaping unequal access to remote work in Slovakia, such as sectoral structure, regional differences, ownership structures, and the quality of organisational support, are active in all of these settings. Therefore, evidence from Slovakia contributes to a broader comparative understanding of how labour market institutions and spatial inequalities condition the distributional consequences of remote work. Furthermore, as European and national policy frameworks increasingly incorporate flexible and hybrid work arrangements as instruments of labour market modernisation and regional cohesion, national evidence on the barriers to equitable access becomes directly relevant for policymakers across the EU.

Addressing this research gap requires not only identifying statistical associations but also constructing interpretable, theoretically grounded prediction models that can speak to both research and policy audiences. This is precisely what the present study sets out to do. Remote work has moved from an emergency measure to a permanent feature of labour market organisation across much of the developed world. Yet remarkably little is known about how the two most consequential outcomes for employees—whether they can access remote work at all and how comfortable or distressing that work is when they do—are shaped by the structural and organisational conditions surrounding them. Understanding this is not merely an academic exercise. For employers, it provides actionable evidence on where organisational support is most needed. For policymakers, it illuminates the structural barriers that prevent equitable access to flexible work arrangements. For international researchers, it offers a rigorously documented case from a CEE economy that is rarely represented in the comparative literature yet shares fundamental characteristics with dozens of economies across Europe and beyond.

To this end, the study pursues two interrelated empirical goals. The first is to construct a prediction model for the match and mismatch between the objective possibility of performing work from home and its actual availability to individual employees. This is the inequality question at the heart of the study: not whether remote work exists in a given economy, but who gets it and who is denied it despite being eligible, and what organisational, regional, and structural factors drive that gap. The second goal of the study is to examine the determinants of experienced work discomfort. Here, the focus shifts from access to lived quality: among employees navigating their current working arrangements, what makes the difference between a manageable and a distressing experience? By treating both goals within a single study and a single sample, we can examine not only each

phenomenon in its own right but also the degree to which they intersect—that is, whether being denied feasible remote work translates into measurably greater discomfort, and what other factors moderate that relationship.

2. Literature Review

2.1. *Defining and Measuring Remote Work and Work Discomfort*

For the purposes of this study, the terms “home office” and “working from home” refer to arrangements in which employees perform their regular job duties from a home-based location, typically using digital communication technologies. While numerous overlapping terms exist in the literature, including teleworking, telecommuting, remote work, and virtual work, this study uses these terms interchangeably, consistent with the broader literature on home-based work [10].

A foundational question in the remote work literature concerns which jobs are structurally compatible with home-based work. Dingel and Neiman [11], in a widely cited analysis, classified the feasibility of remote work for all occupational categories and estimated that approximately 37% of jobs in the United States can be performed entirely from home, with substantial variation across industries, cities, and wage levels. Critically, they also found that jobs amenable to remote work are systematically better remunerated than those that are not—establishing from the outset that access to remote work is not a neutral organisational choice but a dimension of labour market stratification. These findings have since been replicated and extended across many national and regional contexts, consistently confirming that the structural potential for remote work is unequally distributed along occupational, educational, and socioeconomic lines [12].

Alongside questions of access, the literature has increasingly examined the quality of the remote work experience—particularly the discomforts and strains it can generate. Work discomfort, in the context of remote work, is understood as a composite experience encompassing physical, psychological, and organisational dimensions of strain. Physically, improvised home workstation configurations, prolonged screen exposure, and increased sedentary behaviour have been linked to a measurable rise in musculoskeletal problems, fatigue, neck and back pain, and eye strain [13,14]. Psychologically, working from home is associated with increased stress, anxiety, and depressive symptoms, attributable in part to reduced social contact and the difficulty of disengaging from work after hours [15]. Organisationally, the erosion of clear boundaries between work and personal life, reduced access to face-to-face managerial support, and reliance on digital communication tools create additional pressures [16]. The multidimensional character of work discomfort in remote settings has prompted researchers to develop composite measurement approaches that integrate these dimensions into a single analytical construct, enabling systematic comparison across groups and contexts [17].

2.2. *Inequalities in Access to Remote Work*

The scholarly consensus is clear that access to remote work is not equally distributed. Research consistently demonstrates that remote work opportunities are stratified by occupation, education level, and socioeconomic status [12]. Workers in roles requiring physical presence—manufacturing, retail, personal care, and other contact-intensive services—have limited or no access to home-based work, while highly qualified professionals in knowledge-intensive sectors such as information technology, finance, and professional services typically do [11,18]. This occupational stratification translates directly into socioeconomic stratification: since higher-paid and higher-status workers are disproportionately employed in roles compatible with remote work, the expansion of home-based working has tended to deepen existing wage and status inequalities rather than mitigate them.

Recent European evidence further confirms that teleworkability depends not only on individual preferences, but also on the occupational and organisational structure of labour markets. Sostero et al. [19] show that teleworkable employment is concentrated mainly among higher-paid, white-collar and knowledge-intensive occupations, while employees in manual, service-based and place-dependent jobs remain much less able to use this form of work. Their findings also point to the role of work organisation, management culture and national regulation, which may explain why the actual use of remote work differs across countries even when technical feasibility exists. Siegert et al. [20] reach a similar conclusion from a European perspective, showing that telework is connected with spatial and gendered occupational segregation. These findings are important for the present study, because they suggest that access to remote work should be analysed as a structural labour market issue rather than as a matter of individual choice alone.

The distributional consequences of this stratification extend beyond wages. Barnes et al. [21], reviewing UK evidence, found that while approximately three-quarters of firms reported offering some form of flexible working in 2023, actual uptake varied sharply by sector and employment status. Employees in lower-status positions, who often face the greatest need for flexibility due to caregiving responsibilities and longer commutes, were least likely to have access to it. A particularly consequential form of inequality arises when an employee's job is structurally compatible with remote work, yet the employer does not make this option available in practice. This mismatch between feasibility and access has been identified as a source of frustration, reduced job satisfaction, disruption to work–life balance, and a heightened sense of organisational unfairness [22]. Identifying the organisational, sectoral, and individual factors that predict this mismatch, rather than simply describing its prevalence, is therefore an important research priority with direct implications for employment policy and organisational practice.

The role of the organisational environment in shaping both access and discomfort is substantial. Loignon et al. [23] demonstrate that the quality of remote work conditions and the availability of material and social resources are unevenly distributed across organisations, and that employees with access to better resources achieve greater control over their work and report lower levels of strain. Specifically, McAllister et al. [24] found that ergonomic training and workstation adjustability significantly reduce discomfort among remote workers, pointing to the importance of active organisational support rather than simply permitting home-based work. These findings are consistent with broader theoretical frameworks emphasising resource availability as a key mediator of the relationship between working conditions and employee well-being.

Gender is another axis of inequality in the remote work context. Evidence from pandemic-period national surveys indicates that women working from home experienced significantly greater increases in mental distress than men, reflecting the disproportionate burden of combined professional, domestic, and caregiving responsibilities [25]. MacLean et al. [26] similarly found higher levels of physical discomfort among women in home-based work settings. However, these gender differences are not universal—their magnitude appears to be context-dependent, varying with the availability of household support, the degree of work–life boundary control, and the broader institutional context of gender equality in the labour market.

2.3. The Spatial and Regional Dimension: Evidence from Europe and CEE

Beyond individual and organisational factors, the geography of remote work has emerged as a critical dimension of inequality. The potential for and actual uptake of home-based work vary substantially across regions, driven primarily by differences in occupational structure, digital infrastructure, and the sectoral composition of local economies. Luca et al. [27], mapping the diffusion of remote work across 30 European countries

during the pandemic, found that its uptake was substantially uneven across and within countries, with most remote jobs concentrated in capital cities and metropolitan regions. The authors demonstrate that this geographic concentration is primarily attributable to compositional effects, as cities host disproportionately many workers in occupations and sectors amenable to remote work, rather than to place-specific advantages independent of workforce composition. A similar conclusion emerges from the comprehensive analysis by the Eurofound and the European Commission Joint Research Centre [28] of EU regional employment data, which found that among the twenty EU regions with the largest shares of home-based workers in 2022, the majority encompassed national capitals or their immediate surroundings.

These spatial patterns have intensified existing core–periphery inequalities within national labour markets. Workers in rural, peripheral, and less economically developed regions are doubly disadvantaged: their local labour markets are disproportionately concentrated in sectors with low remote work potential, and their access to the digital infrastructure needed to support high-quality home-based work is more limited [9]. Eurofound and the European Commission Joint Research Centre [28] note that while urban regions with high concentrations of knowledge-intensive services proved most resilient to pandemic-era employment disruptions, mainly rural regions faced the greatest structural vulnerabilities.

Within the European context, a pronounced north–south and west–east gradient in remote work uptake has been consistently documented. Remote work rates have been substantially higher in Northern and Western European countries than in Southern and Eastern ones, reflecting systematic differences in occupational structure, digital readiness, and institutional frameworks for flexible work [2]. Post-communist CEE economies occupy a distinctive position in this landscape. Characterised by manufacturing-intensive industrial structures, historically compressed wage distributions, weaker digital infrastructure outside capital cities, and lower pre-pandemic baseline rates of remote work adoption, these economies face a particular concentration of the structural barriers to equitable remote work access. Jerbashian and Vilalta-Bufi [2] document that countries such as Slovakia, Romania, and Bulgaria recorded some of the lowest teleworking rates in Europe both before and during the pandemic, reflecting these structural constraints. Yet, despite their theoretical importance as test cases for resource-based and spatial theories of remote work inequality, CEE economies remain substantially underrepresented in the empirical literature, which continues to be dominated by evidence from Western European, North American, and East Asian contexts.

3. Methodology and Data

This study adopts a quantitative cross-sectional research design. Drawing on the foregoing review and the identified gaps, this study is guided by two research questions:

RQ1: What factors predict the likelihood of a mismatch between an employee’s potential to work from home and their actual access to it?

RQ2: What individual, organisational, and regional factors are associated with the level of work discomfort experienced by employees?

These research questions are addressed within an explicit theoretical framework drawing on three complementary perspectives. Resource-based theory holds that the quality and availability of material, social, and organisational resources determine employees’ capacity to perform effectively and comfortably across different work arrangements [23,24]. Spatial inequality theory posits that structural features of regional economies—including industrial composition, digital infrastructure, and the concentration of knowledge-intensive employment—systematically shape the distribution of labour market opportunities and

outcomes across geographic space [9,27]. Together, these frameworks generate specific directional predictions about the patterns expected in both analytical strands of this study.

With respect to RQ1, resource-based and spatial inequality frameworks jointly predict that the probability of a mismatch between remote work feasibility and actual access will be unequally distributed across employees, following the contours of organisational and regional resource endowments. Specifically, employees in resource-poor environments—peripheral regions with limited digital infrastructure, domestically owned firms with less developed organisational support systems, and sectors with lower knowledge intensity—are expected to face structurally higher odds of mismatch than those in resource-rich settings. This leads to the following hypothesis:

H1. *Employees working outside the capital city region, in domestically owned firms, and in non-knowledge-intensive sectors will face significantly higher odds of experiencing a mismatch between the feasibility and actual availability of remote work.*

With respect to RQ2, resource-based theory predicts that the level of work discomfort will be mediated by the availability of organisational support, as access to ergonomic, technical, and managerial resources reduces the physical, psychological, and organisational strain associated with home-based work. Furthermore, spatial inequality theory predicts that regional location will independently shape discomfort levels, as employees in peripheral regions are likely to work under conditions of lower organisational resource availability. These theoretical expectations imply two hypotheses concerning the determinants of work discomfort:

H2. *Employees receiving greater organisational support for remote work will report significantly lower levels of work discomfort than those receiving little or no support.*

H3. *A capital–periphery gradient in work discomfort will be observed, with employees working outside the capital city region reporting higher discomfort levels than those based in Bratislava, reflecting structural differences in organisational resources and working conditions across Slovak regions.*

Beyond these theoretically derived expectations, the study also examines whether structural inequality in access to remote work translates into measurable differences in experienced well-being—a question that the existing literature has rarely addressed within an integrated empirical framework. Prior research suggests that structural denial of feasible remote work generates frustration, reduced job satisfaction, and a heightened sense of organisational unfairness [22], which leads to a fourth hypothesis:

H4. *Employees experiencing a mismatch between the feasibility and actual availability of remote work will report higher levels of work discomfort than those whose access arrangements are consistent with their job’s remote potential.*

Testing this hypothesis is of particular analytical interest as it directly connects the two analytical strands of the study within a single integrated empirical framework. The empirical analysis is based on primary data collected through a structured questionnaire, presented in Appendix A, administered to employees in Slovakia in 2025. Two outcome variables are central to the analysis: a binary match/mismatch indicator that captures the discrepancy between the potential for and actual access to remote work, and a composite work discomfort index that measures the strain experienced by employees in their current working arrangements. These two outcome variables—the match/mismatch indicator and the composite work discomfort index—are formally defined and constructed in the following subsections.

3.1. Data Used in the Study

The data used in this study were collected in 2025 through a structured questionnaire, presented in Appendix A, distributed online via Google Forms. Participation was voluntary and anonymous, ensuring compliance with ethical principles of data collection and encouraging candid responses. The questionnaire was designed specifically for this study and structured in two parts. The first part collected sociodemographic and employment characteristics: gender, age, education level, and region of permanent residence, as well as sector type, field type, and employer type. The second part contained the substantive questions related to the key constructs under investigation, formatted primarily as Likert-scale statements on a five-point agreement scale. Rather than asking simply whether respondents work from home, the questionnaire was designed to capture the broader context of remote work, including the availability of the arrangement, the respondent's practical experience with it, the support received from the employer, and the perceived benefits and challenges associated with it. The full questionnaire is provided in Appendix A.

During the data preparation phase, logical consistency checks were applied to all responses. In particular, responses were examined for internal contradictions between Question 10: Do you think your job could be performed in a home office form?, which asked whether the respondent's current job could in principle be performed from home, and Question 13: Do you currently have the possibility to work from home?, which asked whether they currently have the option to work from home. Respondents who indicated that their job cannot be performed remotely but simultaneously reported having access to a home office arrangement were identified as logically inconsistent and excluded from further analysis. Following this procedure, 390 valid responses were retained. Additionally, to improve the robustness of the statistical models and avoid unreliable estimates in sparsely populated categories, selected categories of categorical variables were merged where cell frequencies were too small for stable analysis. For instance, the regional variable was consolidated from eight administrative regions into three broader geographic groupings: West, Central, and East, reflecting both geographic proximity and structural similarity. Table 1 presents the distribution of respondents across all categorical variables used in the study.

Table 1. Distribution of categorical variables used in the study.

Variable Name	Categories	Frequency	Percent
Gender	Male (reference)	144	36.9
	Female	246	63.1
Generation (Age)	Generation Z and Alpha (15–25)	87	22.3
	Generation Y and Millennials (26–40)	101	25.9
	Generation X (41–55) (reference)	179	45.9
	Baby Boomer generation (55+)	23	5.9
	Below full secondary	14	3.6
Education	Secondary with graduation	127	32.6
	Bachelor's degree	47	12
	Master's degree (reference)	186	47.7
	PhD or equivalent	16	4.1

Table 1. Cont.

Variable Name	Categories	Frequency	Percent
Region of work	Capital city (reference)	73	18.7
	Western Slovakia	61	15.6
	Central Slovakia	236	60.5
	Eastern Slovakia	20	5.1
Sector type	Private sector (reference)	271	69.5
	Public sector	119	30.5
Field type	Services field (reference)	330	84.6
	Production field	60	15.4
Employer type	Domestic employer (reference)	268	68.7
	Foreign employer	122	31.3
Industry	Banking and insurance	18	4.6
	Transport and communications	10	2.6
	Finance	17	4.4
	Marketing and advertising	9	2.3
	Commerce	32	8.2
	Law and legislation	5	1.3
	Services	61	15.6
	Education	43	11.0
	Public administration/local government	37	9.5
	Healthcare	23	5.9
	Production sectors (Agriculture, Industry, Construction)	66	16.9
	IT and R&D	69	17.7
	Contract work	50	12.8
Social status	Part-time employee	24	6.2
	Full-time employee (reference)	261	66.9
	Self-employed	55	14.1
Support	No support or irrelevant (reference)	211	54.1
	One type of support	68	17.4
	Two types of support	64	16.4
	Three or more types of support	47	12.1

Source: own elaboration.

The sample was predominantly female, with women accounting for nearly two thirds of respondents. In terms of generational composition, Generation X (aged 41–55) was the largest cohort at close to half the sample, while Baby Boomers (aged 55 and above) were the least represented at approximately 6%. The remaining respondents were distributed fairly evenly between Generation Y and Millennials and Generation Z and Alpha, together representing a substantial portion of the productive workforce at different career stages. Educational attainment was high relative to the general working population, with nearly half of respondents holding a Master's degree and a further substantial share holding a Bachelor's degree, suggesting a degree of overrepresentation of highly educated workers in the sample.

Geographically, the Central Slovakia region dominated the sample at close to three-fifths of all respondents, which to a significant extent reflects the geographic networks of the research team rather than the actual regional distribution of Slovak employees. The Bratislava capital region accounted for approximately one-fifth of respondents, while Eastern Slovakia was notably underrepresented at just over 5%.

Regarding employment characteristics, approximately seven in ten respondents worked in the private sector and close to nine in ten in the services field, with employers at domestically owned firms accounting for roughly two-thirds of the sample. Full-time employees were the dominant social status category at approximately two-thirds of respondents, while part-time employees represented the smallest share at just over 6%.

Regarding organisational support for remote work, slightly over half of respondents reported receiving no support or considered it irrelevant to their situation. In this context, organisational support refers to some of the following forms of assistance: necessary technological equipment (laptop, phone, software, etc.); technical support for resolving hardware or connectivity issues; ergonomic equipment for the workspace (chair, desk, etc.); financial support to cover home office-related expenses (internet, energy, etc.); and psychological support to help manage working from home (counselling, psychologist, etc.). The respondents selected all options that applied to them. Among those who received support, roughly equal proportions reported experiencing one or two types, while a smaller proportion reported three or more types.

In terms of industry, the largest shares of respondents worked in IT and R&D, production sectors, and services, which together accounted for approximately half the sample. Education and public administration or local government together represented a further notable portion. The remaining industries—banking and insurance, healthcare, finance, commerce, transport and communications, marketing and advertising, and law and legislation—each accounted for smaller shares.

All categorical variables presented in Table 1 serve as predictor variables in the analyses described in Section 3.3 and the results section.

3.2. Outcome Variable Construction and Optimal Data Preparation

Two outcome variables are central to this study. This subsection describes their construction and validation.

The first outcome variable is a binary indicator of match/mismatch. It was constructed by comparing each respondent's answers to two questions: Question 10: Do you think your job could be performed in a home office form?, which asked whether their current job could, in principle, be performed from home, and Question 13: Do you currently have the possibility to work from home?, which asked whether they currently have the option to work from home in practice. Where both responses were consistent—either the job is not suitable for remote work, and no such option is offered, or the job is suitable, and the option is indeed available—the case was classified as Match (coded 0). Where a discrepancy was identified between the two responses—the job is suitable for remote work, but the option is unavailable, the case was classified as Mismatch (coded 1). This operationalisation is theoretically grounded in the distinction between structural feasibility and realised access: a mismatch does not merely indicate the absence of remote work, but specifically its absence in cases where it would be objectively possible. It therefore captures a form of organisational or structural inequality rather than a neutral difference in job type. Of the 390 valid respondents, 348 (89.2%) were classified as Match and 42 (10.8%) as Mismatch.

The second outcome variable is a composite work discomfort index. It was constructed as the arithmetic mean of 8 Likert-scale items, each measured on a five-point agreement

scale. The items in the index assessed the following dimensions of work-related discomfort: attendance, flexible working hours, comfort, technical skills/problems, feelings of isolation, self-discipline, and work–life balance. All dimensions of the discomfort index are listed in Table 2, along with their descriptive statistics and those of the index itself.

Table 2. Descriptive characteristics of the composite work discomfort index and its components.

	Likert-Scale Items	Min	Max	Mean	Median	Std. Dev
Q15	Working from home is advantageous mainly because the employee does not need to commute.	1	5	4.40	5.00	0.95
Q16	For employees, working from home is advantageous due to flexible working hours.	1	5	4.45	5.00	0.99
Q17	Working from home is more comfortable for the employee.	1	5	4.27	5.00	1.00
Q18	When working from home, employees improve their technical skills.	1	5	3.10	3.00	1.28
Q19	Working from home negatively affects the balance between work and personal life.	1	5	3.45	4.00	1.29
Q20	Working from home requires higher self-discipline from employees.	1	5	4.34	5.00	0.96
Q21	When working from home, employees may feel isolated.	1	5	3.87	4.00	1.15
Q22	When working from home, technical problems often arise, negatively affecting work performance.	1	5	3.06	3.00	1.24
	Discomfort index	1.13	5.00	2.81	2.75	0.61

Source: own elaboration.

The discomfort index includes items assessing both perceived advantages and disadvantages of remote work. Items framed as advantages, such as those assessing the elimination of commuting, flexible working hours, and physical comfort, were reverse-coded prior to aggregation, on the theoretical grounds that low agreement with these advantage statements reflects a form of experienced discomfort or dissatisfaction with the working arrangement. This operationalisation ensures that higher index values consistently indicate a greater overall level of work-related discomfort across physical, psychological, and organisational dimensions. The resulting index therefore captures the overall balance of strain and discomfort in the remote working experience rather than a single unidimensional construct. The internal consistency of the index was assessed using Cronbach’s alpha, which yielded a value of 0.679. While this falls marginally below the conventional threshold of 0.70 [29], it is consistent with the exploratory nature of the research, for which this threshold was originally intended [30], and is within the range considered acceptable for social science research at this stage [31]. The discomfort index should therefore be interpreted as a broad composite indicator of work-related discomfort rather than a fully established psychometric scale.

Given the large number of industry categories and the small cell frequencies associated with several of them, an optimal binning procedure was applied prior to modelling to consolidate the industry variable into a reduced number of analytically meaningful groups. Optimal merging is a data-driven category reduction technique that merges categories based on the similarity of their relationship to the outcome variable, thereby maximising the discriminatory power of the resulting grouped variable while minimising information loss [32]. The procedure yielded three industry groups for the first outcome variable,

match/mismatch, and two industry groups for the second outcome variable, discomfort index. The distribution of optimally merged industries is in Table 3.

Table 3. Optimal merging of industry categories with respect to both outcome variables.

Optimal Merging Match/Mismatch	Industry	Frequency	Relative Frequency	Optimal Merging Discomfort Index	Industry	Frequency	Relative Frequency
industry group 1	Finance	54	13.8	industry group 1	Transport and communications	219	56.2
	Public administration and local government				Marketing and advertising		
industry group 2	Agriculture and forestry	32	8.2		Trade and Commerce		
	Law and legislation				Industry and Manufacturing		
	Construction and real estate				Construction and real estate		
industry group 3 (reference)	Banking and insurance	304	77.9		Education		
	Transport and communications				Public administration and local government		
	Information technology				Science, technology, research and development		
	Marketing and advertising				Healthcare		
	Trade and Commerce			Banking and insurance			
	Industry and Manufacturing			Finance			
	Services			Information technology			
	Education			Agriculture and forestry			
	Science, technology, research and development			Law and legislation			
	Healthcare			Services			

These consolidated variables were used in the subsequent analysis: the former in the logistic regression model and the latter in the linear regression model, in place of the original twelve-category industry variable.

3.3. Statistical Methods Used in the Study

All analyses were performed using IBM SPSS Statistics 27 and IBM SPSS Modeller 30, with a significance level of $\alpha = 0.05$ applied throughout. The analytical strategy was organised around the two research questions. Methods addressing the prediction of match or mismatch in access to remote work (RQ1) are described first, followed by methods examining the determinants of work discomfort (RQ2).

3.3.1. Analytical Strand 1: Predicting Match/Mismatch in Access to Remote Work

As a preliminary step, a Chi-square test of independence was applied to examine bivariate associations between the match/mismatch outcome and each categorical predictor individually, including all sociodemographic characteristics and employment details listed in Table 1. This provided an initial screening of which variables were meaningfully

associated with the outcome before entering them into a multivariate model, and allowed the results of the bivariate and multivariate stages to be directly compared.

The Chi-square test of independence is a nonparametric test used to assess whether a statistically significant association exists between two categorical variables [33]. It evaluates the null hypothesis of independence between the two variables being analysed against the alternative hypothesis of a systematic association between them. The test compares observed frequencies with those expected under the null hypothesis of independence [34]. For a contingency table with r rows and c columns, the expected frequency for cell (i, j) is calculated as:

$$E_{ij} = \frac{n_{i.} \cdot n_{.j}}{n} \quad (1)$$

where $n_{i.}$ denotes the total of row i , $n_{.j}$ denotes the total of column j , and n is the overall sample size. The test statistic is then calculated as the standardised sum of squared deviations between observed (O_{ij}) and expected (E_{ij}) frequencies across all cells of the contingency table [34]:

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad (2)$$

The resulting χ^2 statistic follows a Chi-square distribution with $(r-1)(c-1)$ degrees of freedom under the null hypothesis. A sufficiently large value of the test statistic, corresponding to a p -value below the chosen significance level, leads to rejection of the null hypothesis of independence [32]. A standard requirement for the validity of the test is that no more than 20% of cells should have expected frequencies below 5, and no cell should have an expected frequency below 1 [33]. Where this assumption was not met due to sparse cell counts, categories were merged prior to analysis, as described in Section 3.1.

Where the Chi-square test confirmed a statistically significant association, the strength of that association was quantified using appropriate association measures selected according to the measurement level of the variables involved [32].

For associations involving the binary match/mismatch outcome and a nominal categorical predictor with more than two categories, Cramér's V was used. Cramér's V is a symmetric measure of association derived directly from the Chi-square statistic (2), calculated as:

$$V = \sqrt{\frac{\chi^2}{n \cdot \min(r-1, c-1)}} \quad (3)$$

where χ^2 is the Pearson Chi-square statistic, n is the total sample size, and $\min(r-1, c-1)$ denotes the smaller of the number of rows minus one and the number of columns minus one [35]. Cramér's V ranges from 0, indicating no association, to 1, indicating a perfect association, and is applicable regardless of the dimensions of the contingency table, making it the most versatile general-purpose measure of nominal association [33].

For associations involving two binary variables, specifically, the match/mismatch outcome and binary predictors such as gender, sector type, field type, or employer type, the Phi coefficient ϕ was used. Phi is a special case of Cramér's V restricted to 2×2 contingency tables and is equivalent to the Pearson product-moment correlation coefficient computed on two dichotomous variables [32]. It is calculated as:

$$\phi = \sqrt{\frac{\chi^2}{n}} \quad (4)$$

Phi ranges from -1 to $+1$, where 0 indicates independence and values approaching ± 1 indicate increasingly strong associations, with the sign indicating the direction of the relationship.

For associations involving two ordinal variables or a binary outcome paired with an ordinal predictor, Kendall's tau-b was used. It is a rank-based, symmetric measure of association that quantifies the degree of concordance between two ordinal variables by comparing all possible pairs of observations. A pair is concordant if the relative ordering of both observations is the same on both variables, and discordant if the orderings differ. The coefficient is calculated as:

$$\tau_b = \frac{P - Q}{\sqrt{(P + Q + T_x)(P + Q + T_y)}} \quad (5)$$

where P denotes the number of concordant pairs, Q the number of discordant pairs, and T_x and T_y are the numbers of ties on each variable respectively [36]. Tau-b ranges from -1 to $+1$ and is appropriate for square or near-square contingency tables where ties are present on both variables.

Finally, Somers' d was used as a complementary directional measure of association for ordinal predictors, where a theoretical distinction between an independent and a dependent variable is meaningful. Unlike tau-b, which is symmetric, Somers' d is asymmetric and expresses the excess of concordant over discordant pairs relative to all pairs that are not tied on the dependent variable [37]:

$$d_{Y|X} = \frac{P - Q}{P + Q + T_y} \quad (6)$$

where T_y denotes ties on the dependent variable Y only. Somers' d ranges from -1 to $+1$, with 0 indicating no association and values of ± 1 indicating a perfect monotonic relationship. Its directional character makes it particularly informative in analyses where one variable can be conceptually treated as the outcome, as is the case with the match/mismatch indicator in this study.

While the bivariate analyses described above identify which individual predictors are significantly associated with the match/mismatch outcome and quantify the strength of those associations, they do not account for the simultaneous influence of multiple predictors or control for potential confounding between them. To address this limitation and move from bivariate screening to multivariate prediction, binary logistic regression was employed as the primary modelling method.

Logistic regression is a statistical modelling technique designed to estimate the probability of a binary outcome as a function of one or more predictor variables. Unlike linear regression, which models the outcome directly and can produce predicted values outside the valid probability range of 0 to 1 , logistic regression applies a logistic transformation to ensure that all predicted values remain within this range [38]. The model expresses the probability of the outcome occurring, in this study, the probability of mismatch, as a logistic function of a linear combination of predictors:

$$P(Y = 1 | X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k)}} \quad (7)$$

where $P(Y = 1|X)$ is the probability of mismatch given the values of the predictors, β_0 is the intercept, and $\beta_1, \dots, \beta_k$ are the regression coefficients associated with predictors $X_1, \dots, X_k$. The model can be equivalently expressed in terms of the log-odds, also known as the logit, which is a linear function of the predictors:

$$\ln\left(\frac{P}{1 - P}\right) = \beta_0 + \beta_1 X_1 + \dots + \beta_k X_k \quad (8)$$

where $\frac{P}{1-P}$ is the odds of the outcome occurring. The logit transformation linearises the relationship between the predictors and the outcome, making the model directly interpretable in terms of changes in log-odds. The regression coefficients β_k are estimated using maximum likelihood estimation, which identifies the parameter values that maximise the probability of observing the data given the model [32]. The estimated coefficients are denoted by $b_0, b_1, \dots, b_k$. Then, the exponentiated coefficients, $\exp b_k$, yield odds ratios, which express the multiplicative change in the odds of mismatch associated with a one-unit increase in the corresponding predictor, holding all other predictors constant. Values of $\exp b_k > 1$ indicate increased odds of mismatch, while values below 1 indicate reduced odds.

Given that the match/mismatch variable is binary, binary logistic regression described above was selected as the primary analytical method for RQ1.

All categorical predictors were dummy-coded prior to entry into the model, with reference categories chosen to reflect the theoretically most informative comparison. Specifically, the male, generation X, master's degree, capital city, private sector, services field, industry group 3, domestic employer, full-time employment status and no support or irrelevant were used as reference categories, as already noted in Tables 1 and 3. All candidate predictors were considered for inclusion in the model. Variable selection was carried out using the backward conditional stepwise method, which begins with the full set of theoretically motivated predictors entered simultaneously and iteratively removes those that do not contribute significantly to the model at each step, retaining only predictors with independent explanatory and predictive value in the final solution [38]. This approach was chosen to identify a parsimonious set of significant determinants of mismatch while ensuring that all candidate predictors were given the opportunity to demonstrate their contribution before any removal decisions were made.

Before estimation, the class distribution of the outcome variable was reviewed. The mismatch category was defined as a hit category in the prediction model. This was because it is of great interest to identify the main causes of the discrepancy between the suitability of working from home and its actual unavailability for the worker. However, this mismatch category comprised only 10.8% of observations, while the match category made up 89.2%. This created a significant class imbalance that, if not addressed, could lead the model to predict the majority class almost exclusively, hindering the identification of meaningful predictors of mismatch. To address this imbalance and improve the model's predictive performance, an oversampling procedure was applied to the train sample to balance the effective class distribution, following standard practice for analysing imbalanced binary outcomes [39]. Table 4 presents the distribution of outcome categories before and after the oversampling, together with the weights used for balancing.

Table 4. Distribution of match and mismatch categories before and after weighting.

		Original Frequency		Balance Weight	Balanced Frequency	
		Absolute	Relative		Absolute	Relative
Train	Match	243	88.0	1	243	50.0
	Mismatch	33	12.0	7.36	243	50.0
	Total	276	100	-	486	100
Test	Match	105	92.1	1	105	92.1
	Mismatch	9	7.9	1	9	7.9
	Total	114	100	-	114	100

Source: own elaboration.

The impact of this procedure on model performance is documented in the Results section. The regression model was assessed using two complementary indicators. The Omnibus test of model coefficients evaluates whether the model as a whole fits the data significantly better than a null model containing only the intercept, effectively testing whether the included predictors jointly contribute to explaining the outcome [38]. Nagelkerke's R^2 was used as a measure of overall explanatory power, providing a rescaled pseudo- R^2 that approximates the proportion of variance in the outcome explained by the model, with values ranging from 0 to 1, where higher values indicate a stronger fit [40].

Classification accuracy was evaluated using a confusion matrix, which provides a structured summary of the model's predictive performance by cross-tabulating observed and predicted class memberships across all possible outcomes [38]. For a binary classifier, the confusion matrix distinguishes four types of outcomes [41,42]:

- True positives (TP)—mismatch cases correctly predicted as mismatches;
- True negatives (TN)—match cases correctly predicted as matches;
- False positives (FP)—match cases incorrectly predicted as mismatches;
- False negatives (FN)—mismatch cases incorrectly predicted as matches.

From this matrix, four complementary performance metrics were derived [33,38]. *Sensitivity*, also referred to as the TP rate or recall, measures the proportion of correctly identified mismatch cases among all mismatch cases (i.e., $TP/(TP + FN)$). Given the applied importance of detecting employees who are denied feasible remote work, sensitivity is considered the primary metric of interest. *Specificity*, or the TN rate, measures the proportion of actual match cases correctly classified as such (i.e., $TN/(TN + FP)$). Precision, also known as the positive predictive value, reflects the proportion of cases predicted as mismatches that are indeed true mismatches (i.e., $TP/(TP + FP)$), thereby indicating how reliable the model's positive predictions are in practice. Finally, overall accuracy is the proportion of all cases, both matches and mismatches, correctly classified by the model (i.e., $(TP + TN)/(TP + TN + FP + FN)$) [43].

To provide a comprehensive evaluation of the logistic regression model's discriminatory ability that is independent of any specific classification threshold, the Receiver Operating Characteristic (ROC) curve was constructed, and the Area Under the Curve (AUC) was calculated. The ROC curve plots the model's sensitivity against the complement of its specificity across all possible classification thresholds, thereby visualising the trade-off between correctly identifying mismatch cases and incorrectly classifying match cases as the decision threshold varies [38]. The AUC summarises this curve into a single scalar value representing the probability that the model assigns a higher predicted probability of mismatch to a randomly selected mismatch case than to a randomly selected match case [32]. AUC values range from 0.5, indicating a model with no discriminatory ability beyond random chance, to 1.0, indicating perfect discrimination. Following widely applied conventions, AUC values between 0.7 and 0.8 are considered acceptable discrimination, values between 0.8 and 0.9 indicate excellent discrimination, and values above 0.9 are considered outstanding [38]. The ROC curve and AUC, therefore, complement the confusion matrix metrics by evaluating the model's overall discriminatory capacity across all possible decision boundaries rather than at a single fixed threshold, making them particularly informative for imbalanced binary outcomes such as the match/mismatch variable used in this study.

3.3.2. Analytical Strand 2: Examining the Determinants of Work Discomfort

The analysis of work discomfort proceeded in three sequential steps, moving from descriptive characterisation through group comparisons to multivariate prediction.

First, descriptive statistics for the discomfort index were computed for the full sample and for each sociodemographic and employment subgroup, providing an overview of central tendency and variability across groups. Second, group difference tests were conducted to identify which characteristics were associated with statistically significant differences in mean discomfort levels. For dichotomous grouping variables, independent samples *t*-tests were employed to assess whether the observed differences in mean discomfort levels between two groups were statistically significant or attributable to random sampling variation. The test evaluates the null hypothesis that the population means of the two groups are equal against the alternative hypothesis that there is a statistically significant difference between them [33]. Prior to interpretation, the normality of the discomfort index distribution within each group was assessed, and Levene's test for equality of variances was applied to determine whether the assumption of homogeneity of variances was met. The appropriate *t*-test variant, assuming equal or unequal variances, was selected accordingly. Where statistically significant differences were found, Cohen's *d* was calculated as a standardised measure of effect size, enabling assessment of both practical and statistical significance. It is computed as the difference between the two group means divided by the pooled standard deviation [44]. Values of *d* $\approx$ 0.2, 0.5, and 0.8 were interpreted as small, medium, and large effects, respectively.

For grouping variables with three or more categories, one-way analysis of variance (ANOVA) was used in place of *t*-tests. ANOVA is designed to test whether statistically significant differences in means exist across three or more independent groups simultaneously, while controlling the risk of inflated Type I error that would result from conducting multiple pairwise *t*-tests [33]. The test evaluates the null hypothesis that the population means of all groups are equal, against the alternative that at least one group mean differs significantly from the others. In practice, ANOVA partitions the total variance in the dependent variable into two components: between-groups variance attributable to differences among group means, and within-groups variance attributable to random variation within groups. The ratio of these two components yields the *F*-statistic, and the associated *p*-value indicates whether the null hypothesis should be rejected or retained [44].

Prior to each ANOVA, the key parametric assumptions were verified: the independence of observations was ensured by the study design, the normality of the discomfort index distribution within each group was assessed, and the homogeneity of variances across groups was examined using Levene's test. As these assumptions were satisfied for both the *t*-tests and the ANOVA models, parametric procedures were retained throughout.

For ANOVA models yielding statistically significant omnibus results, post hoc pairwise comparisons were conducted to identify which specific group pairs differed significantly. A statistically significant ANOVA result reveals that at least one group mean differs from the others but does not indicate which specific pairs of groups are responsible for that difference. Post hoc tests address this by performing all possible pairwise comparisons while controlling the familywise error rate [33]. Two post hoc procedures were employed depending on the characteristics of the grouping variable. Tukey's test was applied when group sizes were approximately equal. It controls the familywise error rate exactly under equal sample sizes and is one of the most widely recommended post hoc procedures for balanced designs [45]. Scheffé's test was used for variables with unequal group sizes, given its greater conservatism and robustness under such conditions. Although Scheffé's test is more stringent and therefore less powerful than Tukey's, it is the more appropriate choice when group sizes differ substantially [33]. Effect sizes for statistically significant ANOVA results were quantified using eta squared (η^2), which expresses the proportion of total variance in the discomfort index attributable to group membership. It is computed as the ratio of the between-groups sum of squares to the total sum of squares, yielding a value

between 0 and 1 [44]. Eta squared values were interpreted according to the conventional benchmarks of $\eta^2 \approx 0.01$ (small), 0.06 (medium), and 0.14 (large) [46].

Third, a multiple linear regression model was constructed to identify the independent predictors of the discomfort index while controlling for the simultaneous influence of all other variables in the model. Linear regression was chosen because the discomfort index, as a continuous quantitative variable computed as the mean of multiple Likert-scale items, satisfies the requirements for a continuous dependent variable [33]. Predictors included all sociodemographic and employment characteristics listed in Tables 1 and 3, as well as the match/mismatch indicator described in Section 2.2. The prediction model was developed using backward elimination.

Prior to interpreting the results, the regression assumptions were systematically checked. Multicollinearity was assessed using bivariate correlation coefficients and variance inflation factors (VIF), with values exceeding 10 considered problematic [31,33]. The normality of residuals and homoscedasticity were examined through residual plots [33]. No violations of these assumptions were detected in the final model.

The explanatory power of the linear regression model was evaluated using the coefficient of determination R^2 , which expresses the proportion of total variance in the discomfort index explained by the set of predictors included in the model, with values closer to 1 indicating a stronger fit [33]. Adjusted R^2 was also reported alongside R^2 , as it penalises the inclusion of additional predictors and therefore provides a more conservative and reliable estimate of explanatory power when multiple predictors are present in the model [31].

The statistical significance of the model as a whole was assessed using the F-test, which evaluates the null hypothesis that all regression coefficients in the model are simultaneously equal to zero—that is, that none of the predictors contributes to explaining variance in the outcome. A significant F-statistic confirms that the model performs better than a null model containing only the intercept. For individual predictors, both unstandardised (B) and standardised (β) regression coefficients are reported. While unstandardised coefficients indicate the expected change in the discomfort index for a one-unit change in the predictor, standardised coefficients allow the relative importance of predictors measured on different scales to be directly compared within the model [33].

Beyond the standard regression diagnostics described above, the predictive performance of the linear regression model was further evaluated using two additional measures. First, the Pearson correlation coefficient between the observed and model-predicted discomfort index values was calculated. This measure directly quantifies the strength of the linear relationship between what the model predicts and what was actually observed, with values closer to 1 indicating that the model's predictions closely track the actual values across respondents [33]. Unlike R^2 , which is a global summary of explained variance, the correlation between observed and predicted values provides a more intuitive assessment of predictive accuracy at the individual level and is particularly useful for evaluating how well the model performs as a predictive instrument rather than merely as an explanatory one.

Second, the Mean Absolute Percentage Error (MAPE) was calculated as a scale-independent measure of average prediction error. MAPE expresses the average magnitude of prediction errors as a percentage of the observed values, making it directly interpretable regardless of the dependent variable's unit of measurement [47]. It is defined as:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \cdot 100 \quad (9)$$

where y_i denotes the observed value of the discomfort index for respondent i , $\hat{y}_i$ the corresponding model-predicted value, and n the total number of observations. Lower MAPE

values indicate higher predictive accuracy, with values below 10% generally considered highly accurate, values between 10% and 20% indicating good prediction, and values between 20% and 50% indicating reasonable prediction [48]. Together, the correlation coefficient and MAPE complement the standard regression fit statistics by providing a more complete picture of the model's practical predictive utility.

4. Results

This section presents the empirical findings organised around the two analytical strands described in Section 3.3. The first strand addresses RQ1 and examines the predictors of match/mismatch in access to remote work, progressing from bivariate Chi-square screening through binary logistic regression modelling and model evaluation. The second strand addresses RQ2 and investigates the determinants of work discomfort, moving from descriptive statistics and group difference tests to multivariate linear regression. All results are reported at a significance level of $\alpha = 0.05$.

4.1. Results of Analytical Strand 1: Predicting Match/Mismatch in Access to Remote Work

This subsection reports the results of the analyses conducted to address RQ1, which examines the factors predicting the likelihood of a mismatch between an employee's potential to work from home and their actual access to it.

The analysis proceeded in three sequential steps. First, Chi-square tests of independence were conducted for each predictor individually, supplemented by appropriate measures of association, to identify which variables showed a statistically significant bivariate relationship with the match/mismatch outcome. Second, a binary logistic regression model was estimated to examine the simultaneous influence of all predictors while controlling for their intercorrelations, and to identify which factors independently predict the probability of mismatch. Third, the predictive performance of the logistic regression model was evaluated using the confusion matrix, classification metrics, and the ROC curve with the corresponding AUC value. The results of each step are presented in turn.

As a preliminary step, Chi-square tests of independence were conducted to examine bivariate associations between the match/mismatch outcome and each categorical predictor individually. The results, together with the corresponding measures of association, are presented in Table 5.

Table 5. Bivariate associations between categorical predictors and the match/mismatch.

Predictor Variable	Chi-Square Statistic	df	p-Value	Association Measure	Value	p-Value
Gender	3.475	1	0.062	Phi	0.094	0.062
Generation	0.969	3	0.809	Kendall's tau-b	0.043	0.348
Education	2.185	4	0.702	Kendall's tau-b	0.022	0.636
Region of work	12.148	3	0.007	Cramér's V	0.176	0.007
Sector type	13.054	1	<0.001	Phi	0.183	<0.001
Field type	0.438	1	0.508	Phi	−0.034	0.508
Employer type	10.366	1	0.001	Phi	−0.163	0.001
Social status	11.034	3	0.012	Cramér's V	0.168	0.012
Support	17.664	3	<0.001	Kendall's tau-b	−0.190	<0.001
Industry group	19.603	2	<0.001	Cramér's V	0.224	<0.001

Source: own elaboration.

Of the ten predictor variables examined, six showed statistically significant associations with the match/mismatch outcome. The strongest association was found for industry group (Chi-square = 19.603, $p < 0.001$), with a Cramér's V of 0.224 indicating a weak-to-moderate association. This was followed by the level of organisational support for remote work (Chi-square = 17.664, $p < 0.001$), where Kendall's tau-b of -0.190 indicates a weak but statistically significant negative association, suggesting that higher levels of employer support are associated with a lower likelihood of mismatch. Sector type also showed a significant association (Chi-square = 13.054, $p < 0.001$), with a Phi coefficient of 0.183 indicating that public sector employees were more likely to experience a mismatch than their private sector counterparts. Region of work was similarly significant (Chi-square = 12.148, $p = 0.007$), with Cramér's V of 0.176 pointing to meaningful geographic variation in the likelihood of mismatch across regions. Employer type showed a significant negative association (Chi-square = 10.366, $p = 0.001$), with a Phi coefficient of -0.163 , indicating that employees of foreign-owned firms were less likely to experience a mismatch than those employed by domestically owned organisations. Finally, social status was significantly associated with the outcome (Chi-square = 11.034, $p = 0.012$), with Cramér's V of 0.168 reflecting differences in the likelihood of mismatch across employment contract types.

Four predictor variables showed no statistically significant association with the match/mismatch outcome. Field type ($p = 0.508$), education ($p = 0.702$), and generation ($p = 0.809$) were all clearly non-significant, with insignificant association coefficients close to zero confirming the absence of any meaningful relationship. Gender approached but did not reach the conventional significance threshold ($p = 0.062$), with a Phi coefficient of 0.094, suggesting at most a negligible association.

It is worth noting that, while all statistically significant association coefficients fall within the weak-to-moderate range—none exceed 0.224—this pattern is consistent with the broader empirical literature on labour market inequalities, where individual bivariate predictors rarely account for large proportions of variance in access-related outcomes in isolation. The multivariate logistic regression model presented in the following section examines whether these associations persist after controlling for all predictors simultaneously.

4.1.1. Binary Logistic Regression Model

The logistic regression model was estimated on the oversampled balanced dataset, in which both outcome classes were represented by 243 cases each, ensuring sufficient statistical power for stable parameter estimation across all retained predictors. The backward conditional stepwise procedure retained 10 predictors in the final model, removing all other candidate variables as non-significant contributors to the prediction of mismatch. The Omnibus test of model coefficients confirmed that the model as a whole fit the data significantly better than a null model containing only the intercept ($p < 0.001$), indicating that the retained predictors jointly contribute to explaining the match/mismatch outcome. Nagelkerke R^2 reached a value of 0.43, indicating that the model explains approximately 43% of the variance in the outcome. The resulting model is presented in Table 6.

Several predictor variables showed statistically significant independent associations with the probability of mismatch. With respect to regional location, all three regions outside the capital showed substantially elevated odds of mismatch compared to the Bratislava reference category. The strongest regional effect was observed for Eastern Slovakia (Exp(B) = 25.989, $p < 0.001$), indicating that employees working in Eastern Slovakia had approximately 26 times higher odds of experiencing a mismatch than those based in Bratislava. Central Slovakia (Exp(B) = 13.802, $p < 0.001$) and Western Slovakia (Exp(B) = 10.077, $p < 0.001$) also showed substantially elevated odds of mismatch, confirming a pronounced capital-periphery gradient in access to remote work.

Table 6. Variables in the equation—logistic regression.

	B	S.E.	Wald	df	Sig.	Exp(B)
Step 8a	gender = female	0.694	4.964	1	0.026	2.002
	soc_status = contract work	−0.991	8.417	1	0.004	0.371
	soc_status = self-employed	−1.844	14.825	1	<0.001	0.158
	employer = foreign	−1.838	28.212	1	<0.001	0.159
	education = PhD or equivalent	2.055	12.305	1	<0.001	7.808
	industry = industry group 1	1.606	30.611	1	<0.001	4.981
	industry = industry group 2	1.709	13.838	1	<0.001	5.522
	region = western Slovakia	2.310	17.412	1	<0.001	10.077
	region = central Slovakia	2.625	31.027	1	<0.001	13.802
	region = eastern Slovakia	3.258	26.138	1	<0.001	25.989
	Constant	−2.898	28.762	1	<0.001	0.055

Source: own elaboration.

A similar pattern was observed in industry. The employees in industry group 2, comprising law and legislation and selected production-oriented sectors, had approximately 5.5 times higher odds of mismatch compared to the reference industry group ($\text{Exp(B)} = 5.522$, $p < 0.001$), while employees in industry group 1, comprising finance and public administration or local government, had approximately 5 times higher odds ($\text{Exp(B)} = 4.981$, $p < 0.001$).

Regarding educational attainment, employees holding a PhD or equivalent qualification showed markedly elevated odds of mismatch compared to the reference category ($\text{Exp(B)} = 7.808$, $p < 0.001$), a finding that warrants careful interpretation, given that higher education is typically associated with greater access to remote work in the broader literature.

Gender was a significant predictor, with female employees showing approximately twice the odds of a mismatch compared to male employees ($\text{Exp(B)} = 2.002$, $p = 0.026$), suggesting that women face a greater discrepancy between the feasibility and actual availability of remote work.

With respect to employment type, both contract workers ($\text{Exp(B)} = 0.371$, $p = 0.004$) and self-employed individuals ($\text{Exp(B)} = 0.158$, $p < 0.001$) showed significantly reduced odds of mismatch compared to full-time employees, indicating that non-standard employment arrangements are associated with a lower likelihood of mismatch. Similarly, employees of foreign-owned firms had substantially lower odds of mismatch than those in domestically owned organisations ($\text{Exp(B)} = 0.159$, $p < 0.001$), suggesting that foreign ownership is associated with a significantly lower probability of mismatch, though the organisational mechanisms driving this pattern—whether corporate policy, management culture, or resource availability—cannot be directly established from the present data.

Substantively, these findings indicate that the mismatch in access to remote work is not randomly distributed across employees. It is shaped by gender, employment status and employer ownership, which suggests that unequal access to remote work reflects broader organisational and structural differences in the Slovak labour market.

4.1.2. Logistic Regression Model Evaluation

The predictive performance of the model was evaluated separately on the training and test datasets using the confusion matrix presented in Table 7.

Table 7. Confusion matrix—logistic regression.

Actual	Predicted		Overall Percentage
	Match	Mismatch	
Match	57	48	54.3
Mismatch	1	8	88.9
Overall Percentage			57.00

Source: own elaboration.

On the testing data, the model achieved an overall accuracy of 57.0%, with a sensitivity of nearly 89% and a specificity of slightly over 54%. The substantially higher sensitivity than specificity on the test dataset confirms that the model is particularly effective at identifying true mismatch cases, which is the primary objective of the analysis, given the applied importance of detecting employees who are denied feasible remote work, albeit at the cost of a higher rate of false positives among match cases.

The ROC curve analysis showed an area under the curve (AUC) of 0.702, indicating acceptable discrimination of the logistic regression model according to the conventional benchmarks established by Hosmer and Lemeshow [38]. This result suggests that the model was able to distinguish between match and mismatch cases at an acceptable level, although its discriminatory performance remained moderate rather than high.

The model should therefore be interpreted mainly as a tool for identifying groups with an elevated risk of mismatch, not as a precise instrument for individual-level prediction. This distinction is important because the mismatch group represents a relatively rare outcome, even though it is theoretically and practically meaningful.

4.2. Results of Analytical Strand 2: Examining the Determinants of Work Discomfort

This subsection reports the results of the analyses conducted to address RQ2, which examines the individual, organisational, and regional factors associated with the level of work discomfort experienced by employees. The analysis proceeded in three sequential steps: descriptive characterisation of the discomfort index across subgroups, group difference tests, and multivariate linear regression. The results of each step are presented in turn.

4.2.1. Descriptive Characterisation of the Discomfort Index

The descriptives of discomfort index across the categories of analysed variables are presented in Table 8.

Table 8. Descriptive statistics of discomfort index.

Variable		N	Min	Max	Mean	Median	Std. Dev.
Match or mismatch	Match	348	1.13	5.00	2.80	2.75	0.62
	Mismatch	42	1.63	4.75	2.86	2.88	0.55
Gender	Male	144	1.13	5.00	2.87	2.88	0.64
	Female	246	1.25	4.75	2.78	2.75	0.59
Generation (Age)	Generation Z and Alpha	87	1.25	3.88	2.71	2.75	0.50
	Generation Y and Millennials	101	1.13	4.25	2.68	2.63	0.57
	Generation X	179	1.25	5.00	2.90	2.88	0.65
	Baby Boomer generation	23	2.25	4.50	3.11	3.00	0.67
Education	Below full secondary	14	1.75	4.50	3.11	2.94	0.81
	Secondary with graduation	127	1.25	4.88	2.83	2.88	0.54
	Bachelor's degree	47	1.25	3.63	2.73	2.75	0.51
	Master's degree	186	1.13	4.75	2.81	2.81	0.63
	PhD or equivalent	16	1.50	5.00	2.65	2.56	0.90

Table 8. Cont.

Variable		N	Min	Max	Mean	Median	Std. Dev.
Region of work	Capital city	73	1.25	4.25	2.64	2.63	0.61
	Western Slovakia	61	1.25	3.88	2.60	2.63	0.53
	Central Slovakia	236	1.13	5.00	2.92	2.88	0.62
	Eastern Slovakia	20	2.00	3.75	2.78	2.75	0.44
Sector type	Private sector	271	1.25	4.88	2.75	2.75	0.61
	Public sector	119	1.13	5.00	2.95	2.88	0.59
Field type	Services field	330	1.13	5.00	2.81	2.75	0.62
	Production field	60	1.50	4.00	2.85	2.88	0.59
Employer type	Domestic employer	268	1.13	5	2.90	2.88	0.61
	Foreign employer	122	1.25	4.38	2.63	2.63	0.59
Industry	Group 1	219	1.13	5	2.97	3.00	0.58
	Group 2	171	1.25	4.5	2.61	2.63	0.60
Social status	Contract work	50	1.75	4.5	3.11	2.94	0.81
	Part-time employee	24	1.25	4.88	2.83	2.88	0.54
	Full-time employee	261	1.25	3.63	2.73	2.75	0.51
	Self-employed	55	1.13	4.75	2.81	2.81	0.63
Support	No support or irrelevant	211	1.38	4.88	2.95	2.88	0.58
	One type of support	68	1.13	5	2.83	2.88	0.66
	Two types of support	64	1.25	3.63	2.55	2.63	0.53
	Three or more types of support	47	1.25	3.5	2.53	2.38	0.57

Source: own elaboration.

Table 8 shows that the discomfort index values in all analysed groups are within a relatively narrow range, with minimum values ranging from 1.13 to 2.25 and maximum values reaching up to 5. The average index values are similar in most groups, with slightly higher values among respondents with mismatch status compared to those who report match, indicating a higher level of discomfort with mismatch. Higher maximum values are recorded mainly in groups with lower levels of education and among older generations, indicating greater variability in perceived discomfort in these groups, while lower maximums and narrower ranges of values are typical for younger generations and some regional categories.

4.2.2. Group Difference Tests

To assess whether the level of work discomfort differed across sociodemographic and employment-related groups, independent samples *t*-tests and one-way ANOVA were performed as appropriate for the structure of each categorical predictor. The results of these group difference tests are presented in Table 9, together with the corresponding effect size measures.

Table 9. Group differences in the work discomfort index by categorical predictors.

Predictor Variable	Test Used	Test Statistic	df	<i>p</i> -Value	Effect Size	Value
Gender	Independent samples <i>t</i> -test	<i>t</i> = 1.348	388	0.178	Cohen's <i>d</i>	0.141
Generation	One-way ANOVA	<i>F</i> = 5.691	3	<0.001	η^2	0.042
Education	One-way ANOVA	<i>F</i> = 1.285	5	0.269	η^2	0.016
Region of work	One-way ANOVA	<i>F</i> = 7.258	3	<0.001	η^2	0.053
Sector type	Independent samples <i>t</i> -test	<i>t</i> = −2.959	388	0.003	Cohen's <i>d</i>	−0.325
Field type	Independent samples <i>t</i> -test	<i>t</i> = −0.530	388	0.596	Cohen's <i>d</i>	−0.074

Table 9. Cont.

Predictor Variable	Test Used	Test Statistic	df	p-Value	Effect Size	Value
Employer type	Independent samples <i>t</i> -test	$t = 4.161$	388	<0.001	Cohen's d	0.454
Social status	One-way ANOVA	$F = 1.788$	3	0.149	η^2	0.014
Support	One-way ANOVA	$F = 11.565$	3	<0.001	η^2	0.082
Industry group	Independent samples <i>t</i> -test	$t = 5.972$	388	<0.001	Cohen's d	0.609
Match/mismatch	Independent samples <i>t</i> -test	$t = -0.489$	388	0.625	Cohen's d	-0.080

Source: own elaboration.

Of the eleven predictor variables examined, six showed statistically significant differences in mean discomfort levels across groups.

Among the *t*-test predictors, the industry group approached the largest effect size observed across all predictors ($p < 0.001$, Cohen's $d = 0.609$), indicating that employees in different industry groupings experienced meaningfully different levels of work discomfort, with this difference approaching a large effect by conventional benchmarks. Employer type also showed a strong and most practically significant effect. Employees of domestically owned firms reported significantly higher discomfort than those employed by foreign-owned organisations ($p < 0.001$), with a medium effect size (Cohen's $d = 0.454$). Sector type was also significant, with public sector employees reporting greater discomfort than private sector employees ($p = 0.003$), though the effect was smaller (Cohen's $d = -0.325$, a small-to-medium effect). By contrast, gender ($p = 0.178$) and field type ($p = 0.596$) showed no statistically significant differences in discomfort levels, with negligible effect sizes in both cases.

Notably, the match/mismatch indicator was not significantly associated with the discomfort index ($p = 0.625$), indicating that employees who experience a mismatch between the feasibility and actual availability of remote work do not report meaningfully higher levels of discomfort than those with consistent access arrangements. This finding directly addresses one of the study's core analytical questions.

Among the ANOVA predictors, three variables showed statistically significant omnibus effects. The level of organisational support for remote work showed the strongest effect ($p < 0.001$, $\eta^2 = 0.082$), representing a medium effect size. Post hoc comparisons using Scheffé's test revealed that employees who received no support or considered it irrelevant reported significantly greater discomfort than those who received two types of support ($p < 0.001$) or three or more types of support ($p < 0.001$). No significant differences were found between the remaining support level pairs, suggesting that the critical threshold lies between receiving no support and receiving at least two forms of support.

Region of work was also a significant predictor of discomfort ($p < 0.001$, $\eta^2 = 0.053$), with a small-to-medium effect size. Scheffé post hoc tests identified significant differences between the capital city region and Central Slovakia ($p = 0.007$), and between Western Slovakia and Central Slovakia ($p = 0.003$), with employees in Central Slovakia reporting higher discomfort than those in both the capital city and Western Slovakia regions. No significant differences were found involving Eastern Slovakia, likely reflecting the small number of respondents from that region.

Generation showed a statistically significant effect on discomfort ($p < 0.001$, $\eta^2 = 0.042$), though the effect size was small. Post hoc comparisons using Scheffé's test revealed three significant pairwise differences: between the youngest and the oldest cohorts ($p = 0.045$), between Generation Y and Millennials and Generation X ($p = 0.034$), and between Generation Y and Millennials and Baby Boomers ($p = 0.025$). The consistent pattern across these

comparisons suggests that younger generations report lower levels of discomfort than older ones, with the sharpest contrast observed between the youngest and oldest cohorts.

Education and social status showed no statistically significant differences in discomfort across their respective categories ($p = 0.269$, $p = 0.149$, respectively), with negligible effect sizes in both cases.

Complete results of post hoc tests are provided in Table 10.

Table 10. Post hoc test.

Predictor Variable	Post Hoc Procedure	Compared Groups	<i>p</i> -Value
Region of work	Scheffé	Capital city vs. Central Slovakia	0.007
		Western Slovakia vs. Central Slovakia	0.003
Generation	Scheffé	15–25 vs. 56+	0.045
		26–40 vs. 41–55	0.034
		26–40 vs. 56+	0.025
Support	Scheffé	No support or irrelevant vs. Two types of support	<0.001
		No support or irrelevant vs. Three or more types of support	<0.001

Source: own elaboration.

4.2.3. Linear Regression Model

A multiple linear regression model was constructed to identify the independent predictors of the work discomfort index while controlling for the simultaneous influence of all other variables. Variable selection was carried out using the forward stepwise method, which retained six statistically significant predictors in the final model. The regression coefficients for all retained predictors are presented in Table 11.

Table 11. Variables in the equation—linear regression.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.559	0.060		42.322	<0.001
age = 56+ (Baby Boomer)	0.341	0.103	0.146	3.292	0.001
social status = self-employed	0.250	0.089	0.123	2.814	0.005
support = one type of support	−0.163	0.070	−0.103	−2.336	0.020
support = two types of support	−0.187	0.090	−0.093	−2.075	0.039
region = central Slovakia	0.153	0.057	0.120	2.691	0.007
industry = industry group 1	0.245	0.054	0.203	4.577	<0.001

Source: own elaboration.

The model as a whole was statistically significant, as indicated by the F-test ($p < 0.001$), confirming that the retained predictors jointly explain a statistically significant proportion of variance in the discomfort index. The R^2 value of 0.116 indicates that the model explains approximately 11.6% of the variance in work discomfort.

Among the retained predictors, industry group showed the strongest independent association with discomfort, as indicated by the largest standardised coefficient in the model ($\beta = 0.203$, $p < 0.001$). Employees in industry group 1, comprising finance and public administration or local government, reported discomfort levels approximately 0.245 points higher on the five-point scale than employees in the reference industry group, holding all other predictors constant. This finding is consistent with the group difference results reported in the preceding subsection. Generational belonging was a significant predictor,

with Baby Boomers reporting substantially higher discomfort than the reference generation ($B = 0.341$, $\beta = 0.146$, $p = 0.001$). This is the largest unstandardised coefficient in the model, indicating that belonging to the oldest generational cohort is associated with a meaningful increase in experienced discomfort, even after controlling for all other predictors.

Self-employed individuals reported significantly higher discomfort than full-time employees, the reference social status category ($B = 0.250$, $\beta = 0.123$, $p = 0.005$). This finding is noteworthy given that the logistic regression results showed self-employed individuals to be less likely to experience a mismatch in remote work access, suggesting that while self-employment may provide greater flexibility in access arrangements, it does not protect against higher levels of experienced discomfort.

Regional location was a significant predictor, with employees working in Central Slovakia reporting greater discomfort than those in the capital city, Bratislava ($B = 0.153$, $\beta = 0.120$, $p = 0.007$). This is consistent with the ANOVA findings reported above and reinforces the pattern of geographic inequality in work-related outcomes identified across both analytical strands.

Organisational support for remote work showed a protective effect on discomfort. Employees receiving one type of support reported significantly lower discomfort than those receiving no support or considering it irrelevant ($B = -0.163$, $\beta = -0.103$, $p = 0.020$), as did those receiving two types of support ($B = -0.187$, $\beta = -0.093$, $p = 0.039$). The similarity in magnitude between the one-type and two-type coefficients suggests that the primary benefit of organisational support is realised at the point of receiving any meaningful support, with diminishing additional returns beyond that threshold. It is noteworthy that three or more types of support did not emerge as a significant predictor in the final model, suggesting that beyond a moderate level of support, additional forms do not independently contribute to reducing discomfort.

The linear regression model of work discomfort indicates that experienced discomfort is associated less with access mismatch itself than with the organisational and structural conditions under which employees work. In particular, the protective role of employer support suggests that practical organisational measures can help reduce work-related discomfort.

4.2.4. Linear Regression Model Evaluation

The Pearson correlation coefficient between observed and model-predicted values of the discomfort index was $r = 0.386$ ($p < 0.001$), indicating a weak-to-moderate positive linear relationship between predicted and actual discomfort scores. While statistically significant, this value confirms that the model captures a meaningful but limited portion of the individual-level variation in discomfort. The MAPE reached a value of 16.86%, which, according to the conventional benchmarks established by Lewis [48], indicates a good predictive accuracy. Both evaluation measures were calculated on the testing data. Together, these measures suggest that while the model successfully identifies statistically significant structural predictors of work discomfort and achieves a reasonable level of predictive accuracy at the aggregate level, its precision in predicting individual discomfort scores remains limited. This is an expected outcome given the inherently multidimensional and subjective character of the discomfort construct, which is shaped by a wide range of personal, situational, and psychological factors that extend beyond the sociodemographic and organisational variables available in this dataset. The findings should therefore be interpreted primarily as evidence of systematic group-level patterns rather than as a precise individual-level prediction instrument.

4.3. Hypothesis Evaluation

This subsection summarises the outcomes of the four hypotheses stated in light of the empirical results presented in previous sections.

H1 predicted that employees working outside the capital city region, in domestically owned firms, and in non-knowledge-intensive sectors would face significantly higher odds of experiencing a mismatch between the feasibility and actual availability of remote work. H1 is supported. The logistic regression model confirmed that all three regions outside Bratislava were associated with substantially elevated odds of mismatch, with employees in Eastern Slovakia facing odds approximately 26 times higher than those in the capital. Employees of domestically owned firms showed significantly higher mismatch odds than those in foreign-owned organisations, and industry membership, as a proxy for knowledge intensity, was the strongest bivariate predictor of mismatch in the analysis. In practical terms, this means that where an employee works, who employs them, and what sector they belong to are more powerful determinants of remote work access than individual characteristics such as education or gender. Structural and organisational factors dominate over personal ones in shaping whether feasible remote work is actually made available.

H2 predicted that employees receiving greater organisational support for remote work would report significantly lower levels of work discomfort than those receiving little or no support. H2 is supported. Both the group difference tests and the linear regression model confirmed a significant negative association between the level of employer support and experienced discomfort. Employees receiving no support reported the highest discomfort levels, while those receiving at least two types of support reported significantly lower levels. Notably, the regression results suggest that the benefit of support is realised at the threshold of receiving meaningful assistance rather than increasing proportionally with its quantity. Three or more types of support did not independently predict lower discomfort beyond the effect of receiving one or two types. In practical terms, this finding carries a clear organisational message: even modest, targeted support, such as providing ergonomic equipment or technical assistance, is associated with meaningfully better employee well-being, making it a cost-effective lever for employers seeking to improve the quality of remote work conditions.

H3 predicted that a capital–periphery gradient in work discomfort would be observed, with employees outside the capital city region reporting higher discomfort than those based in Bratislava. H3 is partially supported. The ANOVA and post hoc tests confirmed significant differences in discomfort between the capital city region and Central Slovakia, and between Western Slovakia and Central Slovakia, with Central Slovakia employees reporting higher discomfort in both comparisons. However, no significant differences in discomfort were found involving Eastern Slovakia, likely reflecting the small number of respondents from that region rather than a genuine absence of effect. The linear regression model further confirmed that Central Slovakia remained a significant independent predictor of higher discomfort after controlling for all other variables. In practical terms, the regional pattern in discomfort reinforces the broader picture of geographic inequality in remote work outcomes: employees outside the capital not only face greater barriers to accessing remote work but also experience greater discomfort when working under their current arrangements, suggesting that regional disadvantage operates through multiple reinforcing mechanisms simultaneously.

H4 predicted that employees experiencing a mismatch between the feasibility and actual availability of remote work would report higher levels of work discomfort than those whose access arrangements were consistent with their job’s remote potential. H4 is not supported. The test found no statistically significant difference in discomfort levels between matched and mismatched employees, and the match/mismatch indicator did

not emerge as a significant predictor in the linear regression model. This is the most theoretically unexpected finding of the study. In practical terms, it suggests that in the Slovak context, being structurally denied feasible remote work does not automatically lead to a measurable increase in the strain experienced with one's current working arrangements. This may reflect the historically low prevalence of remote work in Slovakia, which may have shaped employee expectations in ways that reduce the psychological impact of its absence—though this interpretation remains tentative given that expectation levels were not directly measured in this study.

5. Discussion

This study set out to examine two interrelated dimensions of remote work inequality in Slovakia: the structural and organisational factors predicting a mismatch between the feasibility and actual availability of home-based work, and the individual, regional, and organisational determinants of experienced work discomfort. By addressing both questions within a single empirical framework, the study offers an integrated perspective that moves beyond the fragmented treatment of access and well-being characteristic of much of the existing literature. The findings contribute evidence from a post-communist CEE labour market context that remains substantially underrepresented in the international literature, while simultaneously illuminating patterns of broader relevance to manufacturing-intensive economies across Europe and beyond.

5.1. Predictors of Match/Mismatch in Access to Remote Work

The logistic regression model explained approximately 43% of the variance in the match/mismatch outcome. Such a level of explanatory power is satisfactory for a binary labour market outcome and confirms that the identified predictors account for a substantial portion of the structural inequality in access to remote work. The results reveal that mismatch is not randomly distributed across the workforce but is systematically shaped by regional location, industry, ownership structure, social status, and, to a lesser extent, gender and educational attainment.

The support for H1 confirms that structural and organisational factors systematically determine who gains access to feasible remote work, consistent with both resource-based theory and spatial inequality frameworks. The most striking manifestation of this pattern is a strong regional divide in the mismatch probability. Employees working outside the Bratislava capital region faced substantially higher odds of being denied remote work despite its feasibility, and this disadvantage increased progressively with distance from the capital, reaching its peak among employees in Eastern Slovakia, who showed odds of mismatch approximately 26 times higher than those based in Bratislava. This pattern is entirely consistent with the broader European evidence documented by Luca et al. [27] and Eurofound and the European Commission Joint Research Centre [28], who identified capital cities and metropolitan regions as the primary beneficiaries of the remote work expansion, driven by their concentration of knowledge-intensive occupations and superior digital infrastructure. In the Slovak context, these regional disparities are rooted in the country's industrial structure. Knowledge-intensive and digitally compatible jobs are heavily concentrated in Bratislava, while regions outside the capital remain dominated by manufacturing, construction, and on-site service roles that cannot be performed remotely. This uneven distribution of job types across regions was documented by Kapitsinis [9] and Jerbashian and Vilalta-Bufi [2] and is a long-standing structural feature of the Slovak economy rather than a recent development. The finding that this gradient persists in the post-pandemic period, when emergency remote work arrangements have given way to deliberate organisational choices, suggests that regional inequality in remote work access

is not a temporary disruption but a structural feature of the Slovak labour market that requires targeted policy intervention.

Industry membership was the strongest predictor of mismatch in terms of association strength in the bivariate analysis and remained highly significant in the multivariate model. Employees in finance, public administration, and selected production-oriented sectors faced substantially higher mismatch odds than the IT and R&D reference group. This is theoretically consistent with Dingel and Neiman's [11] foundational framework, which established that occupational teleworkability varies enormously across industries and that workers in lower-teleworkability sectors are structurally disadvantaged in accessing remote work. The public administration finding also connects to the broader observation by Barnes et al. [21] that organisations with fixed hierarchical structures tend to implement flexible working arrangements more slowly and less equitably.

The ownership structure finding, with employees of foreign-owned firms showing substantially lower mismatch odds than those in domestically owned organisations, is consistent with the conclusions of Loignon et al. [23], who demonstrated that the quality of remote work conditions is closely tied to organisational resources and management culture. One possible explanation is that foreign-owned firms operating in Slovakia are typically larger and more internationalised, and may be subject to corporate policies developed in contexts where remote work is more normalised, though these organisational characteristics were not directly measured in this study, and this interpretation remains speculative. This finding has a direct practical implication: improving remote work access in the Slovak labour market may require not only regulatory intervention but also the diffusion of organisational best practices from internationally operating firms to domestic employers.

The finding that self-employed workers and contract employees face lower mismatch odds than full-time employees is perhaps the most intuitively straightforward result in the model. Workers in non-standard employment arrangements typically have greater autonomy over where and when they work by the nature of their contracts, meaning that the structural distinction between feasibility and access is less binding for them than for employees subject to employer-determined workplace policies. This finding is consistent with the broader literature on employment flexibility, which consistently identifies non-standard workers as having greater *de facto* autonomy over their working arrangements, even when they lack formal employment protections [21].

The "PhD finding" deserves particular attention, as it directly contradicts the well-established pattern in the literature that higher educational attainment is associated with better remote work access [11,12]. In our study, employees holding a doctoral degree or equivalent qualification showed nearly eight times higher odds of mismatch than those with lower qualifications. One possible interpretation is that in the Slovak labour market context, doctoral-level employees are disproportionately concentrated in academic and research institutions, which are sectors characterised by complex, presence-dependent activities such as laboratory work, fieldwork, or on-site teaching, where the nature of the work limits remote feasibility despite high educational attainment. Alternatively, this finding may reflect a selection effect in the sample, given the relatively small number of PhD holders. This result warrants further investigation in future studies with larger samples of highly educated workers.

Finally, the "gender finding", with female employees showing approximately twice the odds of mismatch as male employees, adds a dimension of intersectional inequality to the picture. While gender was not significant in the bivariate Chi-square analysis, it emerged as a significant independent predictor after controlling for other variables, suggesting that the gender effect is partially masked by the relationship between gender and other structural variables such as sector and industry. This finding is consistent with the broader literature

documenting gendered patterns in remote work access [25] and suggests that women in the Slovak labour market face not only higher discomfort when working remotely, as documented in other national contexts, but also greater structural barriers to accessing remote work in the first place.

5.2. Determinants of Work Discomfort

The explanatory power of the linear regression model, at $R^2 = 0.116$, places it within the range typically reported in survey-based studies of occupational well-being and work-related attitudes. However, such a value of R^2 is consistent with the accepted standards for social science empirical modelling, where the primary goal is to identify statistically significant predictors rather than to achieve high predictive accuracy, and where a minimum R^2 of 0.10 alongside statistically significant predictors is considered acceptable [31,33,49,50]. The large proportion of unexplained variance reflects the inherent complexity of attitudinal and well-being constructs, which are shaped by a wide range of personal, situational, and psychological factors beyond the sociodemographic and organisational variables available in this dataset. This level of explained variance is therefore not a limitation unique to this study but a characteristic of the research domain. The MAPE of 16.86% and the observed–predicted correlation of $r = 0.386$ further confirm that the model performs reasonably well as a tool for identifying systematic group-level patterns, even if individual-level prediction remains imprecise, which is fully consistent with the study’s primary goal of mapping structural determinants rather than forecasting individual outcomes.

The non-support of H4 represents the most theoretically significant departure from prior expectations in this study and warrants the most careful interpretive attention. The match/mismatch indicator was not a statistically significant predictor of work discomfort, indicating that employees who experience a structural mismatch between the feasibility and availability of remote work do not report meaningfully higher levels of discomfort than those whose access arrangements are consistent with their job’s remote potential. This result partially diverges from the predictions of the broader literature, which suggests that unmet preferences for remote work are associated with frustration, reduced job satisfaction, and work–life balance disruption [22]. One possible explanation specific to the Slovak context is that, given the historically low prevalence of remote work in Slovakia, employees may have lower baseline expectations of flexibility, reducing the psychological impact of being denied an arrangement they have rarely experienced. One possible interpretive frame for this finding draws on adaptation-level theory [51], which suggests that well-being assessments are calibrated against experiential reference points formed by prior experience. Employees in contexts where remote work has historically been rare may simply not perceive its absence as a source of discomfort because their baseline expectation does not include it. However, this interpretation is speculative, as employee expectation levels were not directly measured in this study. Establishing whether adaptation-level mechanisms genuinely moderate the mismatch–discomfort relationship would require a dedicated study measuring expectations prior to assessing outcomes—a direction we identify for future research in this area. Alternatively, the non-significance may reflect the relatively small mismatch group in the original sample ($n = 42$), which may have limited statistical power to detect a genuine effect.

The support for H2 provides direct empirical validation of the resource-based prediction that organisational support mediates the relationship between working conditions and employee strain. Employees receiving at least one or two types of employer support reported significantly lower discomfort than those receiving no support, confirming the central role of the organisational environment in shaping the quality of remote work experiences. This finding directly supports the conclusions of McAllister et al. [24], who

demonstrated that ergonomic training and workstation adjustability substantially reduce discomfort among remote workers, and is consistent with the resource-based framework articulated by Loignon et al. [23], who showed that access to material and social resources mediates the relationship between working conditions and employee strain. Importantly, the regression model showed that three or more types of support did not independently predict lower discomfort after controlling for other variables, suggesting that the primary benefit of organisational support is achieved at the threshold of receiving meaningful support rather than increasing proportionally with its quantity. This has a clear practical implication for employers: the priority should be to ensure that all employees receive at least basic support rather than to concentrate extensive support packages on a subset of workers.

The generational pattern in discomfort, with Baby Boomers reporting significantly higher levels than younger cohorts, is consistent with Graham et al. [10], who identified lower adaptability to digital and flexible work forms among older workers. The regression model confirms that this generational effect persists after controlling for industry, region, social status, and other structural variables, suggesting that it reflects genuine age-related differences in the experience of working arrangements rather than a compositional artefact of older workers being concentrated in more discomfort-prone sectors. At the same time, as Graham et al. [10] caution, lower discomfort among younger employees does not necessarily imply better overall well-being. Younger workers may face distinct pressures related to career development, work–life boundary management, and digital overload that are not fully captured by the composite discomfort index used in this study.

The partial support for H3 confirms the existence of a capital–periphery gradient in discomfort, while also revealing its limits—the absence of a significant Eastern Slovakia effect points to the need for caution when treating peripheral regions as analytically homogeneous. The “regional finding”, with Central Slovakia employees reporting higher discomfort than those in the capital region, adds a spatial dimension to the discomfort analysis that mirrors the mismatch findings in Analytical Strand 1. This parallel suggests that regional disadvantage in the Slovak labour market operates through two distinct but reinforcing mechanisms: employees outside Bratislava are both more likely to be denied feasible remote work and, when working under their current arrangements, more likely to experience discomfort.

The “self-employment finding” creates an analytically interesting contrast between the two strands that deserves particular attention. Self-employed workers showed lower odds of mismatch in Analytical Strand 1, suggesting greater flexibility and autonomy in their working arrangements, but reported significantly greater discomfort in Analytical Strand 2. This apparent paradox may reflect the well-documented double-edged character of self-employment: while self-employed individuals have greater control over where they work, they typically lack the organisational support structures, such as ergonomic provision, technical assistance, managerial guidance, and social connection, that employed workers can access [16,23]. The absence of these resources may generate discomfort even when access to remote work is not itself constrained. This finding contributes a nuanced perspective to the literature on non-standard employment and well-being, suggesting that flexibility and comfort are not synonymous and that policies targeting remote work access must be complemented by measures addressing the quality of working conditions for self-employed and contract workers.

The “industry effect” on discomfort, with employees in finance and public administration reporting higher discomfort than those in the IT and R&D reference group, is consistent with the sectoral patterns observed in the mismatch analysis and may reflect structural features of these industries, including higher attendance requirements, more

rigid working hour arrangements, and less developed remote work infrastructure. The persistence of the industry effect in both analytical strands reinforces the conclusion that sectoral belonging is one of the most consequential structural determinants of remote work inequality in the Slovak context.

The absence of significant gender and education effects in the discomfort regression, despite gender emerging as significant in the mismatch model, is noteworthy. The broader focus of the discomfort index may partially explain the non-significance of gender, consistent with the observation by MacLean et al. [26] that gender differences in remote work outcomes are most pronounced for physical health outcomes specifically. This finding does not negate the gendered dimension of remote work inequality identified in Analytical Strand 1 but suggests that its primary manifestation in the Slovak context is in access rather than in experienced quality.

5.3. Integrated Perspective and Broader Implications

Considered together, the two analytical strands of this study make four distinct contributions to the existing literature. First, by jointly modelling access inequality and experienced discomfort within a single framework, the study reveals that these two dimensions of remote work inequality are shaped by overlapping but not identical structural forces—a finding that would not be visible in studies examining either dimension in isolation. Second, the post-pandemic temporal focus reveals that the structural inequalities documented during the pandemic emergency period have not dissolved but have persisted and in some dimensions deepened, now reflecting deliberate organisational choices rather than emergency adaptations. Third, the CEE context provides evidence from a type of economy—manufacturing-intensive, regionally polarised, with historically low prevalence of remote work—that is systematically absent from the comparative literature yet shares fundamental structural characteristics with dozens of economies across Europe. Fourth, and most theoretically significant, the non-support of H4—the finding that mismatch does not predict discomfort in this context—represents a genuine empirical departure from prior expectations that cannot be explained by existing theoretical frameworks alone and points to the need for context-sensitive theorising about the consequences of remote work inequality in post-communist labour markets.

These findings have direct implications for policy. At the organisational level, the evidence that one or two types of support—specifically ergonomic equipment and technical assistance—are associated with significantly lower discomfort, while three or more types produce no additional independent benefit, suggests that universal coverage of basic support measures should take priority over concentrating comprehensive packages on a subset of employees. At the regional policy level, finding that employees in Eastern and Central Slovakia face odds of mismatch many times higher than those in Bratislava, even after controlling for industry and ownership, points to structural barriers requiring region-level interventions—specifically policies targeting the expansion of knowledge-intensive employment in peripheral regions alongside digital infrastructure investment. At the regulatory level, the persistent disadvantage of employees in domestically owned firms relative to those in foreign-owned organisations suggests that organisational-level differences in remote work implementation are a meaningful source of access inequality, which is a finding that could inform the design of policy frameworks addressing equitable access to flexible work arrangements, though the specific regulatory mechanisms most effective in the Slovak context would require further policy analysis.

The study also contributes methodologically by demonstrating that the joint analysis of access inequality and work discomfort within a single empirical framework yields insights that neither analysis could produce in isolation. Most notably, the finding that

mismatch does not translate into higher discomfort in the Slovak context, which has important implications for how the consequences of remote work inequality are theorised and measured in future research.

5.4. Limitations

As with all empirical studies, the findings should be interpreted in light of several methodological constraints. The data were collected through an online questionnaire using a convenience sampling approach, which means the sample cannot be treated as statistically representative of the entire Slovak working population. However, the sample provides substantial variation across all key sociodemographic and employment dimensions, which is the primary requirement for the comparative and regression analyses conducted here. The findings should therefore be understood as evidence of systematic structural patterns rather than precise population-level estimates, a distinction that does not diminish their analytical and practical relevance.

The cross-sectional design, while standard for exploratory survey-based research of this type, means that the identified associations should be interpreted as structural correlates rather than as causal effects. That is a common and widely accepted limitation of cross-sectional labour market research that does not undermine the value of the findings for identifying where inequalities are concentrated.

The relatively small original mismatch group ($n = 42$) was explicitly addressed through an oversampling procedure that balanced the class distribution for model estimation. The observed classification accuracy in the testing dataset reflects a natural consequence of working with a rare outcome category and should be taken into account when interpreting the logistic regression results. The Cronbach's alpha of the discomfort index (0.679), while marginally below the conventional threshold, is consistent with the exploratory nature of the research and falls within the acceptable range in applied social science research [30,31]. The discomfort index should therefore be interpreted as a broad composite indicator of work-related discomfort rather than a fully established psychometric scale. Additionally, the modest R^2 of the linear regression (0.116) reflects the well-documented difficulty of capturing the full complexity of attitudinal and well-being constructs through sociodemographic and organisational variables alone, and is consistent with comparable studies in the field. Key variables not available in this dataset, including individual psychological characteristics such as personality traits and stress coping styles, domestic care responsibilities, and household working conditions, are likely to account for a substantial share of the unexplained variance and represent important targets for inclusion in future research designs. Despite this weakness, the MAPE of 16.86% confirms that the model achieves good predictive accuracy at the aggregate level.

5.5. Directions for Future Research

The findings of this study open several possibilities for future investigation. Most directly, replication using a probability-based sample representative of the Slovak working population would allow the structural patterns identified here to be generalised with greater confidence and would enable more precise estimation of the prevalence of mismatch across sociodemographic and sectoral groups. Then, a longitudinal research design would address the causality limitation of the current study, enabling examination of whether experiencing a persistent mismatch between remote work feasibility and access leads to increasing discomfort over time, or whether adaptation mechanisms moderate this relationship in the longer term.

A further important direction for future research concerns the causal role of organisational support in shaping work discomfort. The present study found that employees

who received organisational support reported significantly lower work discomfort (H2). However, because the data are cross-sectional, this association cannot be interpreted as evidence of a causal effect. A productive way to address this limitation would be to conduct firm-level intervention experiments within a small number of cooperating organisations. In such a design, employees performing comparable roles could be assigned to groups that receive different combinations of organisational support, for example a group receiving only technical equipment, a group receiving technical equipment together with ergonomic adjustments, and a group receiving technical, ergonomic, and financial or psychological support. Work discomfort could then be measured at several points in time, both before the support is introduced and at defined intervals afterwards, using the composite discomfort index applied in this study. Comparing the change in discomfort across these groups would make it possible to estimate how strongly each specific combination of support reduces work discomfort, and which forms of support contribute most to this reduction. A design of this kind would also allow researchers to test directly whether the threshold effect observed in the present study, in which basic support was sufficient to lower discomfort while additional types of support brought no further benefit, represents a genuine causal pattern or merely a feature of the cross-sectional data. Such evidence would be of direct practical value for employers, as it would indicate which support measures deserve priority when resources are limited.

The counterintuitive finding that PhD-level employees face elevated mismatch odds also warrants dedicated follow-up investigation, ideally using qualitative methods to explore the specific occupational contexts and institutional arrangements that drive this pattern. Furthermore, future studies might also examine the self-employment discomfort finding in greater depth, given the growing size of the self-employed workforce across CEE economies and the apparent tension between flexibility of access and quality of working conditions. Next, the study's framework, jointly analysing access inequality and experienced discomfort within a single empirical design, could be extended to comparative cross-national studies across CEE economies, which would allow the Slovak findings to be contextualised within the broader regional pattern and would contribute to the still limited literature on remote work inequality in post-communist labour markets. Finally, the development and psychometric validation of a dedicated instrument for measuring remote work discomfort, designed to go beyond the composite index used in this exploratory study, would represent a valuable methodological contribution to the field.

6. Conclusions

This study set out to examine two dimensions of remote work inequality that have rarely been addressed jointly in the existing literature: the structural and organisational factors predicting a mismatch between the feasibility and actual availability of home-based work, and the determinants of experienced work discomfort among employees navigating their current working arrangements. By treating both outcomes within a single empirical framework and a single national sample, the study offers an integrated perspective that advances beyond the fragmented treatment characteristic of much of the prior research in this area.

The findings indicate that remote work inequality in Slovakia is not a uniform phenomenon but a structurally differentiated one, shaped primarily by where employees work, what industry they belong to, who owns their organisation, and what organisational support they receive. The pronounced capital–periphery gradient in mismatch, with employees in peripheral regions facing odds of being denied feasible remote work that are many times higher than those in the capital city, is arguably one of the most policy-relevant finding of the study. It reflects persistent structural features of the Slovak economy that

the post-pandemic normalisation of remote work has not resolved, and that may require targeted regional and digital infrastructure policy to address. At the organisational level, the finding that employer support for remote work is the most consistently significant predictor of lower discomfort carries a clear and actionable message: the quality of the remote work experience is not primarily determined by who employees are, but by how well their organisation supports them. Even modest levels of support, such as providing ergonomic guidance, technical assistance, or flexible scheduling, are associated with meaningfully lower discomfort, suggesting that practical organisational measures may help reduce work-related discomfort even without large-scale investment.

The study also produces findings that complicate and enrich the existing literature. The absence of a significant relationship between mismatch and discomfort suggests that being denied feasible remote work does not automatically translate into higher experienced strain in every labour market context. The adaptation-level interpretation offered here, grounded in the historically low prevalence of remote work in Slovakia, should therefore be treated cautiously, since employees' expectation levels were not directly measured in this study. The result may indicate that contextual expectations and labour market traditions shape how employees evaluate the absence of remote work, but this mechanism should be tested directly in future research. Similarly, the elevated mismatch odds among PhD-level employees and the greater discomfort among self-employed workers both suggest nuances in the relationship among professional status, employment autonomy, and remote work outcomes that warrant further investigation.

From a methodological perspective, the study demonstrates the value of jointly modelling access inequality and discomfort within a single analytical framework. The two strands produced findings that are both valuable. The overlap between the structural predictors of mismatch and discomfort suggests that remote work disadvantage operates through reinforcing mechanisms, while the divergences between the two outcome models highlight that access and quality are related but distinct dimensions of remote work inequality that should not be conflated in research or policy. Slovakia, as a small, open, manufacturing-intensive economy with pronounced regional disparities and historically low remote work rates, represents a case that is broadly relevant to a wider category of European economies facing similar structural conditions. The findings of this study are therefore a national empirical contribution to the broader comparative discussion on how labour market institutions, industrial geography, and organisational practices jointly shape the distributional consequences of remote work in post-communist and manufacturing-intensive contexts across Europe.

Several limitations should be emphasised. The study is based on cross-sectional survey data, which means that the results show associations rather than causal effects. The sample was collected through an online questionnaire and cannot be treated as fully representative of the Slovak working population. The discomfort index also has an exploratory character. Although Cronbach's alpha approached the conventional threshold, its value of 0.679 indicates that the index should be interpreted as a broad composite indicator of work-related discomfort rather than as a fully established psychometric scale. In addition, the linear regression model explains only a limited share of variance in discomfort, suggesting that other factors not included in the dataset, such as individual expectations, household working conditions, psychological characteristics, or domestic care responsibilities, may also be important.

Future research should therefore examine these mechanisms more directly. Longitudinal data would make it possible to assess whether mismatch in remote work access leads to changes in discomfort over time. Beyond such observational designs, firm-level intervention studies would provide especially valuable causal evidence. In such studies,

cooperating organisations could provide groups of employees with different combinations of organisational support, such as technical equipment, ergonomic adjustments, and financial or psychological assistance, and the resulting changes in work discomfort could be measured over time. This approach would make it possible to assess the effect of specific support measures directly and to identify which of them most effectively reduce work discomfort, moving beyond the correlational evidence presented in this study and offering employers clearer guidance on where to focus their support. Representative samples would allow stronger generalisation to the Slovak working population. Comparative studies across CEE countries could also show whether the patterns observed in Slovakia are country-specific or part of a broader regional model of remote work inequality. Finally, future studies should include direct measures of expectations, household conditions and care responsibilities in order to test the mechanisms that could not be examined in the present study.

Author Contributions: Conceptualization, L.D.; methodology, L.D.; software, V.S.; validation, L.D.; formal analysis, V.S.; investigation, L.D.; resources, L.D.; data curation, V.S.; writing—original draft preparation, V.S.; writing—review and editing, L.D.; visualization, V.S.; supervision, L.D.; project administration, V.S.; funding acquisition, L.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Slovak Grant Agency for Science (VEGA) grant number 1/0509/24 And The APC was funded by Slovak Grant Agency for Science (VEGA) grant number 1/0509/24.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of University of Zilina (Approval Code: Directive No. 207, Approval Date: 31 May 2024).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author(s).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Questionnaire on the Possibilities of Working from Home in Slovakia

Dear respondent,

You are invited to participate in a questionnaire survey focused on the possibilities and conditions of working from home in Slovakia. The aim of this questionnaire is to collect empirical data for scientific research examining the availability, perception, and selected aspects of home office work.

Participation in this survey is voluntary and anonymous. No information that could directly identify individual respondents will be collected, and all responses will be processed only in aggregated form.

By completing and submitting this questionnaire, you confirm that you have been informed about the purpose of the research and that you consent to the use of the collected data for scientific analyses. The results of these analyses may be presented and published in scientific articles and other academic outputs.

Thank you for your time and valuable contribution to this research.

1. Gender

Female/Male/Other

2. Age

15–25 (Generation Z and Alpha)

26–40 (Generation Y and Millennials)

41–55 (Generation X)

56 and over (Baby Boomers)

3. Education

Primary education

Secondary education without a school-leaving examination, with an apprenticeship certificate

Secondary education with a school-leaving examination

Bachelor's degree

Master's degree

Doctoral degree

4. Social status

Agreement-based work

Self-employed person

Part-time employee

Full-time employee

5. Region where work is performed

Banska Bystrica Region

Bratislava Region

Kosice Region

Nitra Region

Presov Region

Trencin Region

Trnava Region

Zilina Region

6. Sector of work activity

Public sector/Private sector

7. Field of work

Services/Manufacturing

8. Industry of employment

Agriculture and forestry

Industry

Construction and real estate

Trade

Services

Transport and communications

Science, technology, research and development

Education

Healthcare

Information technology

Marketing and advertising

Finance

Banking and insurance

State administration and local government

Law and legislation

9. Enterprise ownership

Domestic/Foreign

10. Do you think your work could also be performed from home?

Yes/No

11. Did you have the opportunity to work from home before the COVID-19 pandemic?

Yes/No

12. Did you have the opportunity to work from home during the COVID-19 pandemic?

Yes/No

13. Do you currently have the opportunity to work from home?

Yes/No

14. To what extent do you have the opportunity to work from home?

Once a week

A few times a week

Once a month

Once every few months

I do not have this opportunity

In the following questions, you will respond to statements concerning working from home. Please indicate your agreement or disagreement with each statement.

15. Working from home is advantageous mainly because the employee does not have to commute to work.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

16. Flexible working hours are an advantage for an employee working from home.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

17. Working from home is more comfortable for the employee.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

18. When working from home, an employee improves their technical skills.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

19. When working from home, employees may feel isolated.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

20. Working from home requires a high degree of self-discipline from the employee.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

21. Working from home negatively affects the employee's work-life balance.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

22. When working from home, technical problems often occur and negatively affect the employee's work performance.

Agree

Somewhat agree

Neither agree nor disagree

Somewhat disagree

Disagree

23. What support for working from home did your employer provide during the COVID-19 pandemic?

Necessary technological equipment (laptop, phone, software...)

Technical support in resolving problems with equipment or connection

Ergonomic equipment for the work environment (chair, desk...)

Financial support to cover costs related to working from home (internet, utilities)

Psychological support for managing working from home (counselling, psychologist...)

24. What support for working from home does your employer currently provide?

Necessary technological equipment (laptop, phone, software...)

Technical support in resolving problems with equipment or connection

Ergonomic equipment for the work environment (chair, desk...)

Financial support to cover costs related to working from home (internet, utilities)

Psychological support for managing working from home (counselling, psychologist...)

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