The interplay of job demands, job resources and cognitive outcomes in informatics

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Summary

The present study investigates the issue of match between job demands and job resources in the prediction of employees’ cognitive well-being. Job demands and job resources, as well as job-related strains (and concepts concerned with positive well-being), are not one-dimensional concepts. At a very basic level they comprise physical, cognitive and/or emotional components. The triple match principle proposes that the strongest, interactive relationships between job demands and job resources are observed when job demands, job resources and strains are based on qualitatively identical dimensions. In this study, we specifically hypothesize that cognitive job resources are most likely to moderate the relationship between cognitive job demands and cognitive outcomes. Two measures of cognitive well-being are included: learning motivation and professional efficacy. Using a web-based questionnaire, data were collected in a sample of 207 informatics. Results partially confirm our hypotheses both in terms of main and in terms of interaction effects. Informatics with high cognitive job demands have a higher feeling of competence than informatics with low cognitive job demands. This effect is stronger when matching high cognitive job resources are available. These findings are in line with earlier research on the interaction effects in the prediction of employees’ cognitive well-being at work. Copyright © 2008 John Wiley & Sons, Ltd.

Key Words
job demands; job resources; cognitive well-being; informatics

Introduction

Cognitive functioning and cognitive well-being at work is relevant for most jobs nowadays: more than half of the employees in Europe report that they have to perform complex tasks in their jobs in which efficient information processing is important (cf. van Horn, Taris, Schaufeli, & Schreurs, 2004). In this study, we define cognitive well-being as a broad concept and we will look specifically at learning motivation and professional efficacy as indicators of cognitive well-being. Both indicators are generally assumed to enhance employees’ performance and well-functioning on the job (Taris, 2006).

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Learning motivation is defined as the motivation for learning new behaviour patterns and reflects a cognitively laden outcome (Taris & Kompier, 2005). Our concept of learning motivation corresponds closely to Karasek and Theorell’s (1990) definition of active learning. Professional efficacy is a major dimension in the clinical burnout syndrome. It is described as not or hardly doubting your efficacy as an employee to do your job (Schaufeli & van Dierendonck, 2000) and encompasses both social and non-social aspects of occupational accomplishments (Demerouti, Bakker, de Jonge, Janssen, & Schaufeli, 2001).

Previous research stresses the importance of work characteristics such as job demands and job resources in relation to work-related outcomes (e.g. Kahn & Byosiere, 1992). Most research proposes interactive effects of job demands and job resources (Cooper, Dewe, & O’Driscoll, 2001), in which job resources are assumed to moderate the relation between job demands and outcomes. However, not only the interaction effects but also the nature of the variables used and their operationalizations have been discussed in the literature (Van der Doef & Maes, 1999). For instance, many studies failed to find moderating effects. Early research tended to treat job demands and job resources as global and unidimensional constructs, which obscured the interaction effects (e.g. Viswesvaran, Sanchez, & Fisher, 1999). Job demands are defined as those properties of a job that require emotional, cognitive and/or physical effort, and can have both positive and negative consequences (Jones & Fletcher, 1996). Job resources can be conceptualized as some sort of cognitive-energetic reservoirs that are tapped when the individual has to cope with job demands (cf. Hobfoll, 2002). Job demands and job resources, as well as job-related outcomes (such as strains and concepts concerned with positive well-being), are not one-dimensional concepts. At a very basic level they may comprise of cognitive, emotional and physical components. This is described as the multidimensionality principle by de Jonge and Dormann (2003, 2006). Job demands can be primarily cognitive (e.g. display high levels of concentration and precision), emotional (e.g. deal with people who get easily angered towards him/her) or physical (e.g. having to bend and/or stretch a lot at work). A similar distinction is possible with job resources, which can be primarily cognitive (e.g. have the opportunity to vary complex tasks with simple tasks), emotional (e.g. get emotional support from others) or physical (e.g. be able to use adequate technical equipment to accomplish physically strenuous tasks). Finally, employee outcomes can also be primarily cognitive (e.g. professional efficacy), emotional (e.g. emotional exhaustion) or physical (e.g. low back pain).

Recently, de Jonge and Dormann (2003, 2006) introduced the triple match principle (TMP). The TMP proposes that the strongest, interactive relationships between job demands and job resources are observed when job demands and job resources and outcomes are based on qualitatively identical dimensions. In other words, there should both be a match between job demands and job resources on the one hand, and a match between job demands/resources and outcomes on the other hand. Theoretically, this matching assumption is derived from homeostatic regulation processes. Vancouver (2000) stated that the idea of functional homeostatic regulation can be easily applied to organizational settings. Similar to the activation of matching internal resources in the area of immune and nervous functioning (e.g. Lekander, 2002), cognitive job demands and the matching cognitive job resources are most likely to affect cognitive work outcomes. It is exactly this hypothesis that will be examined in this study with two outcome measures: professional efficacy and learning motivation.

Although the assertion of triple match sounds appealing, empirical evidence with regard to TMP is mixed and mainly derived from samples in the health and service sectors, where employees often have to deal with mainly emotional job demands (for an overview of studies, see de Jonge, Dormann, & van den Tooren, 2008). In order to study the generalizability of the TMP principle, research in other occupational sectors and groups is badly needed (de Jonge & Dormann, 2006).

Also, occupational research on psychosocial well-being and health outcomes mainly stems from the health care and school sectors (Hetland, Sandal, & Johnsen, 2007). However, if a strong personal engagement in work is required, and there is an imbalance between demands and possible renewal of resources, these same outcomes may occur and should be studied beyond the human services and educational settings (Maslach & Schaufeli, 1993). These aspects are evident in many careers within fast-paced firms, where work is often deadline-driven and competitive, with long workdays, and where it is difficult to sepa-
rate work from home life. The current paper is based on data from employees within an information technology (IT) firm, which encompasses all of these characteristics. In the last few decennia there has been an rise in the IT sector (Arvidsson et al., 2006; Sparks, Faragher, & Cooper, 2001), mainly in industrialized countries (Christensen & Lundberg, 2001). Information and communication technology is becoming more and more important in a variety of domains. Since organizations with attention for the development of both a well-designed IT environment and well-being and development of employees are more productive than organizations whose sole interest is in IT and less in well-being and human capital (Sandblad et al., 2003), research dealing with the work environment and the well-being of employees with computerized work is of high importance. Moreover, previous research showed that informatics can be considered as knowledge computer workers with possible health problems such as musculoskeletal symptoms and reduced self-reported productivity (Hagberg, Vilhemsson, Wigaeus Tornqvist, & Toomingas, 2007).

The present study

The aim of the present paper is to study the TMP in the IT sector. More specifically, we investigate how the interaction between cognitive job demands and cognitive job resources is associated with two cognitive well-being outcomes, learning motivation and professional efficacy, in a sample of informatics. This general research question can be transformed into the following two hypotheses.

H1: Informatics’ learning motivation is positively associated with cognitive job demands, and this relation is moderated by matching cognitive job resources. Specifically, we expect that the positive relation between cognitive job demands and learning motivation will be stronger in case of the availability of cognitive job resources.

H2: Informatics’ professional efficacy is positively associated with cognitive job demands, and this relationship is moderated by matching cognitive job resources. Specifically, we expect that the positive relation between cognitive job demands and professional efficacy will be stronger in case of the availability of cognitive job resources.

Method

Procedure and participants

Cross-sectional data were collected using a web-based questionnaire. A total of 660 employees of a consulting, technology and outsourcing specialized company received an email with a link to the researchers’ web site. The response rate was 31.88 per cent, which is in line with de Bruin, van Boxmeer, Verwijs and Le Blanc (2007) that used a similar web-based procedure and questionnaire. Non-response analysis, based on company data, showed no significant differences with regard to demographics. The questionnaire was available both in Dutch and in French since the company is located in bilingual Belgium. Two weeks later, a reminder email was sent. The respondents \( n = 207 \), mean age (M) = 37.8 years, standard deviation (SD) = 9.4] are all higher-educated, full-time employed informatics. In total, 157 men (M = 37.9 years, SD = 9.6 years, range = 22–61 years) and 44 women (M = 37.3 years, SD = 9.0 years, range = 23–54 years) participated.

Measures

Cognitive well-being was measured using the two indicators: learning motivation and professional efficacy. Learning motivation was measured with a subscale (seven items, alpha = 0.76) of the Motivation to Learn Scale (MOLE; Kompier & Taris, 2004). The MOLE items were inspired on a motivation to learn scale used in a study by Van Mierlo, Rutte, Seinen and Kompier (2001). Items were scored on a four-point scale, ranging from 1 (almost never) to 4 (almost always). An exemplary item is: ‘In my job I am stimulated to pick up new things’. A high score refers to a high level of motivation to learn. Professional efficacy was assessed by a subscale of the Dutch version (Schaufeli & van Dierendonck, 2000) of the Maslach Burnout Inventory General Survey. The scale contained six items with a seven-point response scale ranging from 0 (never) to 6 (always, daily). Cronbach’s alpha is 0.79. An example item is: ‘In my opinion, I am good at my work’. A high score refers to a high level of professional efficacy.

Job demands and job resources were measured using the DISQ 1.1. This questionnaire has shown promising psychometrical properties and was
used in previous research (van den Tooren & de Jonge, in press). Translation/back translation procedures were used to obtain the French version that was semantically equivalent to the basic questionnaire in Dutch. Cognitive (five items, alpha = 0.66), emotional (six items, alpha = 0.78) and physical (five items, alpha = 0.77) job demands were scored on a five-point scale, ranging from 1 [(almost) never] to 5 [(almost) always]. Cognitive (five items, alpha = 0.65), emotional (five items, alpha = 0.80) and physical (five items, alpha = 0.89) job resources were also scored on a five-point scale, ranging from 1 [(almost) never] to 5 [(almost) always].

**Statistical analyses**

To test our hypotheses, we first calculated Pearson intercorrelations. Subsequently, two hierarchical regression analyses were performed, with learning motivation and professional efficacy as dependent variables. Consistent with many other occupational stress studies (e.g. Dollard & Winefield, 1998; Zapf, Dormann, & Frese, 1996), age (in years) and gender were included as covariates in the first step, as their relation with health and well-being outcomes is well established. Since all respondents worked for the same company and were all higher educated, there was no need to control for other confounding variables. A double check on their effects showed no significant effects indeed. In the second step, the three types of job demands and three types of job resources were entered as standardized main effects. A match between demands and resources can be statistically modelled by means of a multiplicative interaction term (i.e. demand × resource), in which the main terms are standardized to avoid multi-collinearity. In the third and last step, we included the three matching interaction effects between demands and resources, i.e. cognitive × cognitive, emotional × emotional and physical × physical.1 In line with recommendations of Jaccard andTurrisi (2003) for analysing interactions, unstandardized regression coefficients are displayed in the tables. To better understand the moderating influence of cognitive job resources, the interactions were graphically represented following the recommendations of Aiken and West (1991).

**Results**

Mean scores, SDs and Pearson correlations for the independent variables and the two outcome variables are presented in Table I. Cronbach’s alpha values for the different scales are found on the diagonal (boldface) in Table I. Overall, the informatics in our sample reported moderate levels of job demands and job resources, with an exception for physical job demands that are really low (M = 1.36; SD = 0.47) and cognitive job demands that are highest (M = 3.87; SD = 0.45). In line with our hypotheses, we find the highest significantly positive correlations between cognitive job demands and the two cognitive outcome variables, learning motivation (r = 0.39; p < 0.01) and professional efficacy (r = 0.41; p < 0.01). Cognitive job resources also significantly correlate positively with learning motivation (r = 0.22; p < 0.01) and professional efficacy (r = 0.27; p < 0.01). Cronbach’s alphas are acceptable for cognitive job demands (α = 0.66) and cognitive job resources (α = 0.65), and good to very good for the other scales (from α = 0.76 to α = 0.89).

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1In a fourth step, we also included the six non-matching interactions. R² change for this fourth step was not significant in both cases, and none of the added interactions were significant. More detailed results are available from the first author upon request.
The results of the two hierarchical regression analyses are depicted in Table II. For learning motivation (H1), hierarchical regression analysis showed only significant positive main effects for cognitive job demands ($B = 1.27, p < 0.01$) and cognitive job resources ($B = 0.68, p < 0.05$). Their interaction, however, was not significant.

With regard to professional efficacy (H2), hierarchical regression analysis showed significant positive main effects of cognitive job demands ($B = 2.38, p < 0.01$) and cognitive job resources ($B = 0.86, p < 0.05$), as well as for emotional job resources ($B = 0.84, p < 0.05$). Notably, the interaction between cognitive job demands and cognitive job resources on professional efficacy was significant ($B = 0.58, p < 0.01$). As graphically depicted in Figure 1, the combination of high cognitive job demands and high cognitive job resources ($+1$ SD) was associated with higher professional efficacy. In addition, Figure 1 also shows that at high levels of cognitive job resources ($+1$ SD), the association between cognitive job demands and cognitive job resources became substantially strengthened, which is in line with our second hypothesis. An examination of the regression weights (simple slopes) at $1$ SD above and below the mean of cognitive job resources revealed that cognitive demands were more strongly related to professional efficacy when cognitive resources were high ($B = 6.33, p < 0.01$), as compared with when cognitive job demands were low ($B = 3.53, p < 0.01$). Overall, we were able to explain 23 per cent of the variance in learning motivation and 29 per cent in professional efficacy.

**Discussion**

Based on the TMP, we tested the interplay of job demands, job resources and cognitive well-being in informatics, as this group is becoming more and more important in modern society. Looking at the mean values for the two outcome variables, we see rather high levels of learning motivation ($M = 19.3, \text{with a maximum of 28}$) and professional efficacy ($M = 28.8, \text{with a maximum of 42}$). Due to the fact that our sample consists only of informatics working in office settings, the low mean score ($M = 1.4, \text{with a maximum of 5}$) on physical job demands was to be expected. All other mean scale scores were also in line with expectations, considering the type of job (mainly cognitive work, less contact with clients) the participants in our study have ($M = 3.0$ for emotional job demands, $M = 3.9$ for cognitive job demands).

As expected, we found the highest significant correlations between our two outcome variables when cognitive resources were high ($B = 6.33, p < 0.01$), as compared with when cognitive job demands were low ($B = 3.53, p < 0.01$). Overall, we were able to explain 23 per cent of the variance in learning motivation and 29 per cent in professional efficacy.

Table II. Hierarchical regression of job demands and job resources on learning motivation and professional efficacy.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Learning motivation</th>
<th>Professional efficacy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Step 1</td>
<td>Step 2</td>
</tr>
<tr>
<td>Control variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender†</td>
<td>−0.069</td>
<td>−0.310</td>
</tr>
<tr>
<td>Age</td>
<td>−0.008</td>
<td>−0.015</td>
</tr>
<tr>
<td>Main effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive job demands</td>
<td>—</td>
<td>1.274**</td>
</tr>
<tr>
<td>Emotional job demands</td>
<td>—</td>
<td>−0.068</td>
</tr>
<tr>
<td>Physical job demands</td>
<td>—</td>
<td>0.205</td>
</tr>
<tr>
<td>Cognitive job resources</td>
<td>—</td>
<td>0.681*</td>
</tr>
<tr>
<td>Emotional job resources</td>
<td>—</td>
<td>−0.044</td>
</tr>
<tr>
<td>Physical job resources</td>
<td>—</td>
<td>0.161</td>
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<tr>
<td>Interactions</td>
<td></td>
<td></td>
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<tr>
<td>Cognitive × cognitive</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Emotional × emotional</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Physical × physical</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.001</td>
<td>0.206</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>−0.009</td>
<td>0.173</td>
</tr>
<tr>
<td>$\Delta R^2$</td>
<td>0.001</td>
<td>0.206**</td>
</tr>
</tbody>
</table>

* $p < 0.05$; ** $p < 0.01$; # $p < 0.10$.
† 0 = male, 1 = female.
on the one hand, and cognitive job demands and cognitive job resources on the other. Looking at the results of the two hierarchical regression analyses, we find partial support for our first hypothesis concerning learning motivation. In the second step, only the two main effects for cognitive job demands and cognitive job resources were significant, and no other main effects were found. The interaction term was not significant as opposed to our first hypothesis. These findings are consistent with Davis (2003, as cited in de Jonge et al., 2008), who also found two positive main effects of cognitive work characteristics, but no significant interaction effect of cognitive job demands and cognitive job resources.

With regard to our second hypothesis, we find evidence both in terms of main effects and in terms of a significant interaction effect. This confirms our second hypothesis. In the overview of empirical studies given by de Jonge et al. (2008), four TMP studies found similar results. The important role of the matching of job demands and job resources for understanding employees’ well-being can theoretically be explained by self-regulation mechanisms. For instance, in the area of immune functioning, homeostatic regulation processes are known to cause an activation of internal resources (e.g. T- and B-cells) when particular demands occur (Lekander, 2002). According to de Jonge et al. (2008), functional homeostatic regulation at work involves identical self-regulation processes in order to cope with states of psychological imbalance at work induced by job demands. Individuals activate functional, matching (cognitive) job resources to strengthen the positive effect of cognitive job demands on cognitive well-being indicators. The new behavioural learning response, if effective and usable, will be incorporated in the employee’s repertoire of activities. In accordance with the demand–control theory, we further argue that the potential activity level will increase in the future due to an increasing number of solutions to deal with challenging job demands (cf. Karasek, 1998).

Apart from the cognitive main effects and the cognitive interaction effect, we also found a significant main effect of emotional job resources on professional efficacy. This effect could be explained by the fact that informatics, although primarily having a cognitive job, are also susceptible to emotional job resources, such as social support from colleagues and superiors. This finding is in line with the demand–control–support model (Karasek & Theorell, 1990), in which social support at work is considered as a major work characteristic that can have main and moderating effects on cognitive well-being and strain at work. As expressed by the Demand Induced Strain Compensation model, further qualification of particular kinds of job resources seems to be highly important. In addition, it seems that the TMP is not an exclusive principle, but a major one instead.

**Limitations**

The current study shares some limitations with other studies. Firstly, our cross-sectional design precludes causal interpretations. Longitudinal studies are needed in this respect. Secondly, common method bias (due to self-report measures) might have played a role, although Spector (2006) recently stated that this influence is not as high as could be expected. Thirdly, the low response rate might have consequences for the study’s generalizability, although the non-response analysis did show no differences with regard to the demographics studied. Fourthly, we used nonspecific operationalizations of job demands and job resource in a specific job sector. It would be interesting to see if the use of job-specific operationalizations of job demands and job resources provide additional support for the TMP. Finally, another challenging research avenue is to explore whether only the availability of job resources (as measured in this study) matters.

In conclusion, this paper provides additional empirical evidence that cognitive work characteristics are positively associated with cognitive well-being outcomes and that cognitive job resources moderate the relationship between particular job demands and cognitive well-being. Nonetheless, the influence of emotional job resources should
not be underestimated. From a practical point of view, these findings suggest that informatics can benefit from a matching interplay between their work characteristics. Practitioners should focus on enhancing particular job resources that enable employees to deal with their job demands.

References


