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Can Presenteeism Predict Future Absenteeism? Evidence from the Korean Health Panel Study

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Abstract

Background: Presenteeism, the act of working while ill, is increasingly recognized as a key occupational health challenge with significant consequences for productivity and future work incapacity. Yet, longitudinal evidence on its temporal interplay with absenteeism remains scarce. We aimed to examine the lagged and bidirectional relationships between presenteeism and absenteeism using nationally representative multi-wave panel data from Korean wage workers.

Methods: We analyzed four waves (2019–2022) of longitudinal survey data from 4,180 baseline participants, with follow-up rates of 76.8% (wave 2), 66.6% (wave 3), and 58.4% (wave 4). Mixed-effects logistic regression models estimated the effect of prior-wave presenteeism on subsequent absenteeism, adjusting for covariates measured at the preceding wave. Bidirectional cross-lagged panel models were used to assess reciprocal relationships over time.

Results: Presenteeism prevalence ranged 12.7–25.0%, exceeding absenteeism prevalence (8.6–12.3%) across all waves. In mixed-effects models, prior-wave presenteeism predicted 30% higher odds of absenteeism at the next wave (odds ratio= 1.30, 95% confidence interval: 1.08–1.56, $p = .005$). The bidirectional model showed significant cross-lagged effects from presenteeism to absenteeism in two of three intervals, but absenteeism did not predict future presenteeism. Strong autoregressive effects were observed for presenteeism and absenteeism.

Conclusions: Presenteeism is consistently associated with subsequent absenteeism among Korean workers and may serve as a useful risk

marker for future absence; however, results should be interpreted as longitudinal associations as within-person effects were attenuated in a random-intercept sensitivity analysis. These findings highlight the potential importance of coordinated policy and organizational approaches—such as statutory paid sick leave, supportive sick leave cultures, and proactive health monitoring—in addressing problematic presenteeism.

Keywords: Absence; Korean workers; Longitudinal study; Occupational health; Work while sick

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Background

Presenteeism, defined as attending work despite illness or health problems, is a growing concern in occupational health research due to its substantial impact on productivity, health outcomes, and organizational costs [1–3]. Unlike absenteeism, which is overt and easily measured, presenteeism is less visible but may be linked to greater long-term harm through health deterioration, reduced work capacity, and subsequent labor force withdrawal [2, 4, 5]. Empirical studies suggest that presenteeism reflects current health problems and may also predict subsequent absenteeism, thereby contributing to a cycle of productivity loss and workforce instability [5, 6–9]. Understanding this temporal relationship is essential, as presenteeism may serve as an early indicator of future work incapacity and provide an opportunity for preventive interventions.

International evidence indicates that the prevalence of presenteeism and absenteeism varies considerably across regions, cultures, and labor market structures. Large-scale comparative studies based on data collected in the mid-2010s have shown substantial cross-national differences in presenteeism and absenteeism. For example, analyses of the 2015 European Working Conditions Survey and the 2014 Korean Working Conditions Survey reported higher mean rates of absenteeism (33.0%) and presenteeism (35.3%) across European OECD countries, whereas Korea showed markedly lower absenteeism (9.9%) and moderately lower presenteeism (23.5%) during the same period [10]. These indicators are known to vary over time in response to institutional

arrangements, labor market conditions, and public health contexts, highlighting the importance of considering temporal context when interpreting cross-national comparisons. This pattern has been attributed to cultural and organizational factors—such as strong attendance pressure, limited statutory sick leave, and job insecurity—that discourage sick leave and promote working while ill [11, 12]. In this context, Korean studies based on the 2014 Korean Working Conditions Survey have shown that presenteeism was more prevalent than absenteeism, suggesting potential long-term implications for workforce health and sustainability [13, 14].

Despite this concern, the evidence on the longitudinal association between presenteeism and absenteeism remains limited. Prior empirical research has examined these two behaviors simultaneously. For example, Böckerman and Laukkanen (2010) showed that the predictors of sickness absence and presenteeism differ depending on workers' self-assessed health [15], suggesting that the relationship between these behaviors is not uniform across workers. However, most prior studies are cross-sectional and cannot establish causality or temporal ordering [16–18]. This gap highlights the need for longitudinal approaches to determine whether presenteeism predicts subsequent absenteeism or vice versa. Previous longitudinal studies have demonstrated that higher levels of presenteeism are associated with an increased risk of future sick absences [6, 19–22]. However, many of these investigations have been restricted to single-wave or relatively short-term follow-up periods [7, 8, 19–21]. Moreover, they largely rely on conventional regression

techniques (e.g., Poisson, Cox, or Logistic regression) that are unable to adequately capture bidirectional or lagged associations, thereby constraining insights into potential causal pathways [6, 8, 19–22].

Advances in methodological approaches recommend multi-wave designs and within-person modeling approaches—such as cross-lagged panel models and random-intercept models—to better capture dynamic processes and causal ordering [23].

In addition, the COVID-19 pandemic may have substantially influenced patterns of presenteeism and absenteeism by altering work arrangements, sickness norms, and public health policies [24]. Measures such as remote work, quarantine requirements, and heightened attention to infectious disease control may have reduced attendance while ill in some contexts, whereas economic uncertainty and staffing shortages may have exerted opposing pressures. These pandemic-related dynamics emphasize the importance of examining presenteeism and absenteeism using recent longitudinal data spanning the COVID-19 period.

The present study aimed to examine the lagged and bidirectional associations between presenteeism and absenteeism using nationally representative multi-wave panel data from Korean wage workers. By applying mixed-effects logistic regression and cross-lagged panel modeling, we aimed to provide robust evidence on the temporal ordering of these phenomena and generate insights to guide policy and organizational strategies.

Methods

Study design and population

In this study, we employed a longitudinal panel design using data from the Korean Health Panel Study (KHPS), a nationally representative household survey jointly conducted by the Korea Institute for Health and Social Affairs and the National Health Insurance Service [25]. The KHPS has been conducted annually since 2008 and provides longitudinal information on health status, healthcare utilization, health expenditures, and socioeconomic and occupational factors in the Korean population. The survey employs a stratified multistage probability sampling design to select households across the country and follows all household members over time.

Data are collected through face-to-face interviews conducted by trained interviewers using structured questionnaires, with household- and individual-level modules. The individual survey covers sociodemographic characteristics, economic activity, health conditions, health-related behaviors (e.g., smoking, alcohol consumption, physical activity), and subjective health status. The household survey collects information on medical expenditures, health insurance coverage, and household income and assets. All data are deidentified prior to release for research purposes.

The KHPS is divided into the following two panels: the first panel (2008–2018) and the second panel (2019–present). For this study, we used the second panel, specifically four consecutive waves from 2019 to 2022. The 2022 wave was the most recent data available at the time of analysis. At baseline (2019), 4,180 wage employees aged ≥ 20 years were

eligible. The age threshold of 20 years was applied as an analytical decision to focus on adult wage workers with relatively stable labor market participation. Younger individuals, who are more likely to combine education with short-term or transitional employment, may exhibit different patterns of presenteeism and absenteeism and were therefore excluded to enhance analytical consistency. Participants were included if they were classified as wage workers and had complete information on presenteeism and absenteeism. Individuals who were self-employed, unpaid family workers, or had missing baseline values for key variables were excluded. During follow-up, 3,210 participants were retained in 2020 (76.8%), 2,784 in 2021 (66.6%), and 2,443 in 2022 (58.4%).

Measures

Presenteeism and absenteeism

Presenteeism was measured annually using a standardized question from the Korean Health Panel Study: “During the past 12 months, have you gone to work despite being ill?” Response options included “yes,” “no,” and “I was not sick.” Participants who answered “yes” were classified as having experienced presenteeism in that survey year. If participants responded “no” or “I was not sick,” they were coded as not having experienced presenteeism.

Absenteeism was assessed with the following question: “During the past 12 months, have you been absent from work due to illness or health problems?” Response options were “yes,” “no,” and “I was not sick.” Participants who answered “yes” were categorized as having

experienced absenteeism. Participants who responded “no” or “I was not sick” were coded as not having experienced absenteeism. This binary measure (yes/no) reflects health-related absence from work.

Demographic and socioeconomic characteristics

Age was calculated from self-reported birth year and month and treated as a continuous variable. Sex was recorded as male or female. Marital status was self-reported by the participant, and responses were categorized as married versus unmarried (single, divorced, or widowed). Educational attainment was assessed as the highest completed level and categorized into three groups: high school or less, bachelor’s degree, and master’s degree or higher. Household income was reported as annual individual wage income in units of 10,000 Korean won (KRW; 1 USD $\approx$ 1,350 KRW) and treated as a continuous variable. Region of residence was coded as metropolitan versus nonmetropolitan.

Occupational characteristics

Employment type was derived from the item “What is your working time arrangement?” and dichotomized into full-time versus part-time employment. Occupational position was classified according to the Korean Standard Classification of Occupations. Codes corresponding to managers, professionals, and technicians (11, 12–15, 21–28, 31–33) were grouped as high-skilled, while service, sales, manual, and elementary occupations (39, 41–44, 51–53, 61–63, 71–79, 81–89, 91–95) were grouped as low-skilled.

Health-related characteristics

Smoking status was assessed using questions on lifetime and current smoking. Respondents were asked whether they had smoked at least five packs of cigarettes in their lifetime, and if so, whether they currently smoked every day, occasionally, or had quit. For this study, current smokers (“every day” or “occasionally”) were coded as yes, while former smokers and never smokers were coded as no. Alcohol consumption was measured with the questions “Have you ever consumed alcohol?” (yes/no) and “During the past year, how often did you drink alcohol?” with seven response categories ranging from “not at all” to “almost every day.” For analysis, those reporting no alcohol consumption in the past year or never drinking were coded as no, and those reporting any alcohol consumption in the past year were coded as yes. Physical activity was measured by the question “During the past year, have you regularly engaged in sports or exercise, including walking?” with response options of yes or no.

Chronic disease was assessed using a checklist of physician-diagnosed conditions (e.g., hypertension, diabetes, arthritis). For analysis, participants with one or more chronic conditions were coded as yes, and those with none were coded as no. Subjective health status was assessed with the item “How would you rate your overall health?” with five response categories (very good, good, fair, poor, very poor). Responses were dichotomized into healthy (very good, good, fair) versus unhealthy (poor, very poor). Body mass index was calculated from self-reported height and weight (kg/m^2) and treated as a continuous variable.

Data analysis

All statistical analyses were conducted using Stata (version 19; StataCorp, College Station, TX, USA). Descriptive statistics were calculated to summarize participants' characteristics and the distribution of presenteeism and absenteeism at each wave. For each wave (waves 2, 3, and 4), characteristics at the previous wave ($t-1$) were compared according to subsequent absenteeism status (wave 1 $\rightarrow$ wave 2, wave 2 $\rightarrow$ wave 3, wave 3 $\rightarrow$ wave 4) using chi-square tests for categorical variables and independent-samples t-tests for continuous variables. To examine the association between presenteeism and subsequent absenteeism, bivariate analyses were performed across consecutive waves. Specifically, the proportion of absenteeism (t) between groups with and without presenteeism at the previous wave ($t-1$) was compared using chi-square tests.

Mixed-effects logistic regression models (melogit in Stata) were used to estimate the lagged effect of presenteeism ($t-1$) on subsequent absenteeism (t), accounting for repeated measures and within-subject correlation in the unbalanced panel. Covariates were selected using bivariate analyses as an initial screening step, with all candidate variables drawn from factors commonly examined in prior research on presenteeism and sickness absence, to maintain model parsimony and stability in the longitudinal mixed-effects analyses. All covariates were measured at the previous wave ($t-1$). Multicollinearity among covariates was assessed using variance inflation factors (VIFs) based on the components of the regression models. As a sensitivity analysis to evaluate the robustness of the mixed-effects logistic regression findings, we

applied generalized estimating equations (GEEs) with exchangeable and first-order autoregressive [AR (1)] working correlation structures to confirm whether the association between lagged presenteeism and subsequent absenteeism persisted under a different modeling approach.

Next, we evaluated bidirectional temporal associations between presenteeism and absenteeism across four waves using a bidirectional cross-lagged panel model (CLPM) estimated via generalized structural equation modeling (gsem in Stata), adjusting for prior-wave covariates. The standard CLPM may conflate stable between-person differences with within-person fluctuations [23]; therefore, we conducted an additional RI-based sensitivity analysis using a random-intercept-based within-between decomposition approach. Odds ratios (ORs) and 95% confidence intervals (CIs) were reported for all regression analyses, with statistical significance set at $p < 0.05$.

Ethical considerations

The KHPS dataset is publicly available for research purposes and contains anonymized information, with all personal identifiers removed prior to release. This study was reviewed and approved as exempt from full review by the Institutional Review Board of Chung-Ang University (IRB No. 1041078-20250804-HR-273). All analyses were conducted in accordance with the principles of the Declaration of Helsinki and ethical guidelines for the secondary use of public data.

Result

Participant characteristics and bivariate associations

Across waves, presenteeism rates ranged 12.7–25.0%, whereas absenteeism rates ranged 8.6–12.3% (Figure 1; Supplementary Table 1). Participation patterns indicated that 36.7% of participants reported no absenteeism and 29.1% reported no presenteeism across all waves, while others experienced one or more occurrences at varying points during follow-up, with nearly half having at least one missing observation due to intermittent nonresponse (Supplementary Table 2).

Table 1 presents a comparison of absenteeism status at waves 2, 3, and 4 based on characteristics measured at the preceding wave (t-1). In the bivariate analyses, several prior-wave characteristics were significantly associated with absenteeism at the following wave. For wave 2 absenteeism, significant predictors included age, full-time employment, physical activity, and subjective health status assessed at wave 1. For wave 3 absenteeism, chronic disease and subjective health status measured at wave 2 were significant predictors. For wave 4, age and subjective health status measured at wave 3 were significantly associated with absenteeism. To evaluate potential selection bias, we additionally tested whether attrition from wave 2 to wave 4 was associated with wave 2 age or health covariates; no significant associations were observed (Supplementary Table 3).

Table 2 summarizes the bivariate associations between presenteeism at each wave and subsequent absenteeism at the next wave. Across all waves, presenteeism at the previous wave was significantly associated with increased odds of absenteeism in the following wave (all $p < 0.001$).

Prospective association between presenteeism and subsequent absenteeism

The results of the mixed-effects logistic regression analysis are presented in Table 3. All VIF values ranged 1.02–1.34, with a mean VIF of 1.15, indicating no evidence of problematic multicollinearity. Lagged presenteeism at the previous wave was a statistically significant predictor of subsequent absenteeism (OR = 1.30, 95% CI: 1.08–1.56, $p = 0.005$), indicating that workers who reported presenteeism in the prior wave had 30% higher odds of being absent in the following wave than those without prior presenteeism. Lagged absenteeism (OR = 3.45, 95% CI: 2.75–4.34, $p < 0.001$) showed a strong autoregressive effect, with individuals who had prior absences being over three times more likely to be absent again than those who did not. Of the covariates, subjective health status, age, and chronic disease were statistically significant, whereas full-time employment status and physical activity were not.

To assess the robustness of the mixed-effects logistic regression findings, GEEs were fitted using exchangeable and AR(1) working correlation structures (Supplementary Table 4). Under the exchangeable structure, lagged presenteeism remained significantly associated with increased odds of absenteeism (OR = 1.38, 95% CI 1.14–1.66, $p = .001$), while lagged absenteeism showed a strong persistence effect (OR = 3.37, 95% CI 2.75–4.13, $p < .001$). Results were highly consistent under the AR(1) structure (OR = 1.38, 95% CI 1.14–1.66, $p = .001$ for presenteeism; OR = 4.07, 95% CI 3.24–5.12, $p < .001$ for absenteeism), indicating that the findings were robust to different working correlation

assumptions.

Bidirectional temporal association between presenteeism and absenteeism

The bidirectional cross-lagged panel model (Figure 2) revealed significant cross-lagged effects of presenteeism on subsequent absenteeism from wave 1 to wave 2 (OR = 1.38, 95% CI 1.04–1.85, $p = .027$) and from wave 2 to wave 3 (OR = 1.49, 95% CI 1.05–2.13, $p = .026$), but not from wave 3 to wave 4 ($p = .315$). Lagged absenteeism strongly predicted absenteeism at the next wave across all transitions (ORs = 2.90–4.33, all $p < .001$). In the reverse direction, lagged absenteeism did not significantly predict subsequent presenteeism, whereas lagged presenteeism was a consistent predictor of future presenteeism at all waves (ORs = 2.48–3.64, all $p < .001$), indicating strong autoregressive stability (detailed parameter estimates for all paths are provided in Supplementary Table 5).

To investigate whether the nonsignificant wave 3 presenteeism → wave 4 absenteeism effect was due to the strong autoregressive effect of absenteeism, an additional model excluding the path from wave 3 absenteeism to wave 4 absenteeism was estimated (Supplementary Table 6). In the full bidirectional CLPM, the cross-lagged effect of wave 3 presenteeism on wave 4 absenteeism was nonsignificant ($\beta = 0.191$, $p = .315$, OR = 1.21). However, when the autoregressive path from wave 3 absenteeism was removed, this path became statistically significant ($\beta = 0.504$, $p = .004$, OR = 1.66), suggesting that the strong autoregressive path ($\beta = 1.064$, $p < .001$, OR = 2.90) suppressed the cross-lagged effect

in the full model.

Given the strong autoregressive stability observed in both variables and the potential for standard CLPM estimates to mix between-person and within-person effects, we conducted an additional sensitivity analysis using a RI-based decomposition to separate between-person differences from within-person fluctuations (Supplementary Tables 7A & 7B). In this approach, the cross-lagged associations from prior presenteeism to subsequent absenteeism were not statistically significant at the within-person level across all wave transitions. Meanwhile, between-person (person-mean) components—particularly mean absenteeism for absenteeism and mean presenteeism for presenteeism—showed strong associations, indicating substantial trait-like between-person persistence. Accordingly, the CLPM cross-lagged estimates should be interpreted as reflecting a mixture of within- and between-person effects rather than purely within-person change.

Discussion

This longitudinal analysis indicates that presenteeism is temporally associated with subsequent absenteeism among Korean workers, with findings consistent across mixed-effects logistic regression and GEE models. Although the effect size was modest relative to that of prior absenteeism, it represents a meaningful population-level signal given the high prevalence of presenteeism and its potential as a modifiable organizational factor. From a public health perspective, even a 30% increase in risk, when applied to a large workforce, may translate

into substantial cumulative costs related to productivity loss, healthcare utilization, and workforce sustainability [5, 26]. Importantly, unlike chronic disease status or a prior history of absenteeism—both of which are less amenable to short-term intervention—presenteeism can be targeted through organizational-level policies such as paid sick leave, workload management, and cultural change, making it a practical entry point for preventive action [26, 27].

Our findings are consistent with longitudinal research conducted in Western contexts, such as Bergström et al. [6] and Janssens et al. [21], which demonstrated that sickness presenteeism was significantly associated with higher odds of future sickness absence, with the predictive effect persisting after controlling for health status and demographic factors. However, the magnitude of the association in our study appears slightly lower than the 40–50% increase in future absence risk reported in some European cohorts [21]. One key explanation lies in Korea's distinctive institutional context. Korea remains one of the few OECD countries—along with Ireland and Mexico—without statutory sick leave or a public sick-pay scheme [28], and strong cultural norms discourage taking leave when ill [10]. As highlighted by Kim and Kim [28], baseline absenteeism rates in Korea are comparatively low. Across our study waves, presenteeism ranged 12.7–25.0% and absenteeism 8.6–12.3%, with presenteeism consistently more than twice as prevalent as absenteeism—substantially exceeding ratios reported in European settings [10]—yet both indicators remained below commonly cited international benchmarks. Such structural constraints suppress

observable absenteeism even as presenteeism-related health decline accumulates, thereby attenuating the measurable effect on recorded absence relative to Western cohorts. The marked decline in presenteeism from 2019 to 2020 likely reflects COVID-19-related shifts—including heightened infection control, increased remote work, and stronger norms discouraging working while ill—yet this population-level change does not contradict the strong autoregressive persistence of presenteeism observed at the individual level. When comparing prevalence estimates of presenteeism across studies, caution is warranted due to heterogeneity in measurement approaches. Prior research has applied different operational definitions—including varying frequency thresholds (e.g., defining presenteeism as two or more episodes versus any episode) and differing numbers of items—alongside variation in recall periods (e.g., 6 months versus 12 months) that can substantially influence reported estimates [29]. These methodological differences may partly account for observed variability in prevalence estimates across studies and should be taken into consideration when interpreting our findings in relation to the broader literature.

In contrast to earlier Korean investigations that largely employed cross-sectional designs and examined correlates of presenteeism or absenteeism separately [11, 28], our findings support a temporally ordered association in which prior presenteeism is followed by higher odds of subsequent absenteeism, alongside strong autoregressive stability of both behaviors. Building on Min et al. [24], our study demonstrates that presenteeism continues to serve as a reliable

longitudinal signal of future absence even as overall prevalence fluctuates. The bidirectional cross-lagged panel model revealed a clear temporal asymmetry: presenteeism predicted future absenteeism, whereas absenteeism did not predict future presenteeism. This directional asymmetry is the central finding of this study. It supports conceptualizing presenteeism as an early indicator or marker of health decline rather than a reciprocal counterpart to absenteeism. Framing the relationship in this manner clarifies where within the cycle preventive efforts may be most effectively targeted. Moreover, the strong autoregressive effects observed for both behaviors indicate that once these patterns are established, they tend to persist over time, consistent with prior evidence that organizational and cultural pressures embed such behaviors over time [30, 31].

To interpret this temporal asymmetry, several plausible mechanisms may help explain the observed prospective association between presenteeism and subsequent absenteeism. At the individual level, working while ill may delay recovery, exacerbate existing health conditions, and lead to cumulative physical or psychological strain, which may later manifest as sickness absence [32]. At the organizational level, strong attendance pressure, job insecurity, and limited access to paid sick leave may initially encourage presenteeism but be associated with more severe health deterioration over time [33].

Importantly, the standard CLPM estimates may reflect both stable between-person differences and within-person change over time. Our RI-based decomposition suggests that the cross-lagged association from

presenteeism to later absenteeism is largely driven by between-person differences rather than within-person deviations. Therefore, although presenteeism may serve as a useful risk marker for identifying workers more likely to experience future absence, these findings should not be interpreted as evidence that an individual episode of presenteeism causes a subsequent episode of absenteeism within the same person. Rather, presenteeism and absenteeism may both reflect an underlying trajectory of long-term health vulnerability shaped by chronic conditions, working conditions, and psychosocial stressors. Accordingly, presenteeism should be understood as a potential early signal within a broader process of health decline rather than a direct cause of subsequent absence. This interpretation further implies that presenteeism is not uniformly harmful across all individuals or occupational contexts. Workers without persistent health vulnerability may engage in occasional presenteeism without necessarily progressing toward absenteeism. Future studies incorporating more detailed health measures and longer observation periods are needed to further disentangle these pathways.

Although the observed associations are population-level signals driven primarily by between-person differences rather than within-person causal effects, the predictive relationship between presenteeism and subsequent absenteeism indicates the need for a coordinated response integrating policy reform, organizational strategies, and management practices. At the policy level, our observational data cannot directly establish whether expanding statutory sick leave would reduce

presenteeism. However, cross-national evidence and systematic reviews suggest that such measures lower attendance pressure and improve workforce stability [27]. Given Korea's position as one of the few OECD countries without a statutory sick-pay scheme [28], policy expansion constitutes a structurally logical—though not yet empirically verified in this specific setting—mechanism for reducing the presenteeism burden identified in this study. Organizations can complement structural changes by embedding regular monitoring of presenteeism into occupational health programs, enabling early identification of at-risk employees and timely interventions such as health assessments, workload adjustments, flexible scheduling, and access to mental health resources [26].

Creating a supportive organizational culture around sick leave is also important. Although the present study does not directly assess organizational culture or managerial practices, prior research suggests that when employees perceive that their health needs are respected and absences are not stigmatized, presenteeism rates tend to decline without a corresponding rise in unnecessary absenteeism [31]. Achieving such a cultural shift requires clear communication of sick leave policies, visible leadership commitment to employee well-being, and supervisory training to identify and respond to early signs of presenteeism [34]. In sectors where operational safety and service quality are paramount—such as healthcare, manufacturing, and transportation—reducing presenteeism additionally serves as a risk management strategy given its documented associations with increased

errors, accidents, and compromised service quality [35–37]. By aligning legislative measures with organizational health policies and supportive managerial practices, workplaces can work toward breaking the cycle from presenteeism to absenteeism, safeguarding both employee health and organizational performance.

Limitations

Some limitations of this study should be noted. First, reliance on self-reported measures with a 12-month recall period may have introduced recall and social desirability bias, particularly given the cultural stigma surrounding absenteeism. Longer recall intervals are known to increase measurement error, including both underreporting or overreporting of work-related behaviors [38]. Although annual recall has precedent in seminal presenteeism research—for example, Aronsson et al. employed a comparable 12-month self-report approach in a population-based study [17]—such measures remain susceptible to misclassification. Furthermore, variation in operational definitions across studies—including frequency thresholds (e.g., ≥ 2 episodes vs. any episode) and the number of items used—complicates cross-study comparisons of prevalence estimates. Future studies could improve accuracy by linking survey data with administrative or occupational health records or by using shorter recall periods and validated multi-item instruments.

Second, individual variation in defining "being too ill to work" may have introduced classification bias [38], compounded by the use of single-item binary questions. This approach limits construct validity and

reliability, and dichotomization results in loss of information regarding severity and frequency. As a result, heterogeneity across workers may be obscured, limiting opportunities for sensitivity analyses.

Third, potentially important contextual and organizational factors—including workplace culture, job insecurity, mental health status, and sick-leave policies—were unavailable in the KHPS dataset and therefore could not be incorporated into the analytic models. As these factors likely influence both behaviors [33], the estimated lagged associations should be interpreted as temporal relationships rather than evidence of causal mechanisms. Future studies should incorporate these variables to better elucidate causal pathways.

Fourth, attrition across four waves (58.4% retention at the final wave) raises the possibility of selection bias. Detailed information regarding reasons for loss to follow-up was unavailable, and nonrandom attrition cannot be excluded. Although mixed-effects models incorporate all available observations and partially mitigate bias from unbalanced data [39], selective attrition may still influence longitudinal estimates, particularly in the presence of strong autoregressive effects.

Fifth, although the findings are generalizable to wage workers aged 20 years and older, they may not extend to younger workers in transitional or student employment, nor to self-employed, part-time, or informal workers, whose employment conditions, absence patterns, and job protections differ substantially. Finally, although the RI-based decomposition addresses key limitations of the conventional CLPM, it remains an approximation for binary outcomes and does not fully

substitute for a fully latent RI-CLPM specification. Accordingly, within-person causal interpretations should remain circumspect.

Conclusion

In this longitudinal, nationally representative study, we found that presenteeism is temporally associated with subsequent absenteeism among Korean workers. Across multi-wave analyses, presenteeism may function as a useful risk marker for future absence; however, the within-person component of the association was attenuated in a random-intercept robustness check, emphasizing that these findings should be interpreted as longitudinal associations rather than causal effects. Our findings are consistent with prior international research but also reflect distinct national patterns characterized by higher presenteeism and lower absenteeism rates in Korea, likely influenced by cultural norms and policy contexts. Overall, monitoring presenteeism may help identify workers at elevated risk of future absence and support earlier preventive action. Reducing presenteeism will likely require integrated interventions, including statutory paid sick leave policies, organizational health management strategies, and supervisory practices that reduce attendance pressure.

List of Abbreviations

AR(1): First-Order Autoregressive

BMI: Body Mass Index

CI: Confidence Interval

CLPM: Cross-Lagged Panel Model

GEE: Generalized Estimating Equations

gsem: Generalized Structural Equation Modeling

IRB: Institutional Review Board

KHPS: Korean Health Panel Study

KIHASA: Korea Institute for Health and Social Affairs

KRW: Korean Won

melogit: Mixed-Effects Logistic Regression Command in Stata

NHIS: National Health Insurance Service

OR: Odds Ratio

SEMs: Structural Equation Models

Declarations**Ethical approval and consent to participate**

This study was reviewed and approved as exempt from full review by the Institutional Review Board of Chung-Ang University (IRB No. 1041078-20250804-HR-273).

Availability of data and materials

The data that support the findings of this study are available from the Korea Health Panel Survey (KHPS), which is jointly conducted by the Korea Institute for Health and Social Affairs (KIHASA) and the National Health Insurance Service (NHIS). The dataset is publicly accessible upon request through the official KHPS website (<https://www.khp.re.kr>).

Competing Interests

The authors declare that they have no competing interests.

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Authors' contributions

YJ and AM substantially contributed to the conception or design of the work; and the acquisition, analysis, interpretation of data for the work, and drafting the manuscript. WB reviewed the draft critically for

important intellectual content. All authors have given their final approval for the version to be published.

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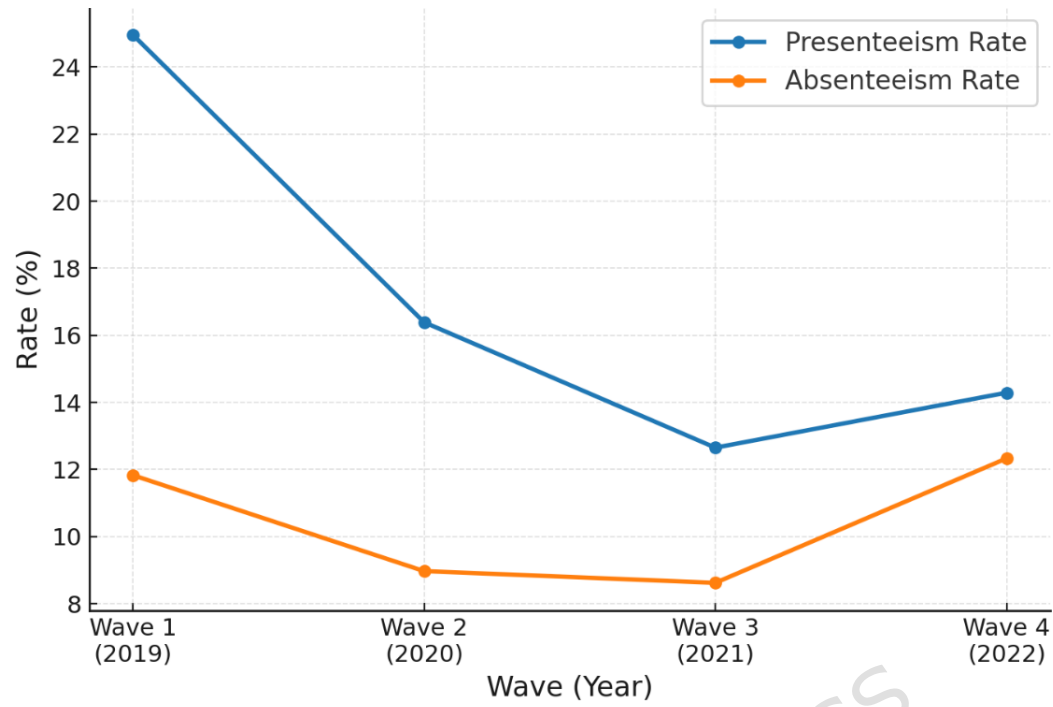
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Figure Legends

Figure 1. Presenteeism and absenteeism rates across four waves. Rates were calculated using the number of participants observed at each wave, reflecting changes in sample size due to attrition over time.

Figure 2. Bidirectional cross-lagged panel model predicting presenteeism and absenteeism across four waves. Covariates were selected from the previous wave based on significance in bivariate analyses. Solid lines indicate statistically significant paths ($p < .05$), and dashed lines indicate nonsignificant paths. OR = odds ratio.

**Figure 1**

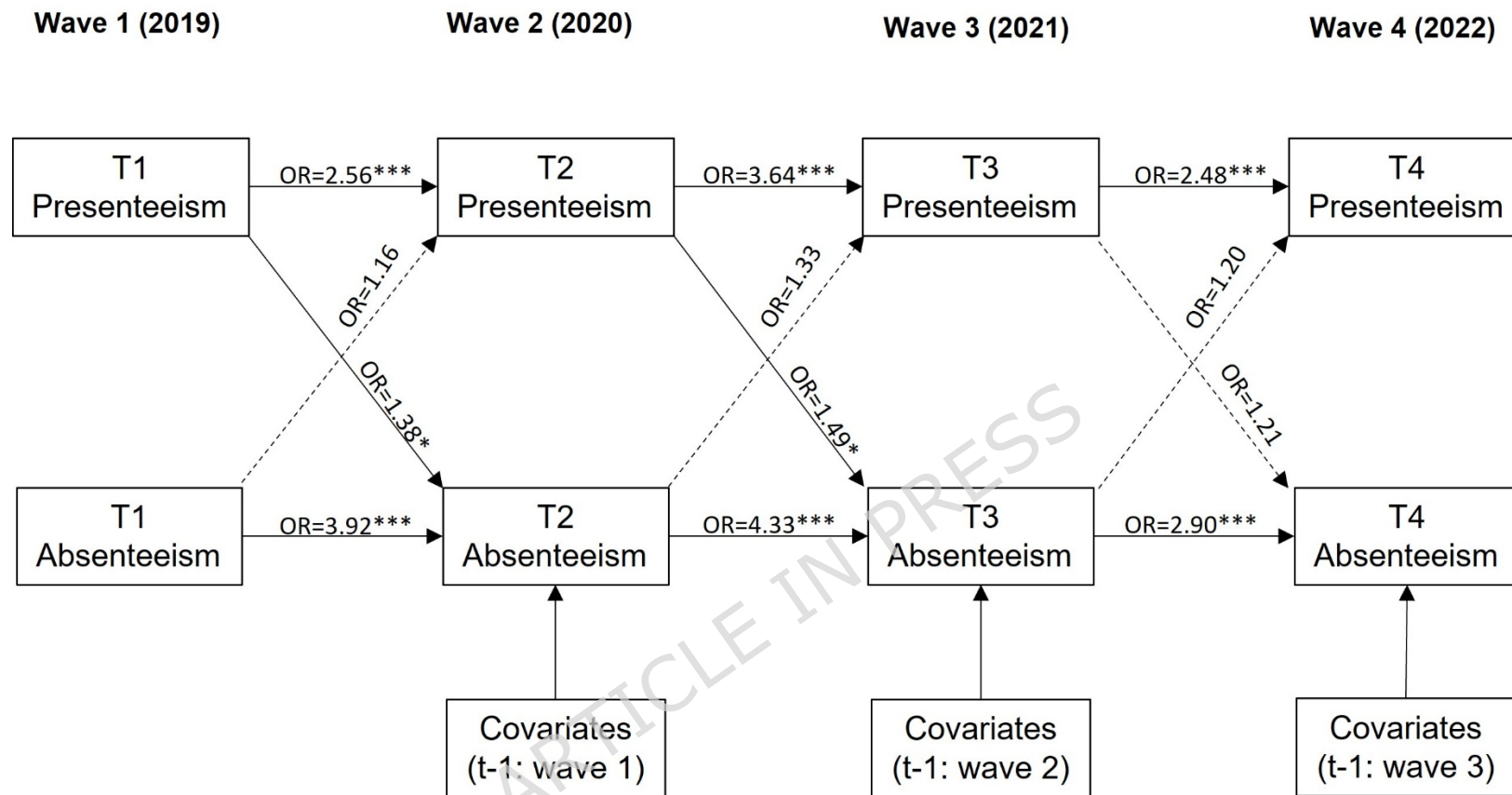
**Figure 2**

Table 1. Comparison of Absenteeism Status in Waves 2, 3, and 4 According to Previous Wave (t-1) Characteristics

Variable	Wave 2 Absenteeism			Wave 3 Absenteeism			Wave 4 Absenteeism		
	No (n=2,922)	Yes (n=288)	p-value	No (n=2,475)	Yes (n=234)	p-value	No (n=2,019)	Yes (n=280)	p-value
Age, mean (SD)	49.3 (12.8)	47.0 (12.5)	0.003	50.0 (12.6)	50.0 (11.8)	0.926	51.5 (12.2)	49.2 (11.4)	0.003
Sex, n (%)									
Male	1,615 (55.3)	143 (49.7)	0.068	1,345 (54.4)	128 (54.7)	0.916	1,116 (55.3)	149 (53.2)	0.516
Female	1,307 (44.7)	145 (50.3)		1,130 (45.6)	106 (45.3)		903 (44.7)	131 (46.8)	
Marital status, n (%)									
Unmarried	787 (27.0)	91 (31.6)	0.090	667 (27.0)	62 (26.5)	0.881	523 (25.9)	77 (27.5)	0.569
Married	2,135 (73.0)	197 (68.4)		1,808 (73.1)	172 (73.5)		1,496 (74.1)	203 (72.5)	
Education, n (%)									
High school or less	1,463 (50.1)	131 (45.5)	0.331	1,214 (49.0)	109 (46.6)	0.626	990 (49.0)	126 (45.0)	0.479
Bachelor's	1,288 (44.1)	139 (48.3)		1,098 (44.4)	113 (48.3)		890 (44.1)	135 (48.2)	
Master's or higher	171 (5.8)	18 (6.2)		163 (6.6)	12 (5.1)		139 (6.9)	19 (6.8)	
Income, mean (SD), 10,000KRW	3,234.7 (2,513.2)	3,274.0 (2,093.5)	0.797	3,342.3 (2,485.6)	3,416.1 (2,503.4)	0.664	3,552.7 (2,473.8)	3,694.5 (2,539.6)	0.371
Region, n (%)									
Metropolitan	1,861 (63.7)	197 (68.4)	0.112	1,558 (63.0)	157 (67.1)	0.209	1,252 (62.0)	186 (66.4)	0.152
Non-metropolitan	1,061 (36.3)	91 (31.6)		917 (37.0)	77 (32.9)		767 (38.0)	94 (33.6)	

[illegible]

Variable	Wave 2 Absenteeism			Wave 3 Absenteeism			Wave 4 Absenteeism		
	No (n=2,922)	Yes (n=288)	p-value	No (n=2,475)	Yes (n=234)	p-value	No (n=2,019)	Yes (n=280)	p-value
Yes	930 (31.8)	104 (36.1)	0.138	877 (35.4)	100 (42.7)	0.026	788 (39.1)	116 (41.4)	0.441
No	1,992 (68.2)	184 (63.9)		1,598 (64.6)	134 (57.3)		1,231 (60.9)	164 (58.6)	
Subjective health status, n (%)									
Healthy	2,688 (92.0)	244 (84.7)	<0.001	2,281 (92.2)	198 (84.6)	<0.001	1,835 (90.9)	239 (85.4)	0.004
Unhealthy	234 (8.0)	44 (15.3)		194 (7.8)	36 (15.4)		184 (9.1)	41 (14.6)	
Body Mass Index (kg/m ²), mean (SD)	23.7 (3.2)	24.1 (3.8)	0.063	23.8 (3.2)	24.0 (3.5)	0.384	23.9 (3.2)	24.2 (3.7)	0.193

Note. All covariates were measured at the previous wave (t-1) for each absenteeism status. **p-values were calculated using chi-square tests for categorical variables and independent-samples t-tests for continuous variables.** SD, standard deviation.

Table 2. Bivariate Association Between Presenteeism (t) and Subsequent Absenteeism (t+1) Across Waves

	Wave 1 Presenteeism			Wave 2 Presenteeism			Wave 3 Presenteeism		
	No	Yes	p-value	No	Yes	p-value	No	Yes	p-value
t+1 Absenteeism: No, n (%)	2,227 (76.2)	695 (23.8)	<0.001	2,103 (85.0)	372 (15.0)	<0.001	1,786 (88.5)	233 (11.5)	<0.001
t+1 Absenteeism: Yes, n (%)	169 (58.7)	119 (41.3)		162 (69.2)	72 (30.8)		225 (80.4)	55 (19.6)	

Table 3. Mixed-effects Logistic Regression Results for the Association Between Presenteeism at Previous Wave (t-1) and Subsequent Absenteeism

	OR (95% CI)	p-value
Presenteeism (ref. no presenteeism)	1.30 (1.08, 1.56)	0.005
Absenteeism (ref. no absenteeism)	3.45 (2.75, 4.34)	<0.001
Age (years)	0.99 (0.98, 0.99)	0.001
Employment type (ref. part-time)	1.26 (0.97, 1.63)	0.084
Physical activity (ref. no)	0.89 (0.77, 1.15)	0.123
Chronic disease (ref. no)	1.33 (1.11, 1.56)	0.002
Subjective health status (ref. unhealthy)	0.69 (0.55, 0.87)	0.001

Note. OR = odds ratio, CI = confidence interval. All covariates were measured at the previous wave (t-1). Only variables that were significant in bivariate analyses were included as covariates in the model.