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Psychosocial Work Factors, Well-Being, and Health Pathways to Sickness Absence: An Integrated GLM–SEM Approach

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Abstract

Sick leave is a key indicator of labour market performance and public health, reflecting employee well-being and working conditions while creating a socioeconomic burden. Rates have increased in Europe due to ageing and shrinking workforces, yet research has focused mainly on medical risks, with limited attention to psychosocial factors and subjective well-being. This study analysed the relationship between sick leave, employees' subjective well-being, self-rated health, and psychosocial work factors. A cross-sectional survey was conducted in Latvia (July–September 2024) among employees in four sectors, public administration, healthcare, pharmaceuticals, and energy, yielding 1628 valid responses (81.6%). Data from online questionnaires (WHO-5, OECD frameworks) were linked to organisational sick leave records. Analyses used descriptive statistics, generalised linear models, bootstrapping, and structural equation modelling. Employees reported an average of 12 sick leave days in 2023, with higher levels among women and healthcare workers. Health problems and work environment risks were positively associated with the likelihood of sick leave, whereas greater job autonomy showed a negative association. Subjective well-being was indirectly related to sick leave through its association with health problems. These findings highlight the multifactorial nature of sick leave and underscore the importance of fostering healthy and supportive psychosocial work environments to promote employee well-being.

Keywords: sick leave; subjective well-being; psychosocial well-being; psychosocial work environment; subjective health problems; occupational sectors; autonomy; Latvia

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1. Introduction

Sickness absence is an important indicator of labour-market functioning and employee health, and it carries substantial organisational and societal costs. Demographic ageing, increasing replacement pressures, and growing demands on work ability highlight the need for timely evidence on factors that shape employees' health and absence patterns. For organisations, high sickness absence disrupts productivity, increases staffing pressures, and raises recruitment and training costs, underscoring the strategic importance of understanding its determinants.

This study examines how psychosocial work factors, subjective well-being, and health problems jointly influence sickness absence among employees in Latvia. Guided by the Job Demands-Resources (JD-R) model and the WHO-5 well-being framework, the study

investigates whether job demands and job resources affect sick-leave days directly or indirectly through self-rated health problems.

The study aims to provide a deeper understanding of sickness absence risks by analysing the interplay among the psychosocial work environment, subjective well-being, and health problems. The specific objectives are to: Describe sectoral and demographic differences in sickness absence; Assess direct associations between work-environment factors, well-being, health problems, and sick-leave days using Tweedie GLM models; Evaluate indirect (mediated) pathways through health problems using SEM; Examine the contribution of demographic and organisational covariates.

This study advances literature in several important ways. First, it addresses sectoral blind spots by analysing sickness-absence determinants across four different organisational contexts rather than focusing on a single occupational group. Second, it broadens existing empirical perspectives by integrating psychosocial job demands, job resources, subjective well-being, and self-rated health within the JD-R framework. Third, the study also incorporates commuting time as an emerging work-related stressor, a factor rarely examined in absenteeism research. Fourth, by applying both Tweedie GLM models and SEM mediation analysis, the study provides additional clarity to previously inconsistent findings in the literature, especially concerning autonomy and job demands, by disentangling their direct and indirect links with sickness absence. Fifth, the linkage of administratively recorded sickness-absence data with psychosocial survey measures provides stronger evidence for the mediating role of health problems in the relationship between job characteristics and absence. Finally, the study contributes by integrating WHO-5 measures of subjective well-being with OECD-recommended indicators of job quality, such as job demands, autonomy, social environment factors, and exposure to health risks, which map directly onto the core components of the JD-R model. This ensures conceptual alignment with internationally recognised labour-market monitoring frameworks while capturing both demands that strain employees and resources that support their functioning. By combining OECD job-quality indicators with subjective well-being measures, the study provides a more holistic assessment of how working conditions and psychological resources jointly shape health outcomes and sickness absence.

The paper proceeds as follows. Section 2 reviews the literature on sickness absence, subjective well-being, and the psychosocial work environment, and formulates a set of testable hypotheses and outlines the analytical approach used to test these hypotheses. Section 3 describes the sample, measures, and analytical procedures. Section 4 presents the results. Section 5 discusses the findings. Section 6 outlines study limitations, Section 7 proposes directions for future research, and Section 8 concludes.

2. Theoretical Background and Hypothesis

2.1. Contextual Background: Sickness Absence as a Societal and Organisational Challenge

Sickness leave is an important indicator of the labour market and public health, reflecting the health status of employees and the quality of the work environment, and placing a significant socioeconomic burden on (Chimed-Ochir et al., 2019). Demographic changes, including the ageing of society, exacerbate this problem as the proportion of the working-age population declines and the need to keep workers healthy for longer increases (Eurofound, 2023).

With the labour market becoming increasingly sluggish due to an ageing population and a growing number of employees retiring, retaining healthy and able-bodied employees is becoming a critical prerequisite for the sustainability of organisations (Dixon, 2003; Ilmarinen & Ilmarinen, 2015). Maintaining work ability is important not only from an economic perspective, but also from a psychological perspective, as the ability to work

directly affects employees' mental health and subjective well-being (Modini et al., 2016). The relevance of this issue is illustrated by Eurostat data—in the fourth quarter of 2020, sick leave among employees in the European Union was 2.3%, a slight increase compared to the beginning of the year and the previous quarter (2.0–2.1%) (Eurostat, 2020a). Overall, the evidence from 2023 Danish cohort study shows that most psychosocial working conditions are associated with higher sickness absence among younger employees (Sørensen et al., 2023). A 2024 population-based study from Sweden similarly concluded that stress from both mental and work-related sources predicted new episodes of sick leave lasting more than 14 days (Mehlig et al., 2024). In addition, recent prospective cohort study evidence from Finland demonstrates that reducing psychosocial risks can substantially decrease the likelihood of sickness absence, underscoring the importance of managing work-related stressors to prevent long-term absenteeism (Fagerlund et al., 2024). Comparable patterns have been reported in the United States, where sickness-absence rates increased from 2.2 percent in 2008 to 3.0 percent in 2020 and further to 3.6 percent in 2022, which represents a 64 percent rise over 14 years (United States Bureau of Labor Statistics, 2022). Similar post-pandemic dynamics have also been observed in healthcare settings, where job grade and psychosocial exposures remain strong predictors of both short- and long-term sickness absence (Sakr et al., 2025). Projections indicate that this upward trend is likely to accelerate in the coming years as population ages and a declining working-age labour force place additional pressure on labour markets. Consistent with these views, recent European panel data reveal that long-term sickness absence continues to rise steadily, particularly due to mental-health-related disorders. Taken together, these findings suggest that increasing psychosocial demands combined with insufficient organisational resources are key contributors to the persistence of sickness-absence trends across diverse labour markets.

In such circumstances, ensuring a healthy workforce that remains in the labour market becomes a strategic priority not only for organisations but also for society. Maintaining work ability is closely linked to mental health and subjective well-being, which ensure resilience to stress and promote long-term productive work ability (Modini et al., 2016). From an economic perspective, sick leave due to illness places a significant financial burden on organisations and healthcare systems. Studies point to significant financial losses associated with work-related illnesses and absenteeism in various European countries (Antczak & Miszczyńska, 2021). For example, sickness-related absenteeism in Latvia peaked between 2006 and 2020, reaching 112 percentage points, which ranks Latvia fourth in the EU in terms of growth rate. Latvia is also one of the EU countries with the highest correlation between sickness absence rates and labour costs, at 0.85 (Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia in the 0.61 to 0.99 range (Antczak & Miszczyńska, 2021).

In Latvia, sick leave in 2023 accounted for 9.3% of total working days for all employees, of which 46% was paid by the employer and 54% by the state. On average, this amounted to 13.7 sick days per employee in 2023, compared to 15.7 days in 2020 (Ministry of Health of the Republic of Latvia, 2024). In the European Union, the average for 2020 was 12.1 sick days per employee (IQR 1.8–14.8) (Eurostat, 2020a). In the European Union, health-related absences represent up to 4% of gross domestic product annually (WHO, 2025). Although Latvia's social protection expenditure on sickness and healthcare benefits as a share of GDP was among the lowest in the European Union in 2020, sick leave compensation nevertheless represents a substantial financial burden for employers (Eurostat, 2020b). Regulations stipulate that the first day of sick leave is unpaid, but the employer must pay sick pay from the second to the tenth day at a rate of at least 75% of the employee's average salary for each illness period. Starting from the 11th day of illness, a benefit of 80% of the salary is paid by the State Social Insurance Agency (2024).

In organisational management, employees are viewed as economic resources (i.e., as a cost to employers relative to their return on investment), and paid sick leave is a direct cost. However, the consequences go beyond direct costs; increased sick leave days can affect productivity, hinder team effectiveness, and burden existing employees who are forced to replace absent colleagues (Oke et al., 2016). In addition, long-term sick leave can reduce workforce stability in organisations and increase recruitment and training costs (Grønstad et al., 2019; Stoetzer et al., 2009). For employees and their families, sick leave can cause not only financial but also social difficulties. In addition, health-related absences often cause job insecurity and anxiety among employees, exacerbating their condition, and potentially leading to long-term illness (Henderson et al., 2011). The management of disease absence has also become one of the most serious problems for National Health Services (NHS), leading to increased operating costs and reduced service efficiency due to staff shortages (Kisakye et al., 2016). It has been shown that sick leave due to illness serves as a marker of mortality risk (Billingsley, 2020). This cyclical relationship highlights the need for preventive strategies that address both physical and mental health components, emphasising the importance of comprehensive health management in the workplace (Mess et al., 2024).

2.2. Sickness Absence Measurement: Conceptual and Methodological Challenges

Despite extensive research, assessing sick leave from work remains problematic due to various methodological limitations. There are divergent definitions of sick leave or absence due to illness, different inclusion and exclusion criteria, and differences in the populations being compared and in the accuracy of the data collected on sickness absence (Antczak & Miszczyńska, 2021). There is no internationally agreed definition of sick leave. The term is used interchangeably with sick days, sickness absence, and illness absence, while related indicators are often described as sick-leave measures. It can be measured in various ways—using self-reports, administrative data, clinical health assessments, or recording days of absence in public registers (Sumanen et al., 2015). Each approach has its limitations. For example, self-reports may be biased due to socially desirable responses or misunderstandings about sick leave entitlements (Weerdesteijn et al., 2020). Administrative data often only reflects the frequency or duration of absences but does not provide sufficient insight into the "health status" of the organisation. They can also be influenced by job security concerns or organisational culture, which creates the risk of a distorted picture of the real situation (Duchemin & Hocine, 2020). Clinical assessments provide a more accurate picture of the health status of employees who take sick leave, but this data is only available in publicly administered systems and is often restricted for privacy reasons. Therefore, policymakers should be particularly cautious when interpreting sick leave rates at national and international levels (Antczak & Miszczyńska, 2023).

Although measuring sick leave provides valuable information, significant challenges remain in accurately identifying the causes. Sick leave reflects multiple, interacting determinants, the causes of which go beyond medical conditions alone. Research confirms that it is influenced by individual, labour market, social, and demographic factors, as well as various organisational conditions (Sun et al., 2016). The most comprehensive study conducted to date, a review and meta-analysis of 109 studies, emphasised the importance of the work environment in explaining sickness absence and the role of mediating factors (Miraglia & Johns, 2016). The influence of psychological factors is particularly significant. Studies show that improving the psychosocial work environment promotes employee health and reduces the frequency of sick leave (Magee et al., 2016). Various unfavourable conditions can contribute to sick leave: poor work–life balance (Antai et al., 2015), low job control (Schulz, 2024), low social support (Silva-Junior & Fischer, 2015), poor psychosocial work

environment (Catalina-Romero et al., 2015), job dissatisfaction (Saastamoinen et al., 2014) and increased stress (Trybou et al., 2014).

2.3. Psychosocial Risks, Subjective Well-Being, and Health: Is the Link Indirect?

Over the last decade, employees' subjective well-being has been increasingly recognised as an important determinant of health and sickness absence. Empirical studies confirm that higher levels of well-being are associated with lower rates of sick leave, while lower satisfaction and negative emotional states significantly increase the risk of absenteeism due to sick leave (Colin-Chevalier et al., 2025). Recent evidence shows that elevated mental and work-related stress substantially increases the likelihood of prolonged sickness absence. A 2024 cohort study found that employees experiencing higher stress levels had significantly greater odds of taking sick leave lasting more than 14 days (Mehlig et al., 2024).

Despite significant research into sick leave, employee well-being and working conditions, there are still major gaps in the scientific literature on these topics. Much of the research to date has focused on specific sectors, such as healthcare, thus paying less attention to the unique challenges and characteristics of other sectors (Davey et al., 2009; Dyrbye et al., 2017; C. Roelen et al., 2014). Furthermore, there is also a limited amount of research analysing the impact of workplace well-being initiatives on sick leave in different professional contexts, especially in less researched areas (Nielsen et al., 2016).

Work environment factors that affect the health and sickness absence of employees are usually divided into psychosocial, (bio)mechanical, physical, and chemical work environment factors (Tynes et al., 2013). Most studies focus on mechanical risk factors for sickness absence, such as heavy physical work and heavy lifting (Andersen et al., 2016; Hanson et al., 2017; Sterud, 2014). In contrast, workplace factors related to physical and chemical working conditions have been studied less frequently, although they may be important in increasing sick days. Other studies have reported that combined "hazardous working conditions," such as dirt and dust, humidity, noise, solvents, or other irritants, are associated with higher levels of sick leave (Alfonso et al., 2016; Halonen et al., 2021; Mänty et al., 2022) and specific factors, including excessive noise (Clausen et al., 2009; d'Errico & Costa, 2012), body vibration (Barrero et al., 2019; Sterud, 2014), skin exposure to cleaning agents (Alfonso et al., 2016). In addition to these environmental exposures, recent studies have also emphasised that long commuting time can increase stress, reduce recovery periods, and indirectly contribute to health deterioration and sickness absence (Gimenez-Nadal et al., 2022; Hansson et al., 2011). Therefore, commuting time was included in this study as an additional work-related factor potentially influencing sickness absence. These indicators show a positive correlation with higher levels of sickness absence in studies of the working population. Work environment factors that affect the health and sickness absence of employees are usually divided into psychosocial, (bio)mechanical, physical, and chemical work environment factors (Tynes et al., 2013). Most studies focus on mechanical risk factors for sickness absence, such as heavy physical work and heavy lifting (Adam et al., 2018; Andersen et al., 2016; Hanson et al., 2017; Sterud, 2014). In contrast, workplace factors related to physical and chemical working conditions have been studied less frequently, although they may be important in increasing sick days. Other studies have reported that combined "hazardous working conditions," such as dirt and dust, humidity, noise, solvents, or other irritants, are associated with higher levels of sick leave (Alfonso et al., 2016; Halonen et al., 2021; Mänty et al., 2022) and specific factors, including excessive noise (Clausen et al., 2009; d'Errico & Costa, 2012), body vibration (Barrero et al., 2019; Sterud, 2014), skin exposure to cleaning agents (Alfonso et al., 2016). In addition to these environmental exposures, recent studies have also emphasised that long commuting time can increase stress, reduce recovery periods, and indirectly contribute to

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In recent years, an increasing number of prospective studies have confirmed the significant role of psychosocial work factors in the risk of sickness absence (Aagestad et al., 2014; Duchaine et al., 2020). Schaufeli and Taris have also emphasised that in an organisational context, a diverse range of job demands and resources must be taken into account, identifying 30 different types of demands and 31 types of resources (Schaufeli & Taris, 2014). Similarly, the OECD job quality assessment system emphasises not only economic but also non-economic aspects of the work environment, such as the nature and content of work, the organisation of working time, and interpersonal relationships (OECD, 2017a). Empirical evidence indicates that several factors in the work environment directly or indirectly influence the frequency of sick leave, including high job demands (Nyberg et al., 2022), low levels of autonomy (Johannessen et al., 2015), and insufficient job support (Kuoppala et al., 2008). In addition, psychosocial factors in the work environment are closely linked to the risk of sickness absence. Scientific studies confirm that emotional demands significantly increase the likelihood of long-term absence, especially for employees with increased susceptibility to stress (Aagestad et al., 2014; Framke et al., 2019, 2021). Similarly, role conflicts have been identified as a significant risk factor contributing to the frequency of sick leave (Aagestad et al., 2014; Rugulies et al., 2010). However, existing empirical evidence provides different and sometimes even contradictory conclusions. In one case, job control or autonomy is seen as a resource that reduces workload, improves health and well-being, and reduces the risk of absenteeism due to sick leave (Gerich, 2019). Other studies, however, show that high demands and complex tasks may not increase risk, but rather promote work engagement and motivation, reducing sick leave (Ko & Glied, 2021; Miraglia & Johns, 2016). In recent years, an increasing number of prospective studies have confirmed the significant role of psychosocial work factors in the risk of sickness absence (Aagestad et al., 2014; Duchaine et al., 2020). Schaufeli and Taris have also emphasised that in an organisational context, a diverse range of job demands and resources must be taken into account, identifying 30 different types of demands and 31 types of resources (Schaufeli & Taris, 2014). Similarly, the OECD job quality assessment system emphasises not only economic but also non-economic aspects of the work environment, such as the nature and content of work, the organisation of working time, and interpersonal relationships (OECD, 2017a). Empirical evidence indicates that several factors in the work environment directly or indirectly influence the frequency of sick leave, including high job demands (V. Aronsson et al., 2018; Nyberg et al., 2022), low levels of autonomy (Johannessen et al., 2015), and insufficient job support (Kuoppala et al., 2008). In addition, psychosocial factors in the work environment are closely linked to the risk of sickness absence. Scientific studies confirm that emotional demands significantly increase the likelihood of long-term absence, especially for employees with increased susceptibility to stress (Aagestad et al., 2014; Framke et al., 2019, 2021). Similarly, role conflicts have been identified as a significant risk factor contributing to the frequency of sick leave (Aagestad et al., 2014; Rugulies et al., 2010). However, existing empirical evidence provides different and sometimes even contradictory conclusions. In one case, job control or autonomy is seen as a resource that reduces workload, improves health and well-being, and reduces the risk of absenteeism due to sick leave (Gerich, 2019). Other studies, however, show that high demands and complex tasks may not increase risk, but rather promote work engagement and motivation, reducing sick leave (Ko & Glied, 2021; Miraglia & Johns, 2016).

This contradictory nature is also reflected in the role of social relationships: although trusting relationships with managers and colleagues are generally considered a protective factor, they can also create indirect pressure to come to work even when sick, thus functioning more as an additional demand than a resource (MacGregor et al., 2008). Furthermore, there are not many studies that have assessed the risk of sick leave associated with employees' subjective well-being and combinations of various working conditions, which could provide a more comprehensive understanding of the impact and offer a solid basis for the development of preventive measures. Comparability is hampered by differences in how well-being is operationalised and measured in studies. There are various systems and instruments that attempt to capture and assess the complexity of employee well-being. The most commonly used ones are WHO-5, the Job Demands-Control Model (Bakker & Demerouti, 2017), PERMA (Seligman, 2011), the Psychological Capital (PsyCap) framework (Luthans & Youssef, 2007). Scientific literature increasingly emphasises the need to develop more nuanced and specific well-being measurement tools for the workplace that are capable of capturing multidimensional aspects of well-being, rather than limiting themselves to general job satisfaction or work environment factors (De Neve et al., 2013).

2.4. The Job Demands–Resources Model as the Conceptual Framework of the Study

The Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2017) provides a comprehensive and flexible framework for understanding how work environment characteristics influence employees' well-being, health, and behavioural outcomes, including sickness absence. The model conceptualises all job characteristics within two overarching dimensions: job demands and job resources. Job demands, such as workload, time pressure, or exposure to physical and health risks, require sustained physical and psychological effort and are therefore associated with strain and depletion of energy. When such demands are not offset by adequate job resources, chronic strain may accumulate, increasing the likelihood of adverse health outcomes and sickness absence (Bakker & Demerouti, 2017; Demerouti et al., 2001).

Conversely, job resources, including autonomy, social inclusion, supportive relationships, and opportunities for professional development, fuel the motivational process by fostering work engagement, satisfying basic psychological needs, and enhancing subjective well-being. Job resources may also buffer the detrimental effects of high job demands, thereby reducing stress-related health impairment and the risk of subsequent absence (Schaufeli & Taris, 2014).

The JD-R model is particularly relevant for explaining sickness absence because it articulates a clear psychosocial → well-being → health → behaviour pathway. According to the health-impairment process, prolonged exposure to high job demands leads to strain, which manifests as health complaints before translating into actual sick leave behaviour (Bakker & Demerouti, 2017). Strain-related indicators, such as subjective health complaints and psychosomatic symptoms are thus considered proximal mediators, transmitting the influence of adverse working conditions to health deterioration and eventually sickness absence (van Veldhoven et al., 2017). This mediational logic is well supported by empirical evidence. Studies show that stress symptoms, psychosomatic complaints, and reduced well-being reliably precede sick-leave episodes (Miraglia & Johns, 2016; Nielsen et al., 2016). Moreover, subjective health complaints repeatedly emerge as strong predictors of absenteeism, reinforcing the JD-R proposition that sickness absence reflects not only medical necessity but also employees' behavioural response to accumulated psychosocial strain (Bakker et al., 2014).

2.5. Hypothesis and Analytical Approach

Building on the theoretical underpinnings developed in the previous sub-sections-conceptual hurdles for measuring sickness absence; indirect pathways from psychosocial risk, through subjective well-being, to health; and the JD-R model as the overarching explanatory framework-the present study now formulates a set of hypotheses which integrate those insights into a coherent analytical strategy. The literature thus underlines that there is a need for comparative, cross-sectoral evidence and theoretically framed models which capture not only direct but also health-mediated associations between work environment factors and sickness absence.

Accordingly, the present study examines how job demands, job resources, subjective well-being, and self-reported health problems jointly shape sickness absence among Latvian employees in four different sectors. Guided by the Job Demands-Resources (JD-R) model and the WHO-5 framework, the hypotheses reflect the assumption that psychosocial working conditions influence sickness absence both directly and indirectly through health-related strain processes.

To model subjective well-being, the WHO-5 Well-Being Index is used—a validated instrument widely employed in population health studies. In line with the JD-R model, subjective well-being is conceptualised as both an outcome of job characteristics and a potential pathway influencing health status and absence behaviour.

Based on the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2017), which explains how job demands and resources jointly influence employee health and well-being, the following hypotheses were formulated and tested using Tweedie Regression Models and Structural Equation Modelling (SEM):

H1a. *Higher levels of subjective well-being are associated with fewer sickness absence days.*

H1b. *Greater access to job resources, specifically autonomy, social inclusion, and professional growth is negatively associated with the number of sick leave days.*

H1c. *Increased job demands, measured as work intensity and perceived health risks, are positively associated with the number of sick leave days.*

H1d. *The presence of self-reported health problems is positively associated with the number of sick leave days.*

H2a. *The relationship between subjective well-being and sickness absence is mediated by self-reported health problems.*

H2b. *Demographic covariates (e.g., age, tenure, and employment sector) may confound or moderate the relationships between psychosocial factors, health problems, and absence of sickness.*

To address these hypotheses, the study applied a three-step analytical strategy:

Descriptive analysis—to examine similarities and differences in sickness absence rates across four organisations representing different sectors, as well as between gender groups.

Regression modelling—to develop and evaluate a direct relationship model including employees' subjective assessments of psychosocial well-being, health status, and commuting time, together with objective data on sickness absence.

Structural equation modelling (SEM)—to analyse the interrelations between sickness absence, subjective well-being, psychosocial work environment factors, and self-reported health problems over the past 12 months.

3. Materials and Methods

3.1. Study Design

This study employed a cross-sectional design with a multistage non-probability sampling strategy. In the first stage, organisations were selected through convenience sampling based on their willingness to participate and their relevance to the targeted economic sectors. In the second stage, all employees within these organisations were invited to participate. This resulted in a census-type sampling of the available workforce. The final sample included employees from organisations operating in four professional fields in Latvia: administrative and support services, healthcare, pharmaceuticals, and energy. These covered both public and private sector contexts. This approach provided insight into diverse occupational environments rather than representing entire sectors. Participation was voluntary and anonymous. Data collection was conducted during regular working hours to facilitate broad employee engagement. Although population-level representativeness could not be established, the participating organisations were among the largest and most typical employers in their respective sectors. This provided a credible reflection of sectoral working conditions and employee experiences. Data were collected from two complementary sources: self-reported survey data on psychosocial work environment factors and subjective well-being, and administratively recorded information on sectoral and organisational characteristics. Integrating these data sources enhanced internal validity and supported a comprehensive assessment of workplace conditions and well-being in different professional contexts in Latvia.

3.2. Participants

A total of approximately 2000 potential participants were approached, of whom 1628 provided valid and fully completed responses, achieving a high response rate of 81.6%. The non-response rate was 18.4%, which confirms the good quality and acceptable representativeness of the data. The selection of respondents was based on the following inclusion criteria: (1) at least 18 years of age, (2) active employment status (full-time or part-time), and (3) sufficient Latvian language skills to understand the questionnaire and obtain reliable data. The sample reflected a range of organisational settings, including administrative and support services, healthcare, pharmaceuticals, and energy. While no claims of demographic representativeness can be made, the inclusion of sectors with different occupational profiles allowed for the examination of how work environment factors and health problems relate to sickness absence in varied organisational contexts. Data collection took place in Latvia between July and September 2024 using a secure online survey platform.

3.3. Procedure

The study was approved by the Ethics Committee of Riga Stradiņš University, Riga, Latvia (Decision No. 2-PEK-4/495/2024). The survey was distributed through partner organisations, covering employees of private companies, state-owned companies, and state institutions in various cities in Latvia. The organisations and their employees were informed that this was a non-commercial research initiative to develop a tool for measuring employee psychological well-being and analyse the relationships between various concepts related to the work environment and health. This study employed a survey instrument developed within the framework of the same research project. Data collection was conducted online between July and September 2024 using the internal communication channels of the participating organisations and personalised email invitations. All potential participants were informed about the objectives of the study, the procedure, the expected duration of the survey, the data processing principles, and confidentiality before the survey began.

Participation in the study was emphasised as voluntary and anonymous, without any risks to participants, with the right to withdraw at any time without negative consequences. At the beginning of the survey, all respondents gave their informed consent to participate. To ensure enough responses, respondents received reminder letters every two weeks. In total, approximately 2000 employees from four industry organisations were contacted. Respondents were guaranteed complete anonymity, and all data obtained was processed and stored in accordance with the requirements of the General Data Protection Regulation (GDPR), ensuring the protection and confidentiality of personal data throughout the study. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki (World Medical Association, 2013), which emphasise respect for human rights, participant autonomy, and data security in scientific research.

3.4. Measures

3.4.1. Dependent Variable: Sick Leave

In this study, absence due to sick leave was identified as the dependent variable and was determined using administrative data from the participating organisations. These organisations provided information on the total number of sick days taken by each employee in 2023 who completed the questionnaire. Sick days were defined as any days absent due to health problems, including childcare responsibilities, but excluding postnatal leave. In Latvia in 2023, however, childcare leave accounted for 9.2% of the total number of sick days, meaning it was included in this definition. The data was provided in a coded format (data pseudonymisation) to preserve the complete anonymity of participants and organisations.

In cases where an employee had not taken any sick leave during the period in question, the number of sick days was recorded as zero.

3.4.2. Independent Variables

Each of the items on job demands and job resources were selected based on a comprehensive review of the European Quality of Life Survey (EQLS), European Social Survey (ESS) The Flash Eurobarometer on Working Conditions capturing the non-economic aspects of job quality, such as work–life balance, the meaningfulness of work, workplace relationships intensity learning and training opportunities, mental and physical risk factors.

The Multidimensional Scale of Psychosocial Well-Being for Employed Persons (MPSWEP), previously developed and validated by the research team, was used to assess employees' psychosocial and subjective well-being. The instrument comprises six factor scales—subjective well-being, autonomy, job demands, social inclusion, professional development, and health risks—reflecting the multidimensional nature of well-being. All items were rated on a seven-point Likert scale (1 = "strongly disagree"/"never", 6 = "strongly agree"/"always", 7 = "cannot answer", coded as missing). The complete survey questionnaire is provided in Supplementary Material. The factor structure of the instrument was evaluated using both exploratory and confirmatory factor analyses. Each psychosocial factor was treated as a separate construct, and the score for each scale was calculated as the mean of its item scores. The instrument demonstrated robust psychometric properties: Cronbach's α ranged from 0.74 to 0.90 across scales; item discrimination indices (DI) ranged from 0.46 to 0.79; composite reliability (CR) ranged from 0.66 to 0.93; and the average variance extracted (AVE) ranged from 0.49 to 0.75, supporting adequate internal consistency and convergent validity. These findings confirm that the MPSWEP is a reliable and valid instrument for assessing employees' psychosocial well-being and is suitable for further statistical modelling in this study. The psychometric properties presented in Table 1 demonstrate robust scale quality.

Table 1. Measurement instrument MPSWEP: factors, items, response scales, internal consistency, and number of items.

Factors /Reference	Example of Items	Number of Items	Scale	Cronbach's Alpha	Diff	DI	CR	AVE
Subjective well-being (Eurofound, 2018)	WHO-5: How often do you feel that you are living a full life? (Eurofound) How often do you feel that your life is in balance (work and personal time)?	7	0—Never 1—Rarely 2—Less than half the time 3—More than half the time 4—Most of the time 5—Always	0.90	3.78–4.42	0.63–0.79	0.93	0.652
Autonomy (Eurofound, 2017)	How often can you choose your own working methods or change them at your own discretion?	2	1—Never 6—Always 7—I don't want to answer	0.8	3.64–4.00	0.66	0.697	0.697
Job intensity (Eurofound, 2017)	How often do you have to work fast at high speed?	3	1—Never 6—Always 7—I don't want to answer	0.74	3.03	0.46–0.63	0.78	0.536
Social Inclusion (Eurofound, 2017; OECD, 2017b)	How often do you feel that you can influence decisions that are important for your work?	6	1—Never 6—Always 7—I don't want to answer	0.83	3.23–4.85	0.52–0.66	0.86	0.494
Growth (Eurofound, 2017)	Over the past year, I have received training that improves my future job prospects	3	1—Yes 2—No	0.78	4.09–4.55	0.50–0.68	0.90	0.755
Health risks (Eurofound, 2017; OECD, 2017a)	How often are you exposed to noise at work?	2	1—Never 6—Always 7—I don't want to answer	0.8	2.56–2.8	0.67	0.86	0.751
Health problems (Eurofound, 2017)	Have you noticed any symptoms of mental ill health in yourself in the last 12 months?	2	1—Yes 2—No 3—I don't want to answer (coded as missing)	0.78				0.691
Sick days (data administered by organisations)	Please indicate the sick days of employee (code…) in 2023 (excluding postnatal leave)		-	-	-	-	-	-
Commuting time (Eurofound, 2017)	1 (multiple choice) How much time do you spend commuting to and from work each day?	1	1—Up to 30 min 5—More than 3 h	-	-	-	-	-

Notes: Discrimination index = DI; Composite Reliability = CR; AVE = Average variance extracted > 0.50, Diff = difficulty index. Likert scale (6-point): normative range 2.0–5.0, Dichotomous scale: normative range 1.2–1.8; DI normative range: 0.2–0.8 (Klein-Braley, 1997).

3.4.3. Employees' Subjective Well-Being

As a part of this study, a survey instrument (questionnaire) was developed based on internationally recognised conceptual frameworks: The World Health Organisation's WHO-5 five-item well-being index (World Health Organization Regional Office for Europe, 1998; Topp et al., 2015) as well as the Organisation for Economic Cooperation and Development (OECD) guidelines for measuring psychosocial and subjective well-being (OECD, 2013a). The OECD defines subjective well-being as an individual's comprehensive cognitive and emotional assessment of their quality of life, which includes a balance of positive and negative emotions, satisfaction with life and work, as well as a subjective sense of meaning and motivation in life (OECD, 2013a). The WHO-5 well-being index, on the other hand, consists of five simple statements that allow respondents to report on their subjective well-being and mood over the past two weeks. The survey used a scale consisting of all WHO-5 items and two additional items describing life balance and fulfilment.

3.4.4. Autonomy

The OECD defines autonomy in the workplace as the degree to which employees have the freedom to make decisions about their work tasks and work schedule (OECD, 2013b). Autonomy is recognised as one of the key indicators of job quality, closely linked to positive work outcomes, including higher job satisfaction, greater motivation, and improved overall well-being. The OECD concludes that employees with higher levels of autonomy are more engaged in their professional roles and exhibit better mental health indicators.

According to the OECD, there are several dimensions of autonomy in the work environment:

Decision-making autonomy—the ability of employees to make decisions related to their job responsibilities without excessive external pressure or strict rules.

Control over work tasks—the ability to determine how employees organise and perform work tasks that promote efficiency and professional development.

Flexibility in the work environment—the ability to manage working conditions and schedules, which promotes a balance between work and private life.

3.4.5. Job Intensity

The OECD defines job demands as the physical, psychological, social, or organisational aspects of work that require sustained or excessive effort from employees. Such conditions can have significant physical and psychological costs, affecting employee health, job satisfaction, and subjective well-being. Empirical studies confirm that increased work demands are often associated with increased stress, which in turn contributes to higher absenteeism and employee turnover. The scale used in this study included two central dimensions—workload and time pressure, which reflect the amount of work and the need to complete tasks within set deadlines (OECD, 2013a, 2019).

3.4.6. Social Inclusion

Multidimensional construct recognised by both the OECD and the Job Demand-Control (JDC) model. It emphasises the importance of equal access, support networks, and active participation in organisational and social contexts. Promoting social inclusion in organisations can improve employee well-being, reduce absenteeism due to illness, and foster a positive workplace culture that benefits both employees and organisations themselves. Within the JDC model, social inclusion is closely linked to social support and relationships in the work environment, which act as protective factors against the negative effects of a demanding work environment.

3.4.7. Sub-Factors

Social support—a strong sense of social inclusion ensures access to emotional and instrumental support from colleagues.

Cooperation and team dynamics—effective teamwork and healthy relationships in the workplace promote an inclusive environment, allowing employees to share experiences, manage stress together, and improve overall well-being (Karasek, 1979; Ogbonnaya, 2019).

3.4.8. Growth

The Organisation for Economic Co-operation and Development (OECD, 2013a, 2019) emphasises professional career growth as an important factor influencing individuals' employment opportunities, economic mobility, and overall well-being. Professional career growth encompasses several interrelated dimensions that are essential for sustainable employment and employee development:

Skills development—continuous learning and training to acquire new competencies necessary for career growth and adaptability to a changing labour market.

Career growth opportunities—access to promotions, professional recognition, and development opportunities within the organisation or industry.

Supportive work environment—organisational policies and practices that promote individual growth, provide mentoring, and create opportunities for leadership positions.

The combination of these elements forms the basis for the professional development of employees, promotes employment stability and contributes to both individual well-being and organisational sustainability.

3.4.9. Health Risks

Research shows that subjective health risk assessments in relation to the work environment are an important tool for identifying health risks associated with exposure in the work environment, including noise and chemicals. According to the OECD definition, physical risk factors describe the degree to which work involves conditions that could potentially impair the physical health of workers. These factors can be perceived subjectively or experienced directly, and their prevalence varies across occupations and overtime. International data sources such as the European Working Conditions Survey (EWCS), ad hoc modules of the EU Labour Force Survey (LFS) and the Eurobarometer Flash module, cover a wide range of risk factors to which workers are exposed, including noise, fumes, vapours, and radioactive radiation.

This study used questions about how often employees had been exposed to these risks in the last 12 months (OECD, 2017a). Empirical evidence shows that subjective health assessments provide important information about the impact of the work environment on health. For example, Usmani et al. (2020) show that such assessments are important for understanding the potential risks associated with exposure to chemicals in the workplace. They not only help to identify potential health effects but also serve as a tool for developing policies and strategies aimed at improving working conditions, reducing the risk of occupational diseases, and reducing the incidence of sick leave.

3.4.10. Health Problems or Subjective Health Assessments (SHA)

This factor characterises psychosomatic symptoms that reflect both physical and mental well-being. Studies show that subjective health complaints are sensitive indicators of the adverse effects of the work environment and are often associated with the use of sick leave (Niedhammer et al., 2021; C. A. Roelen et al., 2010). The literature emphasises that approximately one-fifth of consultations by general practitioners are related to subjective complaints, which account for more than half of long-term absences (Aakvik et al., 2010;

Burton, 2003). SHA is widely used as a valid and cost-effective health indicator in psychosocial and epidemiological studies, and its predictive ability for future health outcomes, particularly mortality, has been demonstrated (Idler & Benyamini, 1997).

In this study, the health problems indicator was constructed using a battery of questions from the European Working Conditions Survey (Eurofound, 2017). The two-item scale (physical and mental health symptoms) showed moderate internal consistency (Cronbach's $\alpha = 0.61$; Cohen's Kappa = 0.405, $p < 0.001$), which is psychometrically acceptable in the case of binary indicators (Briggs & Cheek, 1986). Based on the results, a summarised scale with binary classification was created: "Yes" (1) or "No" (0) symptoms of health problems.

3.5. Covariates

Additional analyses included demographic indicators from the survey, including gender, age, type of a company, length of service in the current organisation, and average daily commute time to and from work.

3.6. Methods

The processing of research data involved several stages. First, descriptive statistics were calculated and the psychometric quality of the scales used was assessed. Spearman's and Kendall's Tau-b correlation coefficients were used for nominal data to determine the mutual associations between variables, while Mann–Whitney U and Kruskal–Wallis tests were used to compare groups. The variable of sick days was then analysed as a continuous indicator, but the data distribution was characterised by a large proportion of zero values (respondents without sick leave) and a positive skew. This type of distribution corresponds to the combined Poisson–gamma distribution, which belongs to the broader Tweedy distribution family and is widely used in healthcare data modelling because it characterises continuous, positively skewed data with zero inflation (Hasan & Dunn, 2011). Based on this, a generalised linear model (GLM) with a Tweedie log-link function was created to analyse non-specific sickness days as the dependent variable. The Tweedie distribution is particularly suitable when the data has continuous distribution and zero inflation that does not fit Poisson or Gamma distributions (Kurz, 2017). As with other GLMs, Tweede models help determine how independent variables (e.g., age, health status) affect the mean and median values of the dependent variable (e.g., sick days). In addition, sensitivity analysis and a bootstrap procedure with 5000 re-samples were performed to test the robustness of the results. To characterise the discriminatory power of the sickness day classification model, the area under the ROC curve (AUC) was calculated, defining the categories: 0—no sickness days (0–1 day) and 1—sickness days ≥ 2. Finally, Structural Equation Modelling (SEM) was used to test the mediation effects, examining how psychosocial work factors and subjective well-being were related to health problems and, indirectly, to the number of sick-leave days. Both a baseline SEM and a model including demographic and organisational control variables (age, tenure, sector) were estimated. Mediation paths were evaluated using standardised effects and bias-corrected bootstrap confidence intervals, and additional WLSMV/MLR corrections were applied because the mediator (health problems) was binary.

The model fit was evaluated using conventional indices, including χ^2 goodness-of-fit test, Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The mediation effects were estimated based on standardised path coefficients (β), and their significance was assessed using bootstrap confidence intervals with 5000 resamples.

Data management and statistical analyses were conducted using R (Version 4.5.2) within the RStudio integrated development environment and IBM SPSS Statistics (Version

31). R and RStudio were used for advanced statistical modelling and reproducible analyses, while SPSS was employed for data preparation and preliminary statistical procedures.

4. Results

4.1. Sample Characteristics

The analysis included 1628 respondents, of whom 65% were women and 35% were men. The average age of women was 46.95 years (SD = 13.0), the median was 48 years, and the average length of service in the current organisation was 12 years (SD = 13.4; median = 9). The average number of sick days for women was 13.84 days (SD = 24.18; median = 5). The average age of men was 43.8 years (SD = 11.4), the median was 43 years, and the average length of service in the organisation was 14 years (SD = 11.0; median = 11). The average number of sick days for men was 7.97 days (SD = 16.04; median = 0). There are statistically significant differences between the sexes in the distribution of sick days (Welch's (1566) = 5.86; $p < 0.001$; Cohen's d = 0.286; $p < 0.001$).

In terms of sectors, 17% of respondents worked in public administration, where 81% were women and 19% were men. The healthcare sector employed 26% of respondents (women—92%, men—7%). 27% worked in the pharmaceutical manufacturing sector (women—65%, men—35%), while 29% worked in the energy services sector (men—69%, women—31%). The distribution of sick leave days by sector is shown in Table 2.

Table 2. Sick days in companies in various sectors in 2023 (administrative data).

Descriptive Statistics Sick Leave Days 2023								
Type of Company	**N**	**Minimum**	**Max**	**Mean**	**Std. Deviation**	**Median**	**Skewness**	**Kurtosis**
All	1631	0	196	11.75	21.81	3	3.57	17.23
Public administration (1)	281	0	180	9.57	19.36	0	4.12	25.59
Healthcare Hospital (2)	421	0	196	17.76	28.65	7	2.81	10.04
Energy (3)	488	0	140	9.31	16.50	0	3.51	18.40
Pharma (4)	441	0	151	10.12	19.81	3	3.81	18.14

Notes: Kruskal-Walis $\chi 2$ (3) = 33.7, $p < 0.001$, $\varepsilon^2 = 0.012$; DSCF pairwise comparisons show statistically significant difference in healthcare sector from all other sectors $p < 0.001$.

4.2. Regression Analysis of Sickness Absence Using Tweedy GLM

This section summarises the results on the relationship between employee sick days and subjective well-being, health status, and psychosocial factors in the work environment, using GLM with Tweedie log-link functionality and SEM. The analysis uses three cpglm models (Table 3) with Tweedie distribution and two structural equation modelling (SEM) models with mediation through health problems. Since the sick leave data were very heterogeneous, bootstrapping and sensitivity analyses were performed in addition to the statistical model to further assess the stability of the results. Model with statistically significant variables (Model 2) (Model 1—all variables and Model 2—only statistically significant variables, to which the variable "commuting time" was added—a dummy variable (question "Please indicate how much time you spend per day traveling to/from work to home"), with a bootstrapping *t*-test (recalculating coefficients for 5000 samples) and sensitivity analysis excluding extreme cases.

The performance of GLM Tweedy logarithmic function models was evaluated using several criteria. The multicollinearity index (VIF) was below 2.3, indicating acceptable mutual correlation between independent variables. The suitability of the models was characterised by AIC values (7568.43–7169.40), which showed a gradual improvement in the selection of the optimal model. Pseudo McFadden's R^2 ranged from 0.19 to 0.20,

which is acceptable for GLM-type models, considering that values around 0.20–0.40 are already considered good (Cox, 2018). Nagelkerke R^2 showed a relatively high value (0.92), which most likely reflects an overestimated explanatory power of the model, especially considering the not normal distribution of the data. In turn, the automatically adjusted Twedie power parameter (1.4–1.3) shows that the data lies between Poisson (p = 1) and Gamma (p = 2), which corresponds to the study data and indicates suitability for positive numerical variables with a pronounced proportion of zero values, making this model appropriate for predicting the number of sick days.

Table 3. Regression models with Tweedy distribution.

	Model 1		**Model 2**		**Model 3**
			Bootstrapping	Sensitivity test	
Variables	Est. coefficient, sig	Est. coefficient, sig	Est. coefficient, sig	Est. coefficient, sig	Est. coefficient, sig
Health risks	0.1034	n.s.	n.s.	0.100 ***	0.09
Autonomy	0.1925	(−0.092) **	(−0.09) ***	−0.181	(−0.082) *
Health problems	0.460	0.447	0.45 ***	0.845 ***	0.398 ***
Healthcare sector	0.402	0.461	0.46	0.819	0.354
Energy services	n.s.	n.s.	n.s.	0.502 ***	n.s.
Manufacturing	n.s.	n.s.	n.s.	0.064 ***	n.s.
Gender	(−0.367) **	(−0.362) **	(−0.36) **	(−0.640) ***	(−0.236) *
Seniority in years	0.010	0.010	n.s.	0.012 ***	0.011
commuting time_2		0.236 **	n.s.	0.352 ***	0.247 *
commuting time_3			n.s.	0.308 ***	n.s.
commuting time_4			n.s.	(−0.146) ***	n.s.
commuting time_5			n.s.	1.024 **	n.s.
Pseudo R^2 (Mc Fadden's)	0.1992	0.1925			0.198
AIC	7568.43	7652.428			7169.4

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; Industry categories were compared against the public sector; gender coded as male vs. female; commuting time compared to "≤30 min per day," with commuting time 2 representing 0.5–1 h per day; Model 1—Generalized Linear Model with Tweedie distribution and log-link function (all predictors, excluding commuting time); Model 2—Generalized Linear Model with Tweedie distribution and log-link function (only significant predictors, including commuting time); additional Bootstrap sensitivity analysis of Model 2 (Tweedie log-link model; 5000 resamples); and Sensitivity analysis of Model 2 excluding extreme observations; Model 3 including statistically significant and excluding extreme cases (final sample: n = 1362).

The main objective of the bootstrap analysis was to assess the stability and robustness of the regression results by calculating confidence intervals for the coefficients, thus going beyond standard errors based on classical assumption methods. This procedure was applied only to Model 2, as it was identified as a valid model that provides an optimal balance between simplicity and explanatory power. It included only statistically significant variables from the full model (Model 1), as well as relevant covariates and commuting time variables. Model 2 was also subjected to a sensitivity test to assess whether the results of the main model (Model 2) remained valid after the exclusion of extreme cases. This was considered a secondary step in the analysis, maintaining an identical model structure to Model 2. Model 3, on the other hand, was developed to test whether the explanatory power of the main model (Model 2) is significantly altered after excluding extreme values compared to the original model. All models examined (1, 2, and 3) demonstrated a stable McFadden pseudo-R^2 value (~0.20), confirming good explanatory power and robustness of results with respect to the impact of extreme observations. In turn, Model 3 was used

to assess the relationship between days of work incapacity and subjective well-being, subjectively reported health problems, and work environment factors, as it showed the best performance and explanatory power parameters (AIC = 7169.4, McFadden = 0.198, n = 1360), which, according to Hughes et al.'s interpretation, indicates sufficient explanatory power in behavioural and health studies. In addition, the model had the lowest AIC value (7169.4) compared to other tested models, indicating an optimal balance between explanatory power and model complexity (Hughes et al., 2019). The model included the most significant factors—statistically significant variables according to Model 2, health problems, demographic variables, industry, and commuting time indicators.

Analysis of the data obtained identified several statistically significant factors that influence the number of days of incapacity for work:

Health problems (estimate = 0.398, $p < 0.001$) emerged as the central factor most strongly associated with a higher number of sick days, supporting H1d. Work environment risks, including exposure to noise and chemicals (estimate = 0.090, $p = 0.015$), also showed a significant positive relationship with the number of days of incapacity for work, in line with H1c.

Work autonomy (estimate = –0.082, $p = 0.039$) demonstrated a negative association with sick days, suggesting that employees with greater autonomy tended to report fewer absences, thereby supporting H1b. Employment in the healthcare sector (estimate = 0.354, $p = 0.018$) was linked to a higher predicted number of sick days compared with other sectors. Gender differences were also observed, with men reporting fewer sick days than women (estimate = –0.236, $p = 0.030$). Length of service (estimate = 0.011, $p = 0.017$) showed a modest positive association with sick leave, while commuting time between 30 and 60 min was related to more sick days compared with shorter commutes (<30 min) (estimate = 0.247, $p = 0.011$) (see Table 3).

Contrary to the initial hypothesis, no significant direct association was found between subjective well-being and the number of sick days, leading to the rejection of H1a. This result suggests that subjective well-being may be indirectly related to sickness absence through health problems or other mediating factors, which should be explored in future studies using alternative modelling approaches. Age was not statistically significant and was therefore excluded from the final analysis.

4.3. Indirect Effect of Subjective Well-Being on Sick Days: Results of Regression and SEM Analyses

Since subjective well-being was not identified as a direct factor associated with sick days in the GLM analysis, it was assumed that its relationship with sickness absence might be indirect and operate through mediation. To test this mechanism and better understand the role of psychosocial factors, including subjective well-being, in sickness absence, two structural equation models (SEM) were estimated: Model 1 without control variables and Model 2 with demographic and organisational controls. This approach enabled the evaluation of both direct and indirect associations between psychosocial factors, health problems, and sick days. Given that the mediator's health problems were measured as a binary variable, the SEM model with control variables was additionally subjected to robust estimation using WLSMV and MLR corrections, which is the appropriate procedure for models that include categorical endogenous variables. This ensured the stability and reliability of the estimated indirect effects.

Model 1: SEM without control variables

In the first step, Model 1 estimated the core psychosocial pathways. Lower subjective well-being ($\beta = –0.271$, $p < 0.001$), higher job demands ($\beta = 0.261$, $p < 0.001$), and fewer growth opportunities ($\beta = 0.079$, $p = 0.01$) were significantly associated with a higher

likelihood of reporting health problems. Health problems, in turn, showed a strong positive association with the number of sick days (β = 0.146, $p < 0.001$).

These results supported H2a, indicating that subjective well-being is indirectly related to sickness absence through health problems. Model 1 explained 32% of the variance in health problems and 7.5% of the variance in sick days.

Model 2: SEM with control variables

Model 2 incorporated demographic and organisational controls (age, tenure, company type). The inclusion of controls slightly strengthened the associations for several pathways. The effect of subjective well-being on health problems increased (β = –0.329, $p < 0.001$), job demands showed a stronger link to health problems (β = 0.329, $p < 0.001$), and health problems showed a larger association with sick days (β = 0.232, $p < 0.001$).

Importantly, some relationships became significant only after controls were included. Work environment health risks (F5) were positively associated with sick days (β = 0.088, $p = 0.043$), while autonomy showed a protective association (β = –0.079, $p = 0.021$). In addition, age (β = 0.091, $p = 0.018$) and employment in the healthcare sector (β = 0.118, $p = 0.011$) were associated with higher levels of sickness absence.

Model 2 showed small improvements in explanatory power ($R^2 = 0.326$ for health problems; $R^2 = 0.081$ for sick days), indicating that demographic and structural factors contribute meaningfully to the overall model (see Table 4).

The increase in path coefficients in Model 2 indicates that the covariates functioned as suppressor variables, clarifying relationships that were partially obscured in Model 1. When variance attributable to age, tenure, and sector was controlled and when estimates were verified through robust WLSMV/MLR procedures appropriate for the binary mediator, the independent associations of subjective well-being, autonomy, growth, and job demand with health problems and sick days became stronger. Notably, the path from subjective well-being to health problems increased by 21.8%, and the path from health problems to sick days increased by 56.8%.

Despite these quantitative changes, the qualitative pattern remained stable, confirming the robustness of the hypothesised mediating pathway. The strengthened Job Demands → Health Problems link in Model 2 provides further support for the JD-R model's health-impairment process, in which higher demands are consistently associated with greater strain. The mediation of subjective well-being through health problems was confirmed in both models, supporting H2a.

The inclusion of demographic and organisational controls also demonstrated their explanatory relevance, as several paths became significant only in Model 2. This provides partial support for H2b, indicating that age and sector-related factors help clarify psychosocial relationships by reducing confounded variance. Overall, Model 2 offers a more precise and less biased representation of the mediating mechanism linking psychosocial factors, health problems, and sickness absence.

Several indicators were used to assess the suitability of the SEM model (see Table 5). They confirm very good data fit, as all values exceed the internationally recommended limits. Specifically, CFI = 0.968 indicates excellent fit (≥0.95), while TLI = 0.929 indicates good fit (≥0.90). Additional indicators, RMSEA = 0.040 (95% CI: 0.019–0.064) and SRMR = 0.019, confirm the quality of the model, as the values are below the recommended thresholds (0.05 and 0.08). In addition, the AIC value = 14,171.01 was the lowest among the compared models, confirming a parsimonious or sufficiently simple and at the same time explanatory model structure. The SEM model including demographic control variables (age, tenure, and sector) was just identified (df = 0), meaning that model fit indices (CFI, TLI, RMSEA, SRMR) could not be meaningfully computed. This is typical for saturated mediation models where each endogenous variable has a full set of predictors. Therefore, model evaluation focused

on the size, direction, and statistical significance of the estimated path coefficients rather than global fit indices.

Table 4. Direct effect results between psychosocial factors and health problems: regression analysis results.

Path	Standardised Effect (Model 1)	Standardised Effect (Model 2)	Interpretation
F1 Subjective well-being → Health problems	–0.271 ***	–0.329 ***	Higher well-being negatively associated with health problems; effect strengthens slightly after adding controls.
F3 Growth → Health problems	0.079 **	0.081 *	Small positive association between growth opportunities and perceived health problems remains.
F4 Job Demands → Health problems	0.261 ***	0.329 ***	Job demands strongly associated with perceived health problems; effect slightly larger with controls.
F6 Autonomy → Health problems	0.088 ***	0.107 **	Autonomy shows a weak positive relation with health problems in both models.
Health problems → Sick days	0.146 ***	0.232 ***	Health problems have a strong positive associations with sick-leave days; effect size increases with controls.
F5 Health risks → Sick days	–	0.088 *	Work-environment risks significantly associated with predicted sick days (only significant when controls are added).
F6 Autonomy → Sick days	–	–0.079 **	Greater autonomy has negative relationships with sick-leave days (protective effect emerging after controls).
F4 Job Demands → Sick days	–	–0.091 **	Job demands show a small negative direct path after controls (possible suppression).
Age → Sick days	–	0.091 **	Older employees report more sick days.
Type company 2 → Sick days	–	0.118 **	Employees in the Health care sector have higher sickness absence.
R^2 (Health problems)	0.319	0.326	Slight improvement after adding controls.
R^2 (Sick days)	0.075	0.081	Slight improvement after adding controls.

Notes: Standardised path coefficients (β) and corresponding *p*-values are reported; SEM Model 2-all effects were estimated within the SEM mediation model using bootstrap confidence intervals with 5000 resamples; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 5. SEM model fit indices.

Fit Index	Value	Interpretation
CFI	0.968	Excellent fit (≥0.95)
TLI	0.929	Good fit (≥0.90)
RMSEA	0.040 (CI: 0.019–0.064)	Excellent (below 0.05)
SRMR	0.019	Excellent (below 0.08)
AIC	14,171.01	Lowest score

Notes: Recommended cut-off values for SEM fit indices were based on established guidelines (Hu & Bentler, 1999; Kline, 2013); CFI ≥ 0.95 and SRMR ≤ 0.08 indicate excellent fit; TLI ≥ 0.90 indicates good fit; RMSEA ≤ 0.05 indicates close fit (0.05–0.08 acceptable); lower AIC values indicate better model parsimony.

The overall pattern of relationships remained highly stable across both the baseline model and the full structural specification (Model 2), confirming the robustness of the hypothesised pathways. Model 2, which incorporates demographic covariates, is considered

the definitive model for interpreting the final results, as it provides a more precise and robust estimation by effectively neutralising any potential masking effects of the control variables, thereby offering a clearer picture of the mediating mechanism. The analysis of the structural paths in Model 2 revealed several key relationships (as illustrated in Figure 1): Predictors of Health Problems: Subjective well-being was negatively associated with health problems $\beta = -0.33$, $p < 0.001$). Job demands showed a strong positive association with health problems $\beta = 0.33$ $p < 0.001$). This strengthened association provides additional support for the Job Demands-Resources (JD-R) health-impairment process. The Job Resources of Growth $\beta = 0.08$, $p < 0.05$) and Autonomy ($\beta = 0.11$, $p < 0.01$) also demonstrated small but statistically significant positive links with health problems. Predictors of Sickness Absence (Sick Days): In turn, health problems were significantly and directly related to more sick days ($\beta = 0.23$, $p < 0.001$). Sickness absence was also influenced by additional direct effects from health risks, age, employment in the healthcare sector, and autonomy.

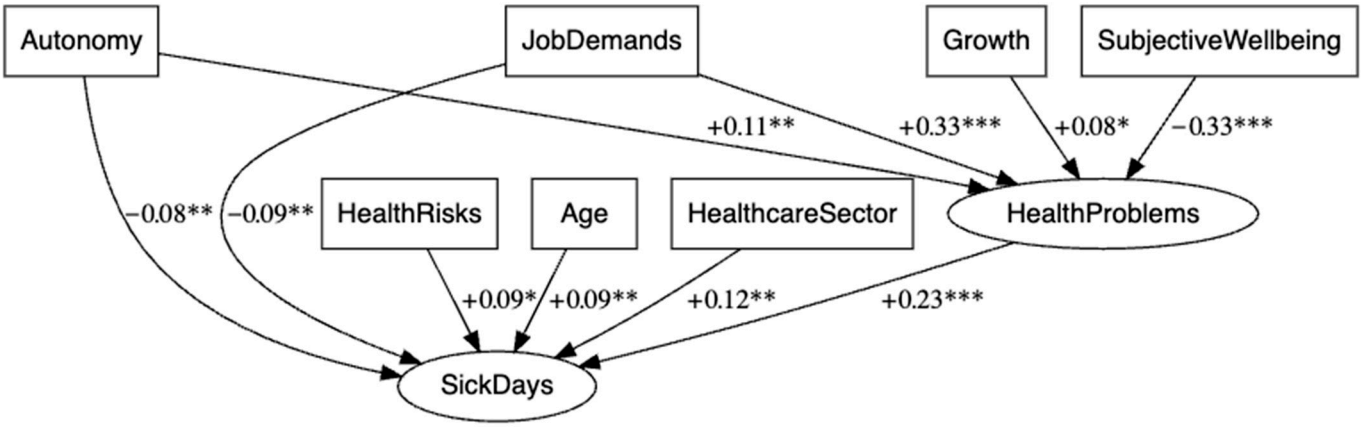

Figure 1. Structural equation model of the relationship between psychosocial factors, health problems, and sick days; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (RStudio, R version 4.5.2).

Overall, the model clearly indicates that sickness absence is primarily linked to an increase in health problems, which are subsequently shaped by key psychosocial factors within the work environment. Model 2, by accounting for covariates, offers the clearest and most precise representation of this mediating mechanism.

4.4. Results of Mediation Analysis

The Generalised Linear Model (GLM) results (Table 3) showed that health problems were strongly associated with absence of sickness, while several psychosocial work factors were related to the presence of health problems (Table 4). Taken together, these patterns suggested that psychosocial factors might be linked to sickness absence indirectly, through employees' health problems. This provided a clear rationale for testing H2a, which proposed a mediating role of health problems, using Structural Equation Modelling (SEM).

The mediation analysis (Table 6) confirmed H2a, demonstrating that health problems functioned as the central mechanism linking psychosocial work factors to sickness absence. Subjective well-being showed a significant negative indirect association with sick days (Model 1: Std.all = −0.040 ***; Model 2: –0.077 ***), while job demands demonstrated one of the strongest and most stable indirect effects (Model 1: 0.038 ***; Model 2: 0.077 ***). These consistent associations underline the important role of well-being as a personal resource and job demands as a central stressor within the JD-R health-impairment process.

Growth opportunities (Model 1: 0.012 **; Model 2: 0.019 *) and autonomy (Model 1: 0.013 **; Model 2: 0.025 **) showed small but statistically significant indirect associations, indicating that these job resources also contribute to the broader pattern connecting work

characteristics with sickness absence. These findings provide partial support for H2b, suggesting that demographic and sectoral controls clarify—rather than alter—the underlying relational structure.

Table 6. Indirect associations between psychosocial factors, health problems, and sick days (SEM Models 1–2).

Mediation Pathway	Indirect Effect (Model 1)	Std.all (Model 1)	Indirect Effect (Model 2)	Std.all (Model 2)	Interpretation
F1 Subjective well-being → Health problems → Sick days	–1.01	–0.040 ***	–0.093	–0.077 ***	Higher well-being is indirectly associated with fewer sick days through lower levels of reported health problems.
F3 Growth → Health problems → Sick days	0.124	0.012 **	0.010	0.019 *	Growth opportunities show a small positive indirect association with sick days via slightly higher levels of health problems
F4 Job Demands → Health problems → Sick days	0.834	0.038 ***	0.080	0.077 ***	Job demands show a strong and stable indirect association with sick days through higher levels of health problems.
F6 Autonomy → Health problems → Sick days	0.231	0.013 **	0.021	0.025 **	Autonomy shows a small positive indirect association with sick days via higher reported health problems.

Notes: Indirect effects and standardised path coefficients (Std.all) are reported from the SEM mediation model; p-values were obtained using bootstrap confidence intervals with 5000 resamples; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Health risks factor (physical exposures) did not reach statistical significance, likely due to its narrow measurement structure (only two items) and its concentration within a single sector (Manufacturing).

In conclusion, the Structural Equation Modelling (SEM) results strongly indicate that health problems serve as the primary mediating mechanism through which psychosocial work factors are linked to objective outcomes, specifically the number of sick days recorded. This central role of health problems connects: Subjective well-being (negatively related to sick days); Job demands (positively related to sick days); Selected job resources (autonomy and growth opportunities) to absence sickness. The indirect effects observed for subjective well-being and job demands were notably strong and stable across both the baseline and full structural models, decisively highlighting their central role in shaping the resulting patterns of sickness absence.

5. Discussion

The aim of this study was to analyse the relationship between sick leave, employees' subjective well-being, self-rated health, and psychosocial factors in the work environment. By combining administrative sick leave data with employee-reported indicators of psychosocial well-being, a multidimensional view of the determinants of sickness absence in Latvia was obtained, covering four sectors.

5.1. Self-Rated Health Problems as the Strongest Predictor

The results consistently showed that subjectively reported health problems had the strongest association with the number of sick days among all variables examined. This finding echoes earlier research demonstrating that subjective health assessments are highly predictive of sickness absence and even mortality risk (Niedhammer et al., 2021). and that self-reported symptoms often outperform clinical diagnoses in forecasting future illness (C.

A. Roelen et al., 2007). SEM results further supported H2a, showing that health problems were the main mechanism through which psychosocial factors, especially subjective well-being and job demands, were indirectly associated with sick days. This pattern aligns with the JD-R health-impairment process (Bakker & Demerouti, 2017), whereby excessive demands and reduced resources contribute to poorer health.

Overall, the findings indicate that self-rated health problems reflect employees accumulated strain and provide an early warning indicator of deteriorating health. Previous studies have consistently supported the relationship between self-assessed mental and work-related stress and concurrent sick leave. In addition, this study shows that work-specific risk factors predict subsequent sick leave better than mental stress per se (Mehlig et al., 2024).

5.2. Physical Risks in the Work Environment and Increase in Sick Days

Although the association between physical hazards and sick days was not statistically significant in the GLM model, the positive direction of the coefficient is consistent with prior studies absence (Alfonso et al., 2016; Clausen et al., 2009; Mänty et al., 2022) and suggests a potential trend that warrants further investigation. Recent analysis from the healthcare sector also shows that physical workload factors remain important predictors of sickness absence, particularly in occupations characterised by high ergonomic and physical demands (Sakr et al., 2025). Within the JD-R framework, these exposures represent job demands that may contribute to cumulative strain even if they do not operate through the same pathways as psychosocial factors.

In this study, the physical risk factor was relevant mainly to the manufacturing sector and was measured with only two items, which may have limited its statistical sensitivity. Nevertheless, strengthening workplace safety measures and reducing exposure to hazardous agents therefore remains essential for preventing sickness absence and supporting employee well-being (Halonen et al., 2021; Sterud, 2014).

5.3. Autonomy at Work as a Protective Factor

In this study, greater autonomy at work was associated with fewer sick days. These results are consistent with the Job Demands-Resources (JD-R) model assumption that autonomy acts as an important resource for maintaining employee health and well-being (Bakker & Demerouti, 2017). Recent evidence shows that strengthening psychosocial resources, including job autonomy, can reduce future sickness absence and mitigate health impairment processes, confirming the protective role of autonomy in contemporary workplaces (Fagerlund et al., 2024). Similar conclusions were reached by Gerich, where autonomy reduced the risk of sick leave (Gerich, 2019). However, other studies show that challenging tasks can also promote work engagement and motivation, pointing to the contextual nature of this factor (Ko & Glied, 2021). SEM results further revealed a small but significant indirect effect of autonomy via health problems, suggesting that part of its association with sickness absence operates through improved health perceptions. Although the indirect pathway was modest compared with job demands and subjective well-being, the consistency of both direct and indirect effects indicates that autonomy contributes to a broader resource system that supports employee health and reduces the likelihood of sickness absence.

5.4. Sectoral Differences: More Sick Leave Days Among Healthcare Workers

Healthcare employees reported significantly more sick days than those in other sectors. Healthcare employees reported significantly more sick days than those in other sectors. Both SEM and GLM results consistently showed a statistically significant positive association between employment in the healthcare sector and the number of sick days.

This pattern suggests that sectoral context meaningfully contributes to explaining variation in sickness absence, and part of this association may operate indirectly through higher levels of health-related strain—a mechanism consistent with the JD-R health-impairment process.

International evidence similarly demonstrates that healthcare work involves elevated emotional and physical demands, lower work-time control, and occasional exposure to workplace aggression, all of which are linked to increased sickness absence (Dyrbye et al., 2017; V. Aronsson et al., 2018; G. Aronsson et al., 2021). Recent evidence establishes that lower job grade is the single strongest predictor of a higher incidence rate of sick leave episodes among Healthcare Workers (HCWs). This finding highlights profound occupational and socioeconomic inequities, suggesting that interventions aimed at reducing absenteeism must be targeted toward mitigating the associated risk factors prevalent in lower hierarchical positions, such as low job control, high physical demands, and poor psychosocial working conditions (Sakr et al., 2025).

These cumulative pressures contribute to burnout, moral distress and somatic complaints (Nagle et al., 2023, 2024), which help explain the higher prevalence of health problems observed in SEM and, indirectly, higher sick-leave days. Overall, the results identify healthcare as a high-risk sector where both direct and indirect pathways to sickness absence are amplified. Targeted preventive interventions, workload management, and resilience-building strategies therefore remain essential for reducing absence and improving staff well-being.

5.5. Gender Differences in Sickness Absence

Men had fewer sick days than women. Recent evidence confirms that women continue to exhibit higher rates of sickness absence across most European countries, partly due to gendered patterns of occupational exposure and health strain (Timp et al., 2024).

This is consistent with many studies in Europe and the US, where women are more likely to take sick leave (Laaksonen et al., 2010). These differences can be explained by several factors. Biological aspects, such as reproductive health characteristics and related health risks, increase the frequency of sick days among women.

In addition, the social dimension is also significant—women more often take on greater family responsibilities and childcare, which may require more frequent absences from work (Bekker et al., 2009). Organisational and cultural factors, such as gendered expectations, workplace flexibility, and the gender-segregated labour market, also contribute to these patterns (Mastekaasa & Olsen, 1998; Mastekaasa, 2014). A larger share of women works in healthcare and education—sectors with elevated rates of sickness absence, which amplifies the gender difference observed in the GLM and SEM results.

SEM analysis further showed that part of the gender effect may operate indirectly through higher levels of self-rated health problems, suggesting that gender-related health strain plays a role in shaping absence patterns. This indicates that gender differences in sickness absence cannot be attributed solely to individual health but must be considered in a broader social and organisational context.

These findings highlight the need for gender-sensitive workplace policies, including flexible work arrangements and family-friendly support systems, to help reduce gender inequalities in sickness absence.

5.6. Length of Service and Sick Leave

In this study, tenure did not show a statistically significant association with sick days in the main GLM or SEM models, although the bootstrap analysis suggested a small positive effect. This likely reflects the high collinearity between tenure and age, which reduces the ability to detect independent effects when both variables are included in the model.

Moreover, tenure was measured only as years worked in the current organisation rather than across the full working life, limiting its ability to capture cumulative exposure to work demands. Although prior research suggests that longer tenure may be linked to greater health-related strain (Hanson et al., 2017; Kiss et al., 2008) and age-related health decline (Ilmarinen & Ilmarinen, 2015), such patterns were not consistently observed here. Future studies should therefore disentangle age and tenure more clearly to assess their distinct contributions to sickness absence.

5.7. Time Spent Commuting to Work as an Additional Risk Factor

Commuting time showed a statistically significant positive association with sick days in both the main GLM model and the bootstrap sensitivity analysis (30–60 min: $\beta \approx 0.24$–0.35, $p < 0.05$). Employees with medium-length commutes therefore tended to report more sick days than those commuting $\leq$30 min. This finding aligns with earlier research showing that longer commuting times are linked to elevated stress levels, lower subjective well-being, and a higher likelihood of sickness absence (Hansson et al., 2011; Künn-Nelen, 2016). Long commutes can reduce opportunities for rest, physical activity, and family time and may contribute to daily fatigue and reduced job satisfaction, factors associated with increased health strain (Chatterjee et al., 2020). Evidence from the latest European working-conditions assessments also shows that commuting-related strain remains an important source of mental fatigue, reduced well-being, and lower work engagement, particularly in urban regions where travel times tend to be longer (Eurofound, 2023).

Overall, these results highlight the relevance of geographical accessibility for employee well-being and suggest that flexible work arrangements, such as hybrid or remote work could help mitigate the risk of sickness absence associated with longer commuting times.

5.8. Subjective Well-Being as an Indirect Factor

Contrary to the initial hypothesis (H1a), subjective well-being did not show a direct association with sick days in the GLM model. However, the SEM analysis demonstrated a clear and statistically significant indirect effect, confirming H2a: employees with higher well-being reported fewer health problems, which in turn were associated with fewer sick days (Std.all = - 0.077 in the full model). This indicates that subjective well-being functions as an indirect resource rather than as a direct predictor of sickness absence. This pattern aligns with the JD-R framework, suggesting that subjective well-being may operate as a resource shaping health-related processes rather than directly relating to sickness absence (Bakker & Demerouti, 2017). Comparable findings have been reported in more recent analyses that psychosocial well-being functions as a significant protective factor against sick leave, demonstrating that favourable scores on the Subjective Well-being Index are associated with a decreased risk and duration of absence in the workplace (Colin-Chevalier et al., 2025).

This is consistent with Miraglia and Johns' meta-analysis, which indicates that psychosocial factors and well-being often act indirectly, influencing sickness absence through health outcomes (Miraglia & Johns, 2016). In practical terms, these results suggest that subjective well-being alone is not a sufficient indicator for assessing sickness absence risk unless employees' health symptoms are simultaneously considered. Prior research demonstrates that reduced well-being is linked with elevated stress, depressive symptoms, and physical complaints (De Neve et al., 2013; Steptoe et al., 2015), which aligns with our model showing that health problems are the central mechanism connecting well-being with absence behaviour.

Overall, the combined GLM and SEM evidence indicates that subjective well-being should be viewed as part of a broader network of psychosocial resources that support health rather than as a standalone predictor of sickness absence. This finding underscores the

value of integrated organisational strategies that simultaneously (1) strengthen psychosocial resources, (2) improve work conditions, and (3) support early detection of health problems. Such a holistic approach is likely to be more effective in reducing sickness absence than interventions targeting well-being in isolation.

6. Limitations

This study has several limitations that should be considered when interpreting the results. First, the cross-sectional design does not allow conclusions to be drawn about the causal relationships between psychosocial factors, subjective well-being, health problems, and sickness absence. Longitudinal studies would be needed in the future to clarify the direction of these relationships and the mechanisms of influence. Second, although administrative records provide objective information on the number of sick days, they may still be affected by organisational culture, reporting norms, and employees' willingness to take sick leave. Third, although validated instruments were used, some constructs—such as social inclusion—showed slightly lower psychometric fit, indicating a need to refine and expand them with additional indicators in future studies. Subjective well-being also did not emerge as a direct predictor of sick days, indicating that additional mediating or contextual factors may not have been fully captured in the current model. A further measurement-related limitation concerns tenure: in this study, tenure was measured only as years spent in the current organisation, rather than cumulative work experience across the entire career. This narrower operationalisation may not fully reflect long-term exposure to work demands and may partly explain the non-significant results. In addition, tenure is often highly correlated with age, which can further obscure independent associations when both variables are included in the same model.

Fourth, the external validity of the study is limited by its national context. All data were collected in Latvia, a small post-transition European economy with specific labour market structures, social protection arrangements, and workplace norms. These contextual conditions may influence attitudes toward sickness absence, health reporting practices, and organisational support systems. Cross-national comparisons are additionally complicated by differences in definition and recording of sickness absence across countries.

Finally, although bootstrap and sensitivity analyses were used to strengthen robustness, the heterogeneity of sickness absence data and the exclusion of extreme outliers may have influenced the results. Future research would benefit from longitudinal designs, multi-source data, improved measurement of psychosocial constructs, and international comparative studies to better understand the generalisability of these findings.

7. Future Research

Based on the findings and limitations of this study, several directions for future research emerge. First, longitudinal designs are needed to establish the causal pathways between psychosocial work factors, subjective well-being, health problems, and sickness absence. Second, future studies should expand and refine measurement tools—particularly for social inclusion, professional development, emotional demands, and environmental health risks—to capture these constructs with greater precision across different sectors. Third, an international and cross-sectoral approach would enhance comparability and provide broader insights into how labour market and institutional contexts shape sickness absence patterns.

Fourth, combining multiple data sources (administrative records, self-reports, and objective health indicators) would strengthen data validity and reduce reliance on a single method. Fifth, future work should examine tenure effects more explicitly. In this study, tenure was included in the analyses but did not show statistically significant associations, which may partly reflect its narrow measurement, capturing only years worked in the

current organisation rather than cumulative work experience. Future studies should standardise outcomes by time at risk and analytically separate tenure from age to clarify their independent contributions to sickness absence.

Sixth, future research should target sectors with higher exposure to physical and environmental risks, such as male-dominated industries, and consider men-only analyses. Because the outcome in this study combined own-illness and family-care leave, and caregiving responsibilities are unevenly distributed by gender, sector- and gender-specific analyses may yield clearer estimates of exposure–outcome relationships.

Seventh, future research should further expand the analytical framework by including moderation mechanisms that are in line with the buffering hypothesis of JD–R, such as coworker relational energy, supportive leadership, or other interpersonal resources that might mitigate negative effects of high job demands. Investigating such interaction effects would lead to a deeper understanding of how specific job resources shield employees from strain and perhaps reduce sickness absence.

And finally, since the current study focused primarily on job resources, future research should incorporate personal resources as an additional layer of protective factors. Examining how personal resources interact with psychosocial job characteristics would offer a more nuanced understanding of how well-being and health-related processes develop at work. Recent extensions of the JD-R model emphasise that job and personal resources form two domains of a broader, integrated resource system that jointly shapes the health-impairment process (Mayerl et al., 2016). Personal resources—such as optimism, self-efficacy, and perceived control represent positive self-evaluations linked to resilience and individuals' capacity to influence their environment successfully (Xanthopoulou et al., 2007). Integrating these constructs would allow future studies to capture a broader set of mechanisms that buffer strain and potentially reduce health problems and sickness absence.

8. Conclusions

The findings of this study carry important theoretical implications, showing that the drivers of sickness absence extend beyond medical causes and are strongly shaped by psychosocial work characteristics. The strongest associations were observed for subjectively reported health problems and occupational risks such as noise and chemical exposure, while greater autonomy was negatively associated with sick leave. These findings align with the Job Demands–Resources (JD-R) model, where excessive demands are linked to health impairment, and job resources—such as autonomy and professional growth—serve a protective role (Bakker & Demerouti, 2017).

Secondly, Structural Equation Modelling (SEM) further refined this understanding by revealing that subjective well-being (WHO-5) was not directly linked to sickness absence but was indirectly mediated through health problems. This pathway supports an important extension of the JD-R framework by integrating subjective well-being as a personal resource. This integration aligns with the Conservation of Resources (COR) theory (Xanthopoulou et al., 2007), which highlights the critical interplay between job resources and personal resources in the maintenance of employee health and the prevention of resource depletion.

Finally, the study demonstrates that the inclusion of demographic and sectoral characteristics significantly clarifies and refines the structural relationships within the model. This reinforces the need for context-sensitive extensions of the JD-R framework, acknowledging that the mechanisms linking demands, resources, and outcomes are not universal but are modulated by organisational and employee contexts, reinforcing the need for context-sensitive extensions of the JD-R framework.

At the same time, the results also offer clear managerial implications. They demonstrate that sickness absence is not solely a matter of individual health but strongly reflects

organisational and psychosocial work conditions. This confirms that improving the work environment is critical for effectively managing absenteeism. The established mediating mechanism suggests that organisations should implement an integrated approach that simultaneously addresses demands, resources, and health monitoring, rather than relying on isolated initiatives. Key practical priorities emerge, such as that organisations must prioritise the early identification of emerging health problems using self-assessment tools or regular screenings, integrating well-being promotion with occupational safety measures to proactively strengthen employee resilience. Simultaneously, they should implement strategies to reduce excessive job demands, which were strongly linked to increased health problems, while actively strengthening key job resources such as autonomy and opportunities for professional growth, which demonstrated protective effects. Furthermore, special attention is warranted for high-risk groups, including female employees and the healthcare sector, necessitating targeted support. Supporting flexible work arrangements and measures aimed at commuting reduction can also contribute to decreased sickness absence by alleviating daily stress. Ultimately, improving both the physical and psychosocial work environment is essential for fostering healthier, more sustainable organisations.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/admsci16010007/s1, Multidimensional scale of Psychosocial well-being for employed persons (MPSWEP).

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Informed Consent Statement: Informed consent was obtained from all individuals who participated in the study. Prior to data collection, participants received an electronic consent form that outlined the study's purpose, procedures, conditions of voluntary participation, and their right to withdraw at any time without negative consequences.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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