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Latent profiles of job demands and job resources and their association with work wellbeing among nurses in South Korea

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The identification of underlying profiles of nurses exhibiting different patterns of job demands (JD) and job resources (JR) is critical for developing targeted interventions that promote healthy work practices and enhance overall well-being within the nursing working population. This study aimed to adopt a person-centered approach to investigate patterns of JD and JR and their association with job burnout, work engagement, and general well-being among Korean nurses. Secondary data analysis was conducted using data from the Sixth Korean Working Conditions Survey. In total, 449 nurses were included in the analysis. Preliminary measurement models were assessed, and latent profile analysis was used to extract job profiles. Finally, we investigated the association between the profiles and work-related well-being. Five latent profiles best represented JD/JR configurations: low demanding job (9.7%), poor job (6.6%), balanced job (42.7%), demanding job (21.4%), and severely demanding job (19.5%). In addition, the highest levels of perceived well-being were reported in relation to low demanding and poor job profiles, whereas poor and severely demanding job profiles were associated with a higher risk of low work engagement and high physical and emotional exhaustion. In this study, the findings showed that nurses in demanding or severely demanding work profiles experienced more emotional and physical exhaustion than those in low demanding or poor work profiles. Work engagement was lowest in severely demanding profiles, whereas perceived well-being was highest among nurses in the low demanding work environments. The study findings can be used to support nurse managers and administrators in developing strategies to reduce JD while maintaining an average level of JR support.

Keywords Latent profile analysis, Job demands–resource model, Nurse well-being, Job burnout, Work engagement

The job demands–resources (JD–R) model was proposed as a comprehensive model for understanding workplace dynamics, focusing on both negative and positive indicators of workers' well-being[1]. The JD–R model postulates that job demands (JD) are "physical, social, or organizational aspects of the job that require sustained physical or mental effort, and are therefore associated with certain physiological and psychological costs" (p. 501)[1]. In contrast, job resources (JR) are the "physical, psychological, social, or organizational aspects of the job that may […] be functional in achieving work goals, reduce job demands and its related costs, or stimulate personal growth and development" (p. 501)[1]. At the core of the JD–R model, JD and JR predict burnout and work engagement, respectively[1].

Background

The JD–R model has been widely applied to different occupational groups because of its flexibility and comprehensiveness in incorporating various job conditions[2,3]. Over the last 20 years, many JD and JR sources have been empirically recognized. Examples include work overload, work–home interference, work interruption, time and work pressure, role conflicts, and uncertainty at work[4,5]. Regarding JR, many studies have emphasized the role of supportive peer and supervisor, autonomy, control, task identity feedback, interpersonal justice, and manager and peer appreciation[4,5].

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While some types of JD and JR (e.g., workload and social support) can be found in almost every occupational group, other types are more distinctive and relevant for specific professions. In the healthcare context, the nursing work environment is characterized by long working hours, unstable work schedules, shifts and overnight work, and the need for substantial resources[6–9], meaning that those in the nursing profession have a higher risk of developing burnout[10–15].

In an integrative review, Broetje and colleagues[4] found that vital JD in the nursing context could be clustered into three macrocategories: (1) 'work overload', such as workload, time pressure and staffing, and demand–control/effort–reward imbalance; (2) 'lack of formal rewards', such as pay/benefits/financial rewards/inequitable pay, growth and development opportunities, and job security; and (3) 'work–life interference', such as work–life or work–family conflict, and rostering/scheduling/shift work. Among JR, Broetje and colleagues[4] identified six JR macro-categories: (1) 'supervisor support', such as social support from supervisor/organization, and organizational/management support; (2) 'fair and authentic management', including factors such as authentic leadership, management trust, fairness, and respect, supervisor civility, and organizational trust and fairness; (3) 'transformational leadership', such as transformational leadership and leadership practices (vision, inspiration, and mentoring); (4) 'interpersonal relationships', such as personal and professional interactions between employees or with other stakeholders, social climate/work climate, community, and mutual respect/professional status; (5) 'autonomy', such as job autonomy, control/skill discretion/decision latitude, and demand–control; and (6) 'professional resources', such as professional practice environment/possibility for high-quality patient care, access to resources, and structure/organization of tasks and work.

Many empirical studies have investigated the role of JD and JR in predicting employee well-being. Several meta-analyses and reviews have examined and confirmed the predictive roles of JD and JR in worker well-being[5,16,17]. For example, in a recent meta-analysis, Mazzetti et al.[17] showed that social support, job control/autonomy, task variety, and feedback are positively related to work engagement. Lesener et al.[5] considered various longitudinal studies to investigate the JD–R model by adopting meta-analytic structural equation modeling. The results of their meta-analysis showed that JD only predicted burnout over time, whereas JR predicted both work engagement and burnout over time. These results agree with the JD–R model, which postulates that JD and JR activate two different processes: JD may lead to exhaustion and health problems, whereas JR may foster work engagement[2].

Concerning the nursing profession, Ge et al.[12], in their recent meta-analysis, showed that the global prevalence of burnout among nurses in the last 10 years was 30.0% (95% confidence interval [CI]: 26.0–34.0%) and was associated with a working environment characterized by high JD (overloaded work, rotating shifts, low salaries, workplace violence, and workplace bullying) and low JR (little autonomy and lack of confidence).

In South Korea, a high proportion of nurses perform three-shift rotations with irregular shift patterns that can disrupt circadian rhythm adaptation[18]. Approximately 30% of nurses work long hours, exceeding 52 h per week[19], which violates the limits set by Korea's Labor Standards Act[20]. In addition, most Korean nurses reported that they did not have regular breaks, and some did not even have a meal break[21]. These hazardous work environments for Korean nurses are worsening because of heavy workloads and inappropriate patient-to-nurse ratios. Excluding special units (e.g., intensive care units and operating rooms), nurses working in acute care settings are responsible for more than 15 patients per shift[22], which is a significantly higher workload than that in Western countries such as the United States and Australia[23]. This highly demanding work environment without sufficient resources may cause Korean nurses to become physically and emotionally exhausted, ultimately hindering their work engagement.

Research on the JD–R model has predominantly used a variable-centered approach, which focuses on maximizing the explained variance of JD and JR on health outcomes such as exhaustion and engagement[24]. However, research over the last decade has emphasized the importance of identifying patterns of JD and JR in understanding which individuals may be at risk of ill health, and then targeting interventions to improve their well-being[25]. This focus has been stimulated by Karasek's constellation of job types, which postulates that varying combinations of JD and control may generate different work experiences, which, in turn, are associated with different health outcomes in relation to high strain, low strain, active, and passive jobs[26]. Subsequently, according to the JD–R model[3], the combination of JD and JR may define four different constellations: (1) low JD/low JR associated with low strain and low motivation, (2) low JD/high JR associated with low strain and high motivation, (3) high JD/low JR associated with high strain and low motivation, and (4) high JD/high JR associated with high strain/high motivation. To identify these constellations empirically, it is crucial to move from a variable-centered to a person-centered approach. The person-centered approach emphasizes individual differences in how people experience and respond to JD and JR by clustering individuals who share similar patterns of JD and JR into different profiles/classes. Latent profile analysis (LPA) is a person-centered statistical method that can be applied to identify subgroups. Few studies have used a person-centered approach to identify distinct constellations of JD and JR. Nevertheless, this approach is likely to help shed light on their impact on workers' well-being, such as job burnout and work engagement[27–32].

To the best of our knowledge, few studies have investigated JD and JR patterns using a person-centered approach among the nursing population. For example, Portoghese and colleagues[33], adopting a different theoretical perspective rooted in the JDC-support (JDCS) model instead of the JD–R model, identified four profiles among a large sample of healthcare professionals: (1) 'isolated prisoner' (high JD and low JR), (2) 'participatory leader' (low JD and high JR), (3) 'moderate strain' (slightly above average levels of JD, slightly below average to low levels JR), and (4) 'low strain' (slightly below average levels of JD, slightly above to moderate levels of JR).

Similarly, Bujacz and colleagues[34] identified four JDCS profiles in a large national cohort of registered nurses in Sweden ($N = 2936$). Specifically, they identified: (1) a supporting profile (low JD and high control/support), (2) a demanding profile (high JD and low control/support), (3) a constraining profile (low JD and low control/support), and (4) a balanced profile (average JD and control/support). Furthermore, the supporting profile showed substantially lower burnout than the other profile groups, whereas the demanding profile showed the highest burnout among nurses. Adopting the same theoretical perspective, Charzyńska and colleagues[35] identified five profiles among nurses and medical service staff in the emergency department: (1) high stress with a good understanding of one's job role, (2) moderate stress, (3) relatively high stress with average JD and a very low understanding of one's job role, (4) low stress, and (5) generally low stress but with very high JD and relational conflicts. Marzocchi and colleagues[36], considering a wider working population of healthcare professionals, identified four profiles among healthcare workers: (1) 'resourceless', characterized by mixed levels of JD and very low JR; (2) 'resourceful', characterized by low JD and high JR; (3) 'high strain', characterized by high JD and low JR; and (4) 'active engagement on the ward', characterized by high JD (interaction with patients) and high JR. Barnard and colleagues[37] identified four JD–R profiles among emergency nurses in South Africa. Specifically, they identified the following: (1) 'poor jobs' (above-average emotional and hindering JD and low JR), (2) 'resourceful jobs' (below-average JD and above-average JR), (3) rich jobs (below-average JD and high JR), and (4) 'demanding jobs' (above-average JD and low JR).

Despite extensive research on the JD–R model, few studies have investigated the connection between JD and JR profiles and nurses' work-related well-being. This underexplored area has significant implications for workplace health promotion and intervention strategies.

This study adopted a person-centered approach to investigate JD and JR patterns and their relationship with burnout, work engagement, and general well-being among Korean nurses. The study-specific objectives were as follows: (1) to empirically identify the latent profiles of JD and JR and (2) to examine the relationship of these profiles with exhaustion, work engagement, and perceived well-being among Korean nurses.

Methods

Study design, setting, and sample

This study analyzed data from the Sixth Korean Working Conditions Survey (KWCS) conducted by the Korea Occupational Safety and Health Agency (KOSHA) in 17 cities and metropolitan areas of Korea between October 2020 and January 2021. The KWCS is a nationally recognized triennial survey that adopts a systematic and representative sampling of the Korean working population. The methodology and survey used by the KWCS are the same as those used by the European Working Conditions Survey[38]. It covers a wide range of topics of working conditions and explores the associations of socioeconomics, occupational environment, and health conditions among wage workers.

The participants to the 6th KWCS were $n = 50{,}205$ and include workers, business owners, and self-employed individuals. According to the study's purpose, the inclusion criteria were as follows: (1) being a registered nurse; (2) educational level of associate degree or higher; and (3) no missing data on relevant items. A total of449 nurses were included in the data analysis.

Measures

Job demands

We considered five items for measuring job demands risk factors from the KWCS survey[39] : (1) physical demands (item: "Carrying or moving heavy loads"), (2) aggressive individual behaviors (item: "Handling angry clients, customers, patients, pupils etc"), (3) emotional demands (item: "Being in situations that are emotionally disturbing for you"), (4) technological demands (item: "Using computerized equipment and tools or machinery whether portable or not"), and (5) work intensification (item: "Working to tight deadlines"). All items were measured on a 7-point Likert scale ranging from 1 (all the time) to 7 (never).

Job resources

We considered five items for measuring job resources from the KWCS survey[39]: (1) peer support (item: "Your colleagues or peers help and support you"), (2) manager support (item: "Your manager helps and supports you"), (3) organizational participation (item: "You are involved in improving the work organization or work processes of your department or organization"), (4) organizational justice (item: "You are treated fairly at your workplace"), and (5) work autonomy (item: "You can influence decisions that are important for your work"). All items were measured on a 5-point Likert scale ranging from 1 (always or strongly agree) to 5 (never or strongly disagree).

Work engagement

The ultra-short three-item version of the Utrecht Work Engagement Scale (UWES-3)[40] was used to measure work engagement. Specifically, three items ($\omega = 0.77$) measured vigor ("At work, I feel bursting with energy"), dedication ("I am enthusiastic about my job"), and absorption ("Time flies when I am working"). All items were measured on a 5-point Likert scale ranging from 1 (always) to 5 (never).

Job exhaustion

Based on the Maslach Burnout Inventory–General Survey, the KWCS adopted two items for measuring emotional exhaustion ("I feel emotionally drained by my work") and physical exhaustion ("I feel exhausted at the end of the working day"). All items were measured on a 5-point Likert scale ranging from 1 (always) to 5 (never).

Perceived well-being

The World Health Organization Five-Well-Being Index (WHO-5) was used to measure perceived well-being. This measure is composed of five items aimed at assessing feelings over the last two weeks (item example: "I have felt cheerful and in good spirits"; $\omega = 0.91$). All items were measured on a 6-point Likert scale ranging from 1 (all the time) to 6 (at no time).

Data analyses

We first assessed the preliminary measurement models using the weighted least squares mean and variance-adjusted (WLSMV) in Mplus 8.9[41]. A series of confirmatory factor analyses (CFA) and exploratory structural equation modeling (ESEM) were performed to evaluate the psychometric properties of the measurement model and to compare the following three competing measurement models: (1) a single-factor CFA model, (2) a two-factor CFA model, and (3) a two-factor ESEM with target rotation to minimize biases in structural parameter estimates[42,43].

We considered several indices to evaluate how well the model fit the data[44]: Chi-square (χ^2, comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and weighted root mean square residual (WRMR). To interpret the fit of these indices, we considered values > 0.90 and > 0.95 for the CFI and TLI, respectively, as indicating adequate and excellent fit to the data. Values smaller than 0.08 or 0.06 for the RMSEA were considered an acceptable and excellent model fit, respectively, as were values ≤ 1.00 for the WRMR. In addition, we calculated model-based omega (ω) coefficients of composite reliability[45] for each factor using standardized estimates from these measurement models.

LPA was then used to extract profiles based on JD and JR levels. Factor scores from the final first-order (CFA or ESEM) models were used as LPA profile indicators. We estimated one to six latent profiles using a robust maximum likelihood estimator (MLR). To prevent suboptimal local maxima, LPA employs 5000 random sets of start values, 1000 iterations, and 500 best solutions for the final-stage optimization[46]. We considered two general criteria when deciding the number of profiles: (1) consistency with the JD–R model and conformity of the extracted profiles[47] and (2) statistical appropriateness of the extracted solution[48]. We considered the following goodness-of-fit indices[49,50]: the Bayesian information criterion (BIC), Akaike information criterion (AIC), constant AIC (CAIC), and sample size-adjusted BIC (SABIC). The bootstrapped likelihood ratio (BLRT) p-value and the adjusted Lo–Mendell–Rubin (aLMR) test[51] were used to compare the current model with the k-1 profile model. Finally, we considered entropy, where a higher value indicates a higher separation between the profiles. Lower values of AIC, BIC, CAIC, and SABIC suggest a better-fitting solution, whereas a statistically nonsignificant p-value for aLMR and BLRT supports the superiority of a model that includes one less profile. Statistical research provides evidence supporting the accuracy of CAIC, BIC, SABIC, and BLRT, but not that of AIC and aLMR[52,53], and suggests that BIC and CAIC should be favored under conditions of high entropy (i.e., entropy ≥ 0.80), whereas SABIC and BLRT should be favored when entropy values are lower (i.e., ≤ 0.60). Thus, although we report all indicators, we placed more emphasis on CAIC/BIC or SABIC/BLRT, depending on entropy. The participants were assigned to each class based on their posterior class membership probabilities. Furthermore, the information criteria were graphically plotted using "elbow plots." When the slope flattens, it is important to examine the optimal number of profiles and consider one or more profiles.

Finally, we investigated the association between the profiles and the external variables. Specifically, we used the AUXILIARY (BCH) function[54] in Mplus, which can evaluate substantial differences across profiles for work engagement, exhaustion, and perceived well-being while accounting for probable classification errors. This function allows for Wald tests to be conducted to compare the mean scores of the outcomes across latent profiles and has been found to provide robust results, even for non-normally distributed variables.

Results

Preliminary analysis and descriptive statistics

First, the measurement model was tested. Single-factor CFA did not provide a satisfactory degree of fit for the data (Table 1). The two-factor CFA provided a good fit to the data for two indices (CFI = 0.971 and TLI = 0.962) as well as an acceptable level of fit (RMSEA = 0.078 and SRMR = 0.044), whereas the ESEM model did not result in a substantial improvement (TLI and RMSEA below the cut-off criteria). Based on this statistical evidence, we opted for two-factor CFA. Parameter estimates from this measurement model showed well-defined and reliable factors for JD (λ = 0.36 to 0.95, M = 0.63, ω = 0.73) and JR (λ = 0.59 to 0.86, M = 0.70, ω = 0.78).

Latent profile analyses

Table 2 shows the fit indices resulting from the latent profile models containing up to six profiles. The BIC decreased as the number of profiles increased, but the decrease became minimal from the five-profile model to the six-profile model. However, because the information criterion did not reach a minimum value, we resorted to an elbow plot (see Fig. 1).

Overall, the 4-, 5-, and 6-profile solutions showed a better fit, as supported by the BIC and SABIC values and the aLMR and BLRT tests (Table 2). However, the 6-profile solution led to a spurious profile comprising less than 5% of the sample, which should not be considered (Hipp and Bauer, 2006). Subsequently, we compared the 4-

Model	χ^2	df	CFI	TLI	RMSEA (90% CI)	SRMR
Single-factor—CFA	1240.942	45	0.625	0.518	0.277 (0.264–0.290)	0.181
Two-factor—CFA	126.157	34	0.971	0.962	0.078 (0.063–0.092)	0.044
Two-factor—ESEM	118.211	26	0.971	0.950	0.089 (0.073–0.105)	0.028

Table 1. Goodness of fit statistics. $n = 449$; χ^2 = Satorra–Bentler scaled Chi-square, *CFA* confirmatory factor analysis, *ESEM* exploratory structural equation modeling, *df* degrees of freedom, *CFI* comparative fit index, *TLI* Tucker–Lewis index, *RMSEA* root mean square error of approximation, *90% CI* 90% confidence interval for RMSEA, *SRMR* standardized root mean square residual.

Model	LL	#fp	Scaling	AIC	CAIC	BIC	SABIC	Entropy	aLMR	BLRT
1 Profile	− 868.90	4	1.039	1745.79	1766.22	1762.22	1749.52			
2 Profiles	− 866.30	7	0.973	1746.60	1782.35	1775.35	1753.14	0.515	ns	ns
3 Profiles	− 854.21	10	1.108	1728.42	1779.49	1769.49	1737.75	0.775	< 0.05	< 0.001
4 Profiles	− 833.62	13	1.066	1693.24	1759.63	1746.63	1705.37	0.877	< 0.001	< 0.001
5 Profiles	− 822.41	16	1.121	1677.91	1759.62	1743.62	1692.84	0.879	ns	< 0.001
6 Profiles	− 806.12	19	0.974	1650.24	1747.28	1728.28	1667.98	0.915	< 0.001	< 0.001

Table 2. Fit indices, entropy, and model comparisons for the estimated latent profile models. *LL* log-likelihood, *fp* number of free parameters, *AIC* Akaike information criterion, *CAIC* constant AIC, *BIC* Bayesian information criterion, *SABIC* sample size-adjusted BIC, *aLMR* adjusted Lo–Mendell–Rubin test, *BLRT* bootstrap likelihood ratio test.

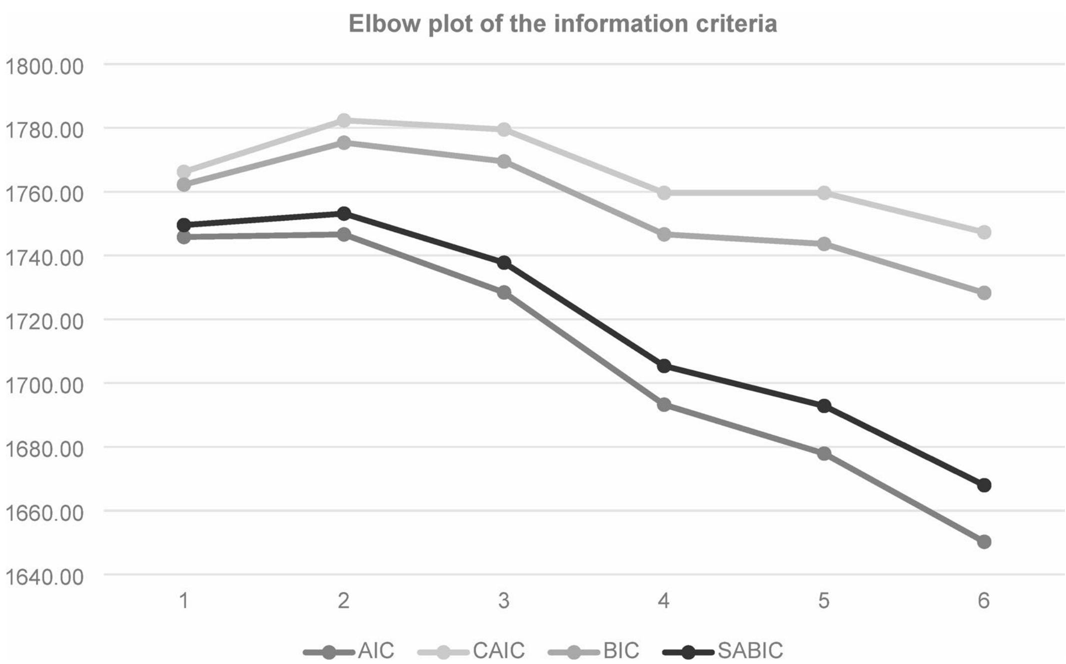

Fig. 1. Elbow plot of the information criteria. *AIC* Akaike Information Criterion, *CAIC* constant AIC, *BIC* Bayesian Information Criterion, *SABIC* sample sized-adjusted BIC.

and 5-profile solutions. The AIC, BIC, and SABIC values for all models were compared using an elbow plot. The results were based on the BIC and SABIC values, and the aLMR and BLRT tests supported the 5-profile solution.

Profile 1 represented 9.7% of the sample (latent profile membership probability = 0.86) and was characterized by very low JD and average JR (Fig. 2). Thus, this profile was denominated "low demanding job." Profile 2 represented 6.6% of the sample (latent profile membership probability = 0.90) and was characterized by very low JD and slightly below-average JR levels. This profile was labeled "poor job". Profile 3 represented 42.7% of the sample (latent profile membership probability = 0.95) and was characterized by the average levels of both JD and JR. This profile was thus labeled "balanced job." Profile 4 represented 21.4% of the sample (latent profile membership probability = 0.93) and was characterized by high JD and average JR levels. Thus, this profile was labeled "demanding job." Profile 5 represented 19.5% of the sample (latent profile membership probability = 0.86) and was characterized by very high JD and average JR levels. Thus, this profile was labeled "severely demanding job."

Profile outcomes

We used the BCH procedure in Mplus to compare the differences across the five profiles in the outcome variables of work engagement, exhaustion, and perceived well-being (Table 3). The lowest levels of work engagement were in profiles 2 (poor job) and 5 (severely demanding job), which were not distinguishable from each other, whereas profiles 1 (low demanding job), 3 (balanced job), and 4 (demanding job) showed the highest levels and were also not distinguishable from each other. Concerning exhaustion, nurses in profiles 4 (demanding job) and 5 (severely demanding job) showed the highest levels of physical exhaustion, followed by profiles 1 (low demanding job) and 3 (balanced job), whereas the lowest levels were observed in profile 2 (poor job). Emotional exhaustion was also highest in profiles 4 (demanding job) and 5 (severely demanding job), followed by profiles

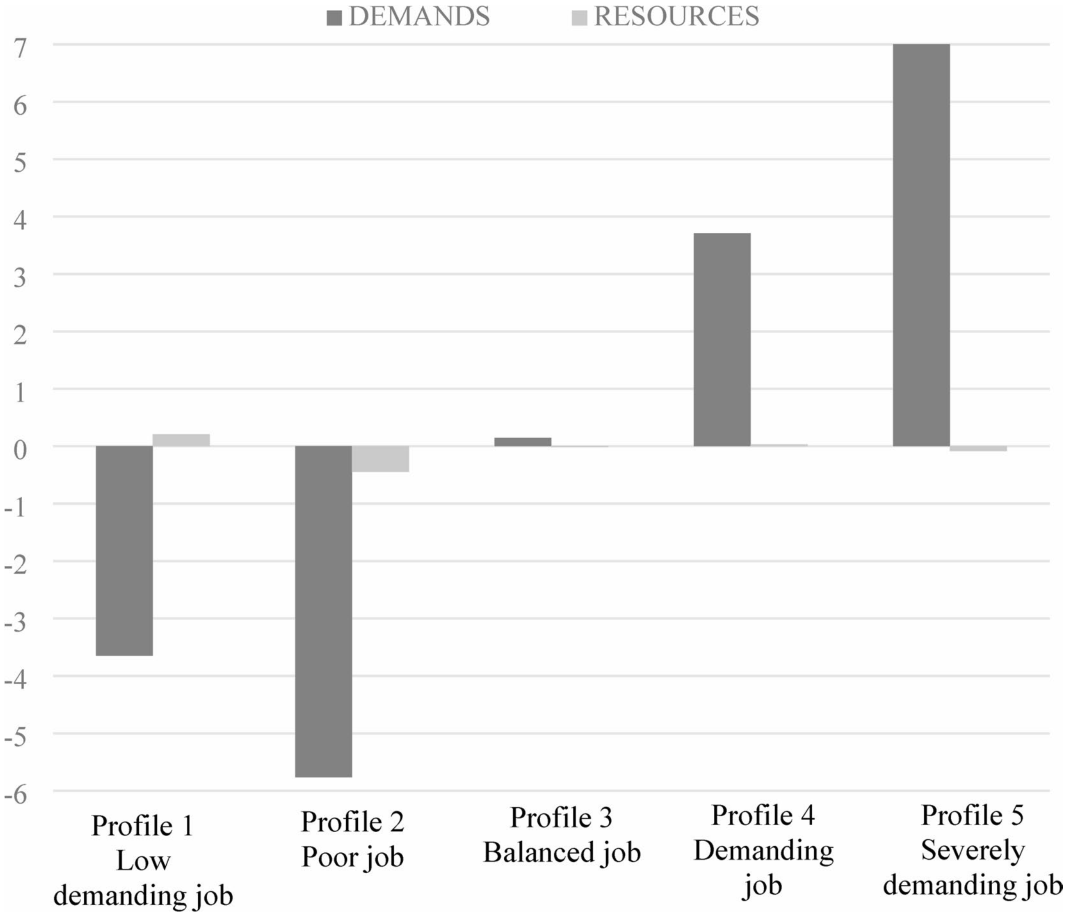

Fig. 2. Results from the latent profile models (standardized values).

Outcome	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Differences between profiles ($p < 0.05$)
	Mean (SE)					
Work engagement	3.65 (0.08)	3.48 (0.10)	3.66 (0.05)	3.63 (0.07)	3.36 (0.10)	1 = 2 = 3 = 4; 2 = 5; 5 < 4 = 3 = 1
Physical exhaustion	2.88 (0.12)	2.15 (0.20)	2.93 (0.07)	3.27 (0.10)	3.62 (0.16)	2 < 1 = 3 < 4 = 5
Emotional exhaustion	2.68 (0.12)	2.25 (0.20)	2.76 (0.06)	3.10 (0.11)	3.48 (0.15)	1 = 2 < 4 < 5; 1 = 3 < 4 < 5; 2 < 3;
Perceived well-being	4.10 (0.12)	4.26 (0.13)	3.91 (0.08)	3.86 (0.10)	3.66 (0.19)	1 = 2; 1 = 3 = 4 = 5; 2 > 3 = 4 = 5

Table 3. Outcome and pairwise comparisons of the five profiles. *SE* standard error, *Profile 1* Low demanding job, *Profile 2* Poor job, *Profile 3* Balanced job, *Profile 4* Demanding job, *Profile 5* Severely demanding job.

2 (poor job), 3 (balanced job), and 1 (low demanding job), which differed from each other. Finally, perceived well-being was highest in profiles 1 (low demanding job) and 2 (poor job), followed by profiles 3 (balanced job), 4 (demanding job), and 5 (severely demanding job), which were indistinguishable from each other apart from profile 1 compared to profile 2.

Discussion

The JD–R model[55] provides a theoretical framework for examining the complex interrelationships among individual, contextual, and organizational factors in predicting work-related well-being. The JD–R model[1,3] postulates that the combination of JD and JR leads to different constellations of job types. Moving from a variable-centered approach and capitalizing on LPA, we expanded the JD–R model regarding the empirical evidence of these job type patterns by identifying five latent profiles among a sample of Korean nurses. We also investigated the relationship between these profiles and three outcomes: (physical and emotional) emotional exhaustion, work engagement, and perceived well-being.

In general, our study revealed that the five profiles best represent the JD–R configurations, and all agree with the profiles identified in previous studies. Specifically, in line with the JD–R model[3], we identified three of the four postulated configurations: poor jobs (low JD and low JR), low demanding jobs (low JD and high/

average JR), and demanding jobs (high JD and low JR). These profiles have been frequently identified in other studies[28–30,32,34,36,37]. Furthermore, considering the JD–C model job types postulated by Karasek[26,56], these three profiles matched the passive (low JD and low JC), low strain (low JD and high JC), and high strain profiles (high JD and low JC), respectively. Among these profiles, both low strain/low demanding/resourceful (low JD and high JR) and high strain/high demanding jobs (high JD and low JR) have been commonly identified in many other studies[57–60], especially among healthcare workers, including nurses[33–37]. These results suggest that these profiles can be considered universal configurations[61]. Interestingly, in line with other studies[25,29,30,34,35], a rich job configuration (high JD and JR) was not identified, suggesting that this profile may not be universal.

The fourth profile identified in our study was balanced jobs, characterized by average levels of both JD and JR. This profile was not hypothesized by the JD–R model[1,3] but has been previously identified in many other studies[25,29,30,60]. Among the nursing/healthcare working population, four studies[33–36] have identified a similar profile, suggesting that jobs characterized by balanced levels of JD and JR are more common than expected in the nursing profession.

Finally, the fifth identified profile was severely demanding jobs, characterized by extreme levels of both JD and JR. To the best of our knowledge, this profile has only been identified once, in a study by De Spiegelaere et al.[28] in a different working population. However, the identification of this profile may be linked to the fact that the data used in this study were collected during the COVID-19 pandemic. In an attempt to combat the pandemic from the beginning of March 2020, the South Korean government changed the conditions of healthcare service provision, resulting in a dramatic increase in the workload of healthcare workers[62,63].

Concerning the JD–R profiles' outcomes, the results from our study were in line with the JD–R model, supporting the general assumption that nurses with poor and severely demanding job patterns are at higher risk of reporting reduced levels of work engagement and high levels of physical and emotional exhaustion. Thus, a combination of very high JD and low JR may expose nurses to job burnout and decrease their work engagement. Furthermore, the highest levels of perceived well-being were reported by those with low JD and poor job profiles. To the best of our knowledge, only Bujacz et al.[34] have investigated JD–R profile outcomes among nurses, showing that demanding profiles (high JD and low JR) had the highest levels of burnout. Although our results are consistent with those of Bujacz and colleagues[34], further studies are needed to confirm these results.

Limitations of the study

Although this study is one of the first to investigate the nature and outcomes of JD–R profiles, several limitations must be acknowledged when interpreting our findings. First, a notable limitation was the study's cross-sectional design. This approach restricted the ability to draw causal relationships between the studied variables because it only captured a single moment in time without considering the dynamic nature of JD and JR. Future research should incorporate longitudinal methods to track the stability and evolution of JD–R profiles over time. Second, further research is required to investigate the predictors of these profiles, including other variables such as personal resources, job crafting, and resilience. Personal resources such as self-efficacy and optimism may play a significant role in shaping an individual's response to JD and JR. Similarly, job crafting, which involves employees proactively altering aspects of their work to better fit their needs and abilities, can influence the formation of JD–R profiles. Third, the timing of data collection during the national lockdowns occurring throughout the pandemic period is another limitation. The extraordinary circumstances of the COVID-19 pandemic in 2020 undeniably affected the work environment of Korean nurses, potentially skewing the representation of JD–R profiles under different conditions. Subsequent studies need to consider the unique impact of such unprecedented events and compare data from the pandemic and non-pandemic periods to discern the differential effects on JD and JR. Fourth, this study was based on the 6th KWCS data and used items from various measures to assess JD and JR, raising concerns about the precision and specificity of the measured constructs. Although evidence of factorial validity has been provided, it is essential to continue refining and validating the measurement tools to ensure that they accurately capture the intended constructs. In addition, although the ultra-short version of the UWES is a reliable measure of work engagement, its use reduced the possibility of analyzing the relationship of the identified profiles with the three dimensions of work engagement. The same limitations emerged when two items of exhaustion were considered to measure burnout. Recently Maslach and Leiter[64] reinforced the assumption that a high level of exhaustion is not necessarily predictive of job burnout. Future research should focus on establishing the reliability and validity of these profiles across different populations and settings to strengthen the integrity of JD–R profile assessments.

Implications and conclusions

The present study offers significant theoretical implications for occupational research by identifying distinct profiles of job stressors. Our findings challenge traditional variable-centered research paradigms and provide support for integrating person-centered approaches. The empirical identification of specific stress profiles provides validation for the theoretical groupings suggested within the JD-C and JD-R models, strengthening the application of a person-centered perspective to the work stress framework. Particularly, while both the JD-C and JD-R models postulate that workers can be categorized based on patterns of working conditions, empirical validation through person-centered methodologies has been limited.

Results from this study highlight the need to move beyond the "simplicity or parsimony of the variable-centered approach" towards embracing the "specificity of the person-specific approach"[65] (p. 456). Future studies should focus on a more holistic understanding of the job stress phenomenon allowing for the identification of potentially universal stress profiles across different working populations.

Concerning practical implications, a comparison of the five job profiles identified JD as the most critical factor affecting nurses' work-related well-being. This study found that nurses in demanding or severely demanding work environments experienced more emotional and physical exhaustion than those in low demanding or poor work environments. Work engagement was lowest in severely demanding environments, which combined high JD with average JR. Notably, perceived well-being was highest among nurses with a low JD/average JR job profile. Therefore, nursing managers and administrators should regularly monitor and evaluate the JD of nurses. They should strive to reduce JD and ensure a balanced distribution while maintaining an average level of JR support. Delegating tasks during overwork or providing better nurse-to-patient ratios can help reduce workload and minimize overtime and time pressures without regular breaks. In addition, nurse managers must comply with the Labor Standards Act by providing one-hour rest breaks during eight-hour shifts.

In Korea, some medical institutions participating in government-led nurses' shift system improvement projects have adopted strategies such as ensuring regular breaks and assigning additional staff to reduce nurses' workloads. Evaluating the effectiveness of these strategies is crucial for their expansion in Korean hospitals.

Furthermore, considering the more emotionally demanding nature of their work compared to other professions because of caring for physically and mentally fragile patients[66], institutions and nurse managers should prioritize reducing the emotionally demanding aspects of nurses' work environment. This should be followed by providing nurses with access to stress management and emotional health services, along with educational programs to train them in emotional labor strategies for managing demanding situations.

Data availability

The survey was nationally authorized and was conducted on the basis of Provisions 1 and 2 of Articles 33 and 18 of the Korean Statistics Law (Authorization No. 380002). Publicly available datasets were analyzed in this study. KWCS microdata and reports are available and can be freely downloaded from the website of OSHRI (http://oshri.kosha.or.kr/eoshri/resources/KWCSDownload.do; accessed October 10, 2024).

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Declarations

Competing interests
The authors declare no competing interests.

Human ethics and consent to participate
The KWCS was approved by Statistics Korea and conducted in accordance with Article 18 of the Statistics Act (approval no: 380002) in South Korea. Data are available to the public with safeguards to protect participants' anonymity and privacy rights. All participants provided informed consent for voluntary participation. Considering the use of completely de-identified open-source data and the participants' privacy rights, this secondary data analysis did not require ethical approval from an internal review board. In Italy, ethical committee approval was not required for retrospective anonymized studies, such as KWCS repositories.

Additional information
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