Medycyna Pracy 2018;69(5):483–496
http://medpr.imp.lodz.pl/en

https://doi.org/10.13075/mp.5893.00709
ORIGINAL PAPER

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ALL EMPLOYEES NEED JOB RESOURCES – TESTING THE *JOB DEMANDS–RESOURCES THEORY* AMONG EMPLOYEES WITH EITHER HIGH OR LOW WORKING MEMORY AND FLUID INTELLIGENCE

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Abstract

Background: The *Job Demands–Resources Theory* (JD-R) is one of the most influential theoretical frameworks for explaining work engagement. The JD-R postulates the existence of a health impairment process in which job demands lead to strain, and of a motivational process in which job resources lead to work engagement. Although cognitive functions are among the most important characteristics of employees related to job, still little is known about its moderating role in JD-R processes; hence in this study we make a novel attempt to test the invariance of JD-R propositions among employees at different levels of cognitive functioning. **Material and Methods:** A group of 383 multioccupational employees completed a set of questionnaires measuring job resource: co-worker support, supervisor support, performance feedback; job demands: emotional demands, occupational constraints, work-home interferences; *Utrecht Work Engagement Scale*; *Oldenburg Burnout Inventory* along with 2 working memory and 3 fluid intelligence tests. **Results:** The multigroup invariance analysis with latent variables revealed that both the health impairment process and the motivational process as postulated by JD-R are invariant across groups of employees with either high or low levels of fluid intelligence and working memory capacity. **Conclusions:** This result provides the first piece of evidence for JD-R robustness among employees at different levels of cognitive functioning. Our findings counterintuitively suggest that employees with high cognitive functioning are not more resistant to job demands than employees with low cognitive functioning and that in order to be work-engaged they need job resources, no less than their colleagues with low cognitive functioning. Med Pr 2018;69(5):483–496

Key words: cognitive functioning, work engagement, working memory, fluid intelligence, UWES, *Job Demands–Resources Theory*

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Received: November 7, 2017, accepted: March 6, 2018

INTRODUCTION

The Job Demands–Resources Theory

Since a growing body of research has provided evidence that work-engaged employees are healthier and perform their jobs better [1,2], work engagement has become one of the most important topics in contemporary occupational science and the *Job Demands–Resources Theory* (JD-R) is one of the most influential modern frameworks for explaining work engagement that has been "applied in thousands of organizations and inspired hundreds of empirical studies" [3, p. 273]. The JD-R proposes that all types of job characteristics may be classified into one of 2 categories, i.e., job demands and job resources. Job demands are: "those physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological (i.e., cognitive or emotional) effort and are therefore associated with certain physiological and/or psychological costs" [4, p. 296]. In contrast, job resources "refer to those physical, psychological, social, or organizational aspects of the job that either/or (1) reduce job demands and the associated physiological and psychological costs; (2) are functional in achieving

Funding: this work was financed by the Polish National Science Center (project No. UMO-2015/19/N/HS6/00795 entitled "New perspectives in Job Demands-Resources Theory. Working memory capacity as a predictor of work engagement," project manager: Konrad Kulikowski, M.A. While preparing a final version of this article Konrad Kulikowski obtained financial support in the form of the doctoral scholarship Etiuda 5 from the Polish National Science Centre (Narodowe Centrum Nauki), scholarship agreement No. UMO-2017/24/T/HS6/00527).

work goals; (3) stimulate personal growth, learning and development" [4, p. 296]. The most important postulate of JD-R is that job demands and job resources initiate 2 processes, namely the health impairment process and the motivational process. In the health impairment process, job demands lead to strain and negative outcomes as, e.g., exhaustion, which is a general sense of lack of energy, feeling overloaded at work, and experiencing a strong need for rest [5]. In the motivational process, job resources predict work engagement, which is a positive work-related state of mind that is characterized by dedication, vigor, and absorption [3].

An additional but still not fully tested proposition of the JD-R theory is that not only the employees' work characteristics but also their individual characteristics might be related to their job stress and motivation. Individual characteristics "that are generally associated with resiliency and that refer to the ability to control and impact one's environment successfully" are defined as personal resources in the scope of JD-R [6, p. 49]. It is speculated [6] that personal resources might play different roles in JD-R as: directly impact well-being, moderate or mediate relationship between job characteristics and well-being and influence perception of job characteristics. However as Schaufeli and Taris [6] noted there is a lack of systematic studies testing and comparing different effects of personal resources and it is still unclear what place should personal resources take in JD-R framework. In similar vein in the most up-to-date description of the JD-R theory it is also pointed out that the role of personal resources in the JD-R theory is still not fully understood [3].

However, on current state of JD-R development the authors of the theory [3] proposed that personal resources might affect employees' well-being at least in 2 main ways. Firstly, personal resources similarly to job resources might positively predict work engagement [3,6]. Secondly, personal resources might modify the strength of relationships between work characteristics and job stress and motivation, thus moderating the health impairment and motivational processes as proposed by JD-R, e.g., personal resources might buffer the negative impact of job demands on the employees' exhaustion and enhance the positive effect of job challenges on work engagement [3], although there is only limited evidence supporting this interaction [3,7]. In this study we are particularly concentrated on the second role of personal resources. This is, because although Xanthopoulou et al. [8] call for more research on personal resources of a diverse nature, the attention of researchers has so far been paid mainly to limited types of personal resources, such as optimism or self-efficacy [3]. It seems that the role of employees' other individual characteristics which might potentially act as personal resources moderating JD-R processes is overlooked; therefore, also Bakker and Demerouti [3] have postulated that more empirical research studies are required to test how employees' individual characteristics interact with job characteristics in predicting employees' stress and motivation.

In order to respond to this call for research and to gain further insight into how employees' individual characteristics influence relationships between job characteristics (i.e., job demands and resources) and employees' job stress and motivation (i.e., work engagement and exhaustion) as postulated by the JD-R theory, in this study we made a novel attempt to analyze the possible moderating role of one of the most meaningful individual characteristics of employees' related to work, namely cognitive functioning represented by fluid intelligence and working memory capacity.

Testing the *Job Demands–Resources Theory* among employees with either high or low cognitive functioning

Although the cognitive functioning of employees may be operationalized in many ways, we suggest to concentrate on 2 important human cognitive characteristics, mainly fluid intelligence and working memory capacity. Fluid intelligence (Gf) represents the ability to solve novel problems and to adapt our thinking in situations in which previously acquired knowledge is not applicable [9]. Working memory is a term used for describing the functioning of the memory system responsible for processing, updating, maintaining, and storing information in the short-term memory [10]; working memory capacity (WMC) is a label used for representing individual differences in the working memory [11]. The debate on the differences and similarities between Gf and WMC is still vital in the field of cognitive psychology [9], but it seems that WMC and Gf represent closely related but probably to some extent distinct aspects of human cognitive functioning. We decided to analyze the role of WMC and Gf in the context of the JD-R theory, not only because they represent constructs that are most discussed in the field of cognitive psychology but also due to their large independence from culture and previous knowledge [12], thus they might represent the core aspects of human cognitive functioning.

The other important fact is that employees' cognitive functioning is one of the best predictors of job performance [13] and a negative predictor of counterproductive work behavior [14]. Additionally research studies have shown that WMC might influence cooperation when working in groups [15], job performance [16], and even human functioning in social relations [17]. Generally, according to Schmidt [18], there cannot be a debate that employees with higher cognitive functioning learn faster and more effectively solve work-related problems than their low cognitively functioning colleagues [18].

Thus it seems that available research studies provide some evidence that employees' efficiency of storing and manipulating information in memory as represented by WMC and the ability to solve novel problems as represented by Gf might be related to the level of control over their jobs and their effectiveness of influencing on work environment. Therefore as personal resources in the JD-R theory are defined as psychological characteristics of employees associated with their ability to gain control of and impact upon their environment successfully, useful in coping with job demands and fostering the attainment of work goals [3,8], represented not only by employees' self-evaluations (e.g., optimism) but also taking various forms e.g., intellectual complexity [19], then at least at the conceptual level, it seems reasonable to predict that cognitive functioning of employees might be considered as a personal resource. Then in line with the JD-R [3], personal resources might possibly moderate the relationships between job characteristics and employees' well-being. Thus, it is possible that cognitive functioning, as personal resources, might moderate the health impairment and motivational processes postulated by the JD-R. In fact there is some evidence that individual differences in cognitive functioning might have an impact on how employees interact with their work environment, e.g., Ganzach and Fried [20] have suggested that dissatisfaction that comes from a lack of work challenges is stronger for highly intelligent employees than for less intelligent ones.

In a similar vein, Ganzach [21] has provided evidence that intrinsic rewards are more strongly related to job satisfaction among employees who are highly rather than less intelligent, whereas extrinsic rewards are more strongly related to job satisfaction among less rather than highly intelligent employees. However, according to our best knowledge, the moderating role of cognitive functioning within the scope of the JD-R has not been tested yet, but, from the JD-R theoretical perspective it seems conceivable that a high level of cognitive functioning might weaken (buffer) the health impairment process (job demands → exhaustion) and boost the motivational process (job resources → work engagement).

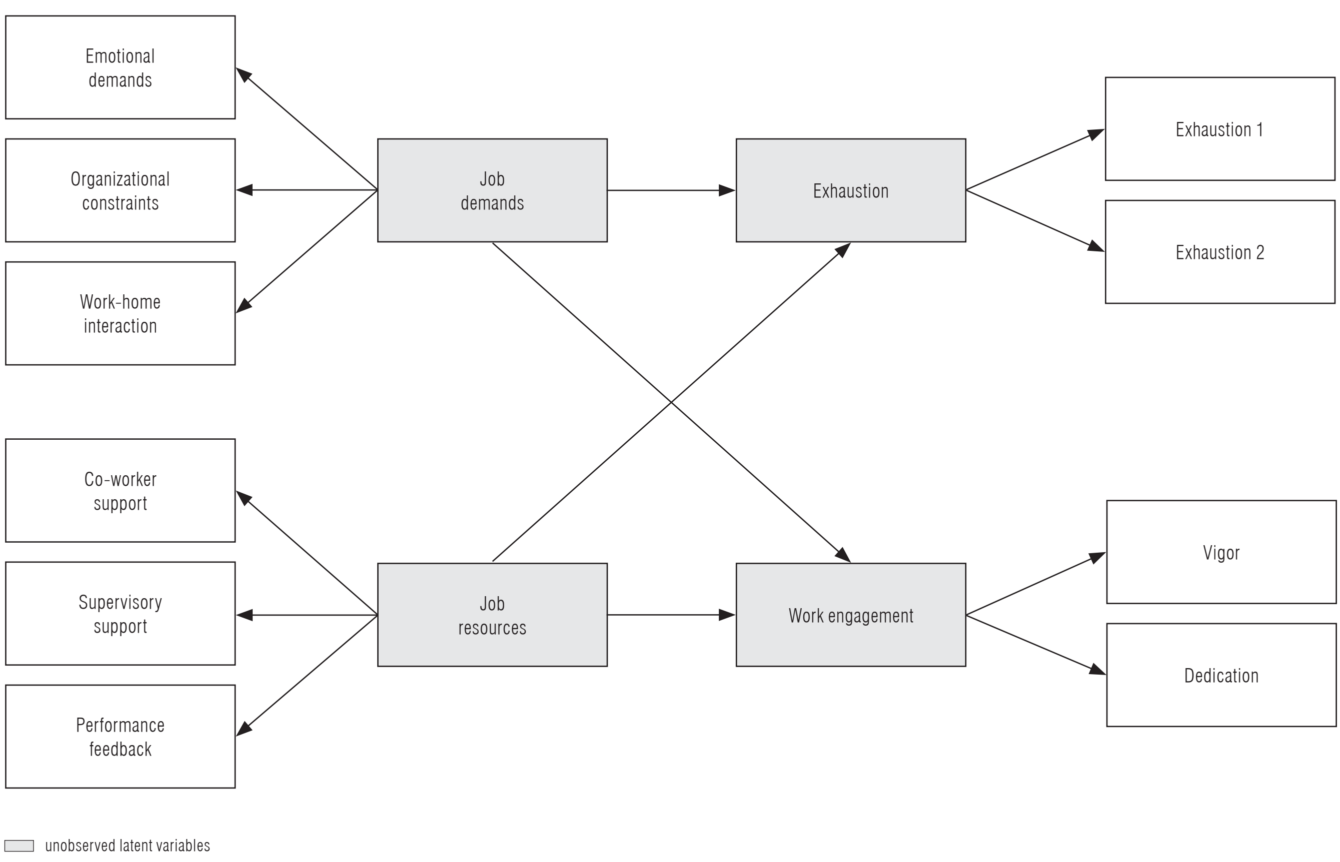
Drawing from Xanthopoulou et al. [7] description of personal resources it might be proposed that employees' cognitive functioning might possibly act as a buffer in health impairment process, i.e., the same job demands level might be weakly related to exhaustion among employees high in cognitive functioning rather than among employees low in cognitive functioning. This is because better cognitive functioning allows employees to analyze work-related information more accurately and effectively solve work-related problems, thus better cognitively functioning employees may more effectively cope with job demands and therefore these job demands might have a weaker impact on their well-being than among low cognitively functioning ones. In contrast, employees with low cognitive functioning might be less capable of controlling their work environment successfully and might have more difficulties when coping with job demands, hence the job demands might have more negative impact on their well-being. It is also possible that higher cognitively functioning employees as having tendency to engage in more challenging work tasks than their lower cognitively functioning colleagues [20] might perceive demanding work conditions more as challenges then hindrances which also might reduce a negative relationship between job demands and exhaustion.

Cognitive functioning of employees might also have a potential to boost the motivational process (job resources–work engagement). This is because better cognitive functioning seems to give a potential to more effective utilization of possessed job resources [13,18]. Employees with higher cognitive functioning, thanks to their better work-related information processing and reasoning abilities, might be more competent in utilizing job resources. For example among employees with the same level of supervisor support more cognitively capable employees might exploit supervisory support more efficiently than their less cognitively capable colleagues (e.g., by better understanding of supervisor suggestions, or ability to more precisely describing their work problems etc.). Thus, more cognitively capable employees might possibly take more advantage of the job resources offered by the job and this might result in stronger relations between job resources and work engagement among employees high rather than low in cognitive functioning.

Therefore, testing the invariance of the JD-R theoretical proposition among employees with either high or low levels of cognitive functioning is not without merit and might allow to gain new knowledge with both practical and theoretical contributions. The results of this study might possibly help to build a better understanding of the factors amending relations between work conditions and work engagement/exhaustion, which are of increasing importance in contemporary occupational science.

To sum up, the aim of this study was to test the invariance of the JD-R theory among employees at different levels of cognitive functioning by answering the following question: Are the health impairment process (job demands → exhaustion) and the motivational process (job resources → work engagement) as postulated by the JD-R theory invariant among employees at different levels of cognitive functioning operationalized as Gf and WMC? A graphical representation of the JD-R model that was tested among either high or low Gf/WMC employees in this study is presented in the Figure 1.

It is important to notice that it is possible to introduce into the framework of the JD-R theory other variables than job demands and job resources depicted in the Figure 1, e.g., job performance, job crafting or self-undermine behavior [3]. The role of job-crafting and self-undermine behavior in motivational and health impairment processes is still not fully explored and according to our best knowledge they are not currently considered as a vital part of these processes [3]. Thus, adding job-crafting and self-undermine behavior into a model tested in this study might complicate and blur the 2 processes that are our main interest, as Bakker and Demerouti wrote: "job demands were the unique predictors of exhaustion, whereas job resources were unique predictors of (dis)engagement" [3, p. 274]. When it comes to job performance it is rather an outcome of 2 analyzed processes than a part of these processes and additionally in our analysis we are concentrated on employees' subjective well-being not on job performance as an effect of work. At this point it is



Error terms of emotional demands and organizational constrain were correlated in a tested model.

Fig. 1. Job demands–resources model tested among employees with levels of either high or low cognitive functioning (working memory capacity and fluid intelligence)

worth to notice that when we present WMC and Gf as personal resources within JD-R then we might also predict not only WMC and Gf influence on strength of health impairment and motivational process but also direct and indirect relations of WMC and Gf with job resources and work engagement. However, in our estimation the question if the JD-R theory is robust among employees at different levels of cognitive functioning is substantially different from a question of how cognitive functioning might be related to job resources and work engagement. As former question is to test invariance of JD-R in its current well-established form, the latter is an attempt to introduce a new component to an already formed JD-R framework. We recognize a potential of WMC and Gf as possible predictors of job resources and work engagement but in the same time we suggest that it requires different means of the analysis and constitutes different research problem. Therefore we intend to discuss it in a separate paper devoted to better understanding possible direct and indirect relations of WMC and Gf with work engagement [22]. Therefore in this paper for the sake of robustness and clarity of our analysis we concentrated only on invariance of 2 main and most robust processes postulated by the JD-R theory, i.e., motivational and health impairment processes among employees at different levels of cognitive functioning.

Hence we estimate that testing the model presented in the Figure 1 among employees at different levels of cognitive functioning might significantly broaden our current state of understanding of a possible moderating role of cognitive functioning for JD-R theory and additionally might be a good starting point to further analysis advancing our understanding of employees' well-being in a workplace. Obviously, JD-R model tested here, as any scientific models, is not a perfect representation of a real world, however, it might be seen as one of the most useful models explaining work-related well-being [3] and might be a reasonable trade-off between precision of the scientific analysis and possibility of generalization of obtained conclusions.

MATERIAL AND METHODS

Participants and procedure

The data reported here constitutes a part of a larger research project devoted to gain a better understanding of the role of cognitive functioning for employees' work engagement. In this article we reported only data that was used for investigating the moderating role of cognitive functioning in the framework of the JD-R theory. The data presented here and other data from this project will be also used in the future analysis and testing of direct and indirect relationships between WMC, Gf, job resources and work engagement, that exceed the scope of this paper [22]. A detailed description of the procedures and all of the measures used here are available upon request from the author.

We recruited 400 volunteers through local advertisement portals. The participants received compensation worth ca. EUR 12. The minimum of 1 year of total work experience and at least 80 working hours per month during the previous 12 months were the inclusion criteria. The participants were obligated to present documents confirming employment status in order to confirm the inclusion criteria. After deleting responses with an accuracy of < 80% in the WMC measures, and after deleting multivariate outliers according to the Mahalanobis distance [23], a total of 383 records (66% women) were analyzed. Two hundred and sixty-one participants (68.2%) had a university degree and 122 (31.8%) had a lower level of education; 143 (37.4%) participants described themselves as ordinary workers and 240 (62.6%) described their position in an organization as that of a specialist or managerial; 289 (75.5%) were working on a job contract, while 94 (24.5%) were working on other forms of job agreement. The mean age among the participants was 30.4 (SD = 7.8); the mean monthly work time was 154 h (SD = 35 h); the mean tenure at their current workplace was 3.6 years (SD = 4.6), and the mean monthly net wage was PLN 2219 (approx. EUR 515) (SD = PLN 915).

The participants first completed Gf paper pencil tests, then the WMC computerized test and then computerized questionnaires. The cognitive tests were conducted first in order to use the participants' maximum motivation. The study lasted about 2 h and took place in a specially prepared psychological computer laboratory equipped with computers having the same parameters.

Measures

Work engagement was measured with 2 scales representing the core dimensions of work engagement vigor and dedication from the shortened version of the *Utrecht Work Engagement Scale* (UWES-9) [24]. The *Vigor* scale consisted of 3 items; the sample item being: "At my job, I feel strong and vigorous," and the dedication scale consisted of 3 items, the sample item being: "My job inspires me." The subjects answered on a 7-point frequency scale, ranging from 0 – never to 6 – always/every day. We used 2 instead of 3 scales from the UWES-9 because the 2-factorial version of the UWES seems to present better psychometric properties than the 3-factorial one in the Polish context [25].

Exhaustion was measured with an 8-item *Exhaustion* scale from the Polish version of the *Oldenburg Burnout Inventory* (OLBI) [26]. The sample item is: "After my work, I usually feel worn out and weary;" the items were scored on a 4-point Likert scale ranging from 1 – totally disagree to 4 – totally agree. The scale was divided into two 4-item subscales in order to create latent exhaustion variable items from the exhaustion scale.

In this study as indicators of job resources we used: co-worker support, supervisor support, and performance feedback. We used the Polish version of the Karasek's *Job Content Questionnaire* [27] in order to measure co-worker support and supervisory support. Performance feedback was measured with 3 items based on *Feedback from Others* scale [28] (sample item: "I receive information about the quality of my work"). All job resources were scored on a 4-point Likert scale ranging from 1 – totally disagree to 4 – totally agree.

In this study as indicators of job demands we used: emotional demands, occupational constraints, negative work-home interaction. Organizational constraints were measured using 4 items from the Polish version of the Spector and Jex's *Organizational Constraints Scale* [29]; a sample item is: "How often do you find it difficult or impossible to do your job because of poor equipment or supplies?". Negative work–home interaction was measured based on Geurts et al. [30] definition of negative work–home interaction using 4-item self-constructed negative work–family conflict scale. The items were:
1. "How often do you quarrel with people close to you because of your work?"
2. "How often do you have too little time for people close to you because of your work?"
3. "How often do you have difficulty with fulfilling your obligations toward people close to you because of your work?"
4. "How often does your work have a negative impact on your family life?"

Emotional demands were measured using 4-item self-constructed general emotional demands scale. The items were developed to capture general emotional job demands not specific to any particular work context. Two items were created based on the Xanthopoulou et al. [7] emotional demands scale: "How often do you face emotionally charged situations in your work?", "How often is your work emotionally demanding?" and 2 items were newly developed: "How often do you have to deal with the emotions of other people in your work?", "How often in your work are you struggling with the things that arouse in you strong emotions?". Self-constructed scales presented good psychometric properties demonstrated by their validity, predicted by JD-R theory patterns of correlation with other scales used in this study, high reliability (Table 1) and good fit in structural models as job demands indicators. All job demands items were scored on a 5-point frequency scale ranging from 1 – less than once per month or never to 5 – several times per day. Cronbach's α and Pearson's r correlations of the scales used in this study are presented in the Table 1.

The *Operation Span Task* (OSPAN) and the *Reading Span Task* (RSPAN) were used as indicators of WMC [31] because they are considered to be some of the most accurate measures of WMC [11]. These computerized tasks required from the subject to remember a list of letters while attempting to solve a series of mathematical equations (OSPAN) or when evaluating whether the presented sentence made logical sense or not (RSPAN). The participants first solved the math equation/evaluated the sentence and then a letter to be remembered was displayed on a computer screen; after the letter was displayed another math equation/sentence appeared, and so on. In RSPAN and OSPAN, there were 2 blocks with 5 letter sequences from 3 to 7 letters in length each, totaling 50 letters in each task. After each sequence of letters had been displayed the participants were asked to recall the letters by clicking on the appropriate letters out of those presented on a screen. The sum of all correctly recalled letters in the entire task was used as a final score in RSPAN and OSPAN.

The first indicator of Gf was accounted for by *Raven's Advanced Progressive Matrices* (RAPM), which consisted of 18 odd-numbered items from the original, 36-item Polish RAPM. In each item of the RAPM the participants were presented with a 3×3 matrix filled with geometrical shapes creating a logical pattern but with one bottom-left shape missing. The participant's task was to correctly select 1 out of 8 provided test shapes that matched the pattern created by the shapes already shown in the matrix. The second indicator of Gf was the *Test of Analogical Reasoning* (TAR). Similarly as in the RAPM, we used 18 odd-numbered items out of the original, 36-item set. In this task, each item was constructed to create an analogy in the form of: shapes in the model pair are related to one another as the third shape is related to A, B, C, or D test shapes? The par-

Table 1. Statistics of the scales used in this study to test the *Job Demands–Resources Theory* among multioccupational employees (N = 383) with either high or low cognitive functioning

Scale	M	SD	Pearson's r correlation														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Co-worker support	2.94	0.46	0.75														
2. Supervisor support	2.62	0.60	0.43*	0.78													
3. Performance feedback	2.76	0.61	0.34*	0.45*	0.75												
4. Emotional demands	2.96	1.15	–0.07	–0.18*	–0.06	0.87											
5. Occupational constrains	2.12	0.86	–0.17*	–0.31*	–0.16*	0.50*	0.72										
6. Work–home interaction	1.93	0.85	–0.20*	–0.24*	–0.11*	0.48*	0.47*	0.84									
7. Exhaustion part 1	2.25	0.49	–0.33*	–0.37*	–0.33*	0.25*	0.32*	0.42*	0.64								
8. Exhaustion part 2	2.70	0.67	–0.28*	–0.35*	–0.28*	0.36*	0.39*	0.52*	0.61*	0.83							
9. Dedication	3.23	1.51	0.31*	0.39*	0.29*	0.02	–0.21*	–0.06	–0.46*	–0.42*	0.84						
10. Vigor	2.97	1.38	0.37*	0.40*	0.29*	–0.07	–0.28*	–0.20*	–0.56*	–0.55*	0.79*	0.83					
11. WMC – OSPAN	36.86	8.85	0.10*	0.15*	0.13*	–0.08	–0.06	–0.03	–0.13*	–0.10*	0.06	0.06	0.77				
12. WMC – RSPAN	34.10	8.24	0.15*	0.21*	0.18*	–0.05	–0.08	–0.06	–0.10	–0.07	0.05	0.05	0.63*	0.75			
13. Gf – RAPM	9.11	2.96	0.19*	0.19*	0.09	–0.11*	–0.03	–0.07	–0.17*	–0.13*	0.04	0.09	0.40*	0.35*	0.71		
14. Gf – NST	9.93	3.31	0.12*	0.13*	0.07	–0.17*	–0.01	–0.06	–0.11*	–0.11*	0.03	0.07	0.33*	0.25*	0.54*	0.73	
15. Gf – TAR	10.83	3.44	0.17*	0.11*	0.07	–0.15*	–0.02	–0.09	–0.17*	–0.13*	–0.01	0.07	0.37*	0.23*	0.64*	0.58*	0.78

WMC – working memory capacity, OSPAN – *Operation Span Task*, RSPAN – *Reading Span Task*, Gf – fluid intelligence, RAPM – *Raven's Advanced Progressive Matrices*, NST – *Number Series Task*, TAR – *Test of Analogical Reasoning*.
* $p < 0.05$.

ticipant was asked to choose 1 shape out of 4 options to create a pair of shapes, which was analogical to a model pair of shapes. As a third Gf indicator we created the *Number Series Task* (NST) based on Thurstone's idea of a number series task [32]. This task contained 18 items and the participants were asked to choose the next number in a series of numbers arranged in a logical order (e.g., 3, 6, 9, 12, ?) out of 4 given numbers (e.g., 7, 9, 11, 15). In each of the 3 Gf tasks, 10 min were given to complete all items and a final score for each task was calculated as a sum of all correctly solved problems; descriptive statistics and reliabilities for all measures used in this study are presented in the Table 1.

During the research procedure the participants additionally completed an n-back task and the *Symmetry Span* task, but the results of these tasks are not reported here as the confirmatory factor analysis revealed that they created other factors distinct from WMC and Gf, and an analysis of these constructs is beyond the scope of this article.

Strategy of statistical analysis

In order to assign the participants to low or high Gf and WMC groups, we computed the Gf and WMC total scores. First of all, we conducted the principal component analysis on all Gf and WMC measures with varimax rotation, and it revealed the existence of 2 distinct factors. Then, the confirmatory factor analysis also confirmed better fit for the model assuming the existence of 2 distinct factors, WMC and Gf (df = 4, $Chi^2 = 10.8$, root mean square error of approximation (RMSEA) = 0.067, goodness-of-fit index (GFI) = 0.989, comparative fit index (CFI) = 0.990, Tucker-Lewis index (TLI) = 0.974, normed fit index (NFI) = 0.984) than 1 common factor integrating all of the cognitive functioning measures used here (df = 5, $Chi^2 = 145.8$, RMSEA = 0.271, GFI = 0.878, CFI = 0.787, TLI = 0.575, NFI = 0.783). Next, we calculated the factor score for Gf and WMC by multiplying each indicator's score by the factor loading for this indicator and then summing them up, i.e., WMC total score = OSPAN score × 0.85 + RSPAN score × 0.91; Gf total score = RPMT score × 0.80 + TAR score × 0.82 + NST score × 0.87; mean for total score for Gf was 24.8 (SD = 6.86) and for WMC it was 62.36 (SD = 13.57); correlation between WMC and Gf was 0.42 ($p < 0.001$). Then we computed the median (Me) for the total scores of Gf (Me = 63.9) and WMC (Me = 24.9) and, based on the median value, we split the participants into groups of low/high scores. Participants with scores above the median were assigned to high WMC/Gf groups and participants with a score equal to or less than the median were assigned to low WMC/Gf groups.

To test the invariance of the JD-R model among employees with either a high or low cognitive functioning level, we conducted latent variable structural equation modelling with the multi-group invariance test [22] in IBM AMOS 24. In this approach, the JD-R model (Figure 1) was simultaneously fitted in groups of either high or low Gf/WMC employees, i.e., we conducted 2 separate multigroup invariance tests, one for high/low WMC and one for low/high Gf groups. We went through 3 steps of the analysis in each of the 2 multigroup invariance tests.

In the first step, we created an unconstrained model in which all JD-R model parameters (e.g., regression weights, factor loadings) were allowed to freely vary between high and low groups. In this step we assumed that the JD-R model might differ across the tested groups.

In the second step we created and tested the measurement invariance model. In this step, factor loadings on indicators of latent variables were constrained to be equal across the 2 tested groups but regression weights were still not constrained and were free to vary across the groups. This step allowed us to test the equivalence of the measurement structure across the tested groups. If the measurement invariance model fit the data no worse than the unconstrained model we can state that we were measuring the same latent constructs in the high and low WMC/Gf groups.

In the third step of the invariance analysis we evaluated the structural invariance model. In this step, factor loading and the regression weights of the JD-R model from the Figure 1 were constrained to be equal across both the high and low WMC/Gf groups; in other words, in the third step we imposed an assumption that the structure of the JD-R model (Figure 1) was invariant across the tested groups.

If the measurement invariance model fit the data in an acceptable way and it fit the data no worse than the unconstrained model, and the structural invariance model fit the data in an acceptable way and fit the data no worse than the measurement invariance model, we can state that there was model invariance among the tested groups, otherwise we might state that the tested structural model was not invariant across the groups involved in the multigroup analysis [22].

To test change in the model fit caused by imposing a restriction on the model parameters in the multigroup analysis, we observed changes in CFI (ΔCFI) between models of increasing restriction (i.e., the unconstrained model vs. the measurement invariance model and the measurement invariance model vs. the structural invariance model) where ΔCFI < 0.01 suggested model invariance among the tested groups and ΔCFI > 0.01 indicated that the model meaningfully differed between the tested groups [22]. To test the models' fit to the data, we analyzed RMSEA, CFI, NFI, TLI, and GFI.

RESULTS

The descriptive statistics, reliabilities, and correlations for all measures used in this study are presented in the Table 1. All measures present good reliability, i.e., > 0.7, except for one, namely exhaustion part 1; Cronbach's α was 0.64, but in the context of this study this value might still be considered as acceptable, taking into account that the scale consists of 4 items only and that the second indicator of exhaustion is highly reliable; Cronbach's α = 0.83.

The coefficients for the JD-R model paths (Figure 1) tested in the low/high WMC and low/high Gf groups without imposing constraints on any parameters are presented in the Table 2. In this step of the analysis the so-called unconstrained model was created in which all parameters of the tested JD-R structure might vary freely between the tested groups. This step of the analysis allows us to initially compare the JD-R model structure across the tested groups. The results in the Table 2 are split into 2 sections, i.e., the measurement model and the structural model. The measurement model describes the structure of latent variables in each tested group, whereas the structural model describes relations

Table 2. Standardized regression weights for groups of low/high working memory capacity and low/high fluid intelligence employees*

Paths	Working memory capacity		Fluid intelligence	
	low (N = 193)	high (N = 190)	low (N = 190)	high (N = 193)
Measurement model				
job demands				
emotional demands	0.51	0.63	0.55	0.59
occupational constrains	0.56	0.56	0.55	0.57
work–home interaction	0.82	0.84	0.82	0.84
job resources				
co-workers support	0.57	0.61	0.56	0.62
supervisor support	0.78	0.71	0.79	0.70
performance feedback	0.64	0.47	0.65	0.51
exhaustion				
exhaustion 1	0.75	0.76	0.74	0.75
exhaustion 2	0.80	0.80	0.78	0.82
work engagement				
dedication	0.85	0.81	0.87	0.81
vigor	0.97	0.94	0.92	0.97
structural model				
job demands				
exhaustion (health impairment process)	0.59	0.57	0.54	0.61
work engagement	−0.07 n.s.	0.02 n.s.	−0.02 n.s.	−0.01 n.s.
job resources				
exhaustion	−0.31	−0.51	−0.45	−0.37
work engagement (motivational process)	0.47	0.70	0.55	0.62

* The sample of 383 employees was median split by fluid intelligence level, then merged and split again by working memory capacity level.
n.s. – not statistically significant; all coefficients are significant at a 0.05 level except for these marked as n.s.

between latent variables in each group. Inspection of the measurement models revealed that in all of the tested groups all indicators loaded significantly on the latent variables assigned to them, additionally, inspection of the model fit indices for unconstrained models as presented in the Table 3 suggested an acceptable fit of the models. This suggests that we used a relevant measure to successfully represent our theoretical latent construct of interest in each of the tested groups.

As for the relationship between latent variables as described in the structural model section of the Table 2, first of all, it can be noted that job resources significantly negatively predict exhaustion and job demands are not significantly related to work engagement in all of the tested groups. Then we can observe 2 important facts. Firstly, the standardized coefficients in all of the tested groups are quite similar in magnitude. Secondly, in line with JD-R propositions, job demands significantly predict exhaustion (the health impairment process) and job resources significantly predict work engagement (the motivational process), and these relationships were replicated across the employees' groups at different cognitive functioning levels. Only for the motivational process (job resources → work engagement) could we observe some small relative differences in the standardized regression weights among the tested groups: β low WMC = 0.47 vs. β high WMC = 0.70 and β low Gf = 0.55 vs. β high Gf = 0.62, but these differences seem to be without practical meaning. However, the comparison of regression weights in the different groups is insufficient to state model invariance among groups; therefore, in the next step of our analysis we conducted a more precise test of model invariance, i.e., the multigroup invariance test [22].

Detailed results of the multigroup invariance tests for the JD-R model among groups of low/high WMC/Gf employees are presented in the Table 3. We conducted 2 separate multigroup analyses – one for low/high WMC groups and one for low/high Gf groups. In order to format the groups, a sample of 383 employees was first split by the WMC level and multigroup analyses were conducted, then the groups were merged and split again by the Gf level to conduct the second multigroup analysis. In the first step of each invariance analysis the so-called unconstrained model was constructed. As it may be seen in the Table 3, this liberal model that allows for different parameters across the tested groups presents acceptable fit to the data in both the low/high WMC (CFI = 0.971, RMSEA = 0.044) and low/high Gf (CFI = 0.962, RMSEA = 0.050) groups.

Table 3. Multigroup invariance test of the job demands–resources model among groups of employees created according to their working memory capacity (WMC) and fluid intelligence (Gf) levels

Model	Chi^2	df	GFI	NFI	IFI	CFI	RMSEA	Model comparison			
								U vs. MW		MW vs. SW	
								ΔCFI	ΔChi^2 p	ΔCFI	ΔChi^2 p
WMC high vs. WMC low											
U	97.30	56.00	0.95	0.94	0.97	0.97	0.04				
WM	101.50	62.00	0.95	0.93	0.97	0.97	0.04	0.002	0.650		
SW	106.50	66.00	0.95	0.93	0.97	0.97	0.04			0.001	0.287
Gf high vs. Gf low											
U	110.00	56.00	0.95	0.93	0.96	0.96	0.05				
WM	116.00	62.00	0.94	0.92	0.96	0.96	0.05	0.002	0.469		
SW	120.00	66.00	0.94	0.92	0.96	0.96	0.05			0.003	0.354

GFI – goodness-of-fit index, NFI – normed fit index, IFI – incremental fit index, CFI – comparative fit index, RMSEA – root mean square error of approximation, U – unconstrained, MW – measurement weights invariance, SW – structural weights invariance.

In the next step, a measurement invariance model was constructed imposing constraints on all of the loadings of the latent variables' indicators across the tested groups. This model again presents good fit in the low/high WMC (CFI = 0.973, RMSEA = 0.041) and low/high Gf (CFI = 0.963, RMSEA = 0.048) groups. Importantly, the more restrictive measurement invariance model fit the data no worse than the liberal unconstrained model; for low/high WMC groups the changes in the model fit were: ΔCFI = 0.002, ΔChi^2 p = 0.650 and for the low/high Gf groups the changes in the model fit were: ΔCFI = 0.002, ΔChi^2 p = 0.469. The values of ΔCFI lower than the threshold of 0.01 and p values for ΔChi^2 higher than the significance level of 0.05 suggest that there were no significant changes in model fit due to imposing a restriction on the model parameters. In the third step, the structural weight invariance model was tested in which all regression weights and factor loadings were constrained to be equal across the tested groups. Despite the imposed constraints, this model presented acceptable fit for both the low/high WMC (CFI = 0.972, RMSEA = 0.040) and low/high Gf (CFI = 0.962, RMSEA = 0.046) groups. Additionally, imposing a restriction of equality on the regression weights among the models did not significantly worsen model fit in comparison to the measurement invariance model: for low/high WMC: ΔCFI = 0.001, ΔChi^2 p = 0.287 and for low/high Gf: ΔCFI = 0.003, ΔChi^2 p = 0.354.

To conclude, the results of the conducted multigroup invariance tests suggest that the tested relationships postulated by the JD-R theory (Figure 1) are invariant across groups of low/high WMC and low/high Gf employees.

DISCUSSION

The main aim of this study was to test the robustness of the JD-R theory among employees at different levels of cognitive functioning. Specifically, we tested if the health impairment process (job demands–exhaustion) and the motivational process (job resources–work engagement) as postulated by the JD-R theory are invariant across employees with either a high or a low level of cognitive functioning as represented by WMC and Gf. Although the level of employees' cognitive functioning has the potential to influence the strength of relationships between work characteristics and well-being [20,21], our findings revealed that processes postulated by the JD-R theory [3] are invariant across groups of low/high WMC and Gf. Mainly in line with the JD-R theory predictions job resources were significantly positively related to work engagement and job demands were significantly negatively related to exhaustion independently from the cognitive functioning level. The detailed discussion on a role of job resources and demands in the JD-R and their effect on well-being largely exceed the scope of this analysis and might be found elsewhere [3], thus we limit our descriptions of job resources and demands here. Since cognitive functioning is among the most important characteristics of employees related to job [13–18] and interest in work engagement is rapidly increasing among occupational scientists [1–3,6], we believe that our findings might inspire further research and have some important practical and theoretical contributions.

Our results contribute to development of the JD-R theory [3,6], which is one of the most widely used contemporary theoretical model for explaining stress and motivation in the workplace. Our findings support JD-R robustness among employees at different levels of cognitive functioning, which is a context in which, according to our knowledge, JD-R invariance has not been previously tested. These results provide some proof that JD-R predictions hold independently from the level of the employees' cognitive functioning, and this is strong support for the proposition that job resources and job demands are among the most important predictors of work-related well-being. However, in future research it is also worthy to test not only job demands as a general latent construct as was done in this study but also to test specific job demands conceptually more closely related to cognitive functioning as e.g., not fulfilled aspirations or job boredom as they might be of particular importance in the case of job demands – cognitive functioning interactions.

The findings presented in this article might also give new insight into the understudied proposition of the JD-R theory that employees' individual characteristics might moderate the relationship between job characteristics and work engagement/exhaustion [3,7,8]. The results of this study show, for the first time, that objectively measured cognitive individual characteristics of employees, namely WMC and Gf, at least in a sample studied here do not significantly influence the relationships between job demands and exhaustion, and neither between job resources and work engagement. Although it is possible that some of the employees' personal characteristics, e.g., self-efficacy, may influence processes of work engagement and exhaustion formation [8], our findings provide some first suggestions that the level of cognitive functions might not be among them.

Among the theoretical implications of our research it is also worth to notice that, similarly to other authors [4,6], we revealed a significant negative relationship between job resources and exhaustion, and this relationship was invariant across employees at different levels of cognitive functioning. Although this finding is not new and was previously reported [4,6], it might give some additional support for suggestion that not only are there health impairment and motivation processes, but also a third process, in which job resources negatively predict exhaustion within the JD-R theory.

It is also worth to notice that there were observed correlations between WMC, Gf and job resources measures (Table 1). This might suggest that although WMC and Gf do not moderate 2 main processes postulated by the JD-R theory they might act as indirect predictors of work engagement in motivational process. However, adding a completely new component to the JD-R theory is a different research problem that needs different means of the analysis and goes beyond the scope of this paper, thus, it will be analyzed in details elsewhere [22].

Another noteworthy finding is the fact that occupational constrains and work-home interaction are not significantly related to Gf, WMC (Table 1) but being insignificant seems to be hard for unambiguous interpretation. However, it might be speculated that cognitive functioning of an employee is related in different ways to positive and negative aspects of work characteristics. Based on the obtained result we might put forward a proposition for further testing that cognitive functioning might be related to positive characteristics of job e.g., job resources but not to a negative aspect of jobs as job demands. This claim does not seem to be without a merit as a highly cognitive functioning employee might have more complex and prestigious jobs offering, more job resources, but more complex jobs albeit richer in job resources not necessarily are less demanding. Therefore our findings might inspire further research in this topic.

From a practical point of view, the results of the study suggest that job demands are similarly harmful to employees with either low or high cognitive functioning and that job resources help to develop work engagement in a similar way among these employees. These findings seem to be somewhat in contradiction with everyday intuition, as generally common sense might suggest that we could expect more cognitively capable employees to suffer fewer costs when coping with job demands and to use the available resources more efficiently than their less cognitively capable colleagues. Moreover, in the workplace the most difficult tasks are usually delegated to the "smartest" employees because they may better deal with them, thus they are confronted with the highest job demands. Concurrently when providing high demands, managers and co-workers might be tempted to limited job resources provided to these employees with high cognitive functioning, believing that a high level of cognitive functioning may substitute the job resources (e.g., supervisor might think: he/she is as very intelligent person so I can reduce my personal support to him/her). However, the results of this study show that even a "smart," an employee with high cognitive functioning significantly suffers from job demands (e.g., work–home interaction, emotional demands, organizational constraints) and needs job resources (e.g., supervisor support, co-workers support, performance feedback) to minimize exhaustion and to promote work engagement. Although highly cognitively functioning employees perform their job better [13,18] our results suggest that this does not mean that they concurrently are more psychologically resistant to job demands. Importantly does it seem that little attention has been paid to the empirical analysis of possible moderation between employees' cognitive functioning and job demands–resources so far, thus our findings provide a new knowledge allowing to gain an insight into this understudied topic.

One possible limitation of our study might be its cross-sectional design, however, we estimate that the strategy of the analysis presented in this article allows us to reliably test our research questions and gain some valuable insight. First of all, our research questions and the tested model are rooted in the well-established theoretical framework of JD-R, previously tested in many empirical research studies confirming its structure and validity [3]. Additionally, to test our research questions we used the multigroup measurement method with structural equation modelling and latent variables approach allowing us for more robust conclusions and giving us a chance for an assessment of the model fit to covariance matrices of collected data. Finally, in this study we refer to well-established psychological construct, measured by valid and reliable instruments. More importantly, cognitive functioning was measured by objective performance tests not self-descriptive measures, thus we used different methods to measure the construct of our main interest, reducing a common-method bias. Taking all this into consideration we estimate that despite the limitations our research findings might be seen as contribution to the literature. However, as our research study presents novel ideas and is among the first testing a possible moderating role of cognitive functioning in the JD-R theory it might be advisable to attempt to replicate our findings in future research.

CONCLUSIONS

The most important message that arises from the presented study is that:
1. Employees with high cognitive functioning are not more resistant to job demands than workers with low cognitive functioning.
2. We cannot expect employees with high cognitive functioning to be more work-engaged when they have the same job resources level as their colleagues with low cognitive functioning. Our research has shown that high level of cognitive functioning cannot compensate for the lack of job resources, thus employees with high cognitive functioning facing high job demands should be supported with high level of job resources.
3. The findings presented in this article for the first time give support for the JD-R theory robustness among employees of different levels of cognitive functioning, providing another piece of evidence of the JD-R validity as a work engagement theoretical framework.

We believe that our results, despite some limitations, might add to the literature and spur a further debate on the moderating role of employees' individual characteristics and cognitive functions in the processes of employees' stress and motivation. As employers across the world strive to provide a high work engagement level in their organizations, we hope that our findings might contribute to development of the work engagement promotion process, especially among high cognitive functioning employees.

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Publisher: Nofer Institute of Occupational Medicine, Łódź, Poland