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How job resources influence employee productivity and technology-enabled performance in financial services: The job demands-resources model perspective

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Abstract

Purpose: This study aims to provide insight into the relationship between job resources (job control and possibilities for development at work) and employee performance, measured as employee productivity and technology-enabled performance, by examining the role of employee well-being (work engagement and emotional exhaustion).

Design/methodology/approach: The data comprised two overlapping data sets collected from a large financial institution; Study 1 employed survey data (N = 636), whereas study 2 employed register data on job performance collected over a one-year period combined with survey data (N = 143). The data were analysed through structural equation modelling.

Findings: Study 1 indicated that job resources were positively associated with technology-enabled performance more strongly through work engagement than emotional exhaustion. Study 2 revealed that emotional exhaustion was associated with lower employee productivity, whereas work engagement was not. Furthermore, the results indicated that job control was related to higher productivity through a lower level of emotional exhaustion.

Originality: This is one of the first studies to measure employee productivity longitudinally as a ratio of inputs (working time) to outputs (relevant job outcomes) over one year. Our study contributes to the job demands-resources model (JD-R) literature by showing the importance of job control in fostering both employee productivity and more positive perceptions of technology.

Practical implications: Our study's findings point to the importance of developing interventions that decrease emotional exhaustion.

Keywords: Employee wellbeing, information technology, work environment, job performance, productivity

Introduction

The happy-productive-worker hypothesis (Cropanzano and Wright, 2001) argues that employees with a high level of well-being are more productive than their less satisfied counterparts. In line with this, emotional exhaustion (EE) is linked to worse job performance (Halbesleben and Bowler, 2007), whereas work engagement (WE) is related to better self-rated and other-rated job performance (Borst *et al.,* 2020) and higher employee financial returns (Xanthopoulou *et al.,* 2009). Nevertheless, studies on the relationship between employee well-being and job performance present a somewhat contradictory picture. More specifically, this relates to the question of whether negative or positive manifestations of employee well-being in terms of EE or WE, respectively, play a more crucial role with respect to employee productivity (c.f., Hakanen and Koivumäki, 2014). It has been suggested that the use of varying approaches to measure employee well-being and job performance, as well as divergent study designs, may explain differences in findings (Nielsen *et al.,* 2017; Miller, 2016).

Furthermore, an increasing number of employees are struggling amidst the continuous transformation of work practices due to technology (Tarafdar *et al.,* 2017). This may lead to growing feelings of technostress, which has been shown to decrease job satisfaction among sales professionals (Pullins *et al.,* 2020). Employee dispositions in terms of job satisfaction and EE seem to determine employees' willingness to adopt new technological systems (Bala and Bhagwatar, 2018), suggesting that employee well-being may play a role as to whether technology is perceived as conducive to customer service.

In this paper, we propose that job resources operationalised as job control (JC) and possibilities for development at work (PD) are related through employee well-being to higher technology-enabled performance (TEP) as well as employee productivity. We extend previous findings that indicate employee well-being is related to higher employee productivity (e.g., Hakanen and Koivumäki, 2014) by exploring the role of job resources as potential working conditions that may advance productivity. Empirical evidence has indicated that job resources might contribute directly to job performance, contradicting the assumptions of the Job Demands-Resources (J-DR) model (Nielsen *et al.,* 2017). Our study makes two contributions to the existing literature. First, this study seeks to extend the basis of the JD-R model by building on insights derived from economics to measure employee productivity more rigorously. To our knowledge, this is one of the first studies to address the relationship between job resources and employee productivity by measuring productivity longitudinally at the employee level. Second, our study explores the idea of linking job resources and employee well-being to TEP, which has been previously explored mainly from the perspective of technostress, focusing largely on technology-related aspects of working conditions—i.e., technostress creators (Tarafdar *et al.,* 2017).

This paper is based on two sub-studies comprising partly overlapping datasets derived from a financial institution. Study 1 focuses on examining the antecedents of TEP by employing survey data collected through an online survey (N = 636). Study 2 aims to explore the antecedents of employee productivity by using register data on job performance collected from financial service professionals over a one-year period combined with a survey data response (N = 143). We used convex nonparametric least squares (CNLS) (Hildreth, 1954; Kuosmanen, 2008) as a method to calculate productivity. We empirically tested our hypothesis through structural equation modelling.

Employee well-being

We rely on insights based on the JD-R model, which considers both the dark and bright sides of employees' functioning in terms of well-being (Bakker and Demerouti, 2017). Generally, employee well-being can be viewed from hedonic and eudemonic perspectives (Grant and McGhee, 2011). The former involves pleasure-seeking behaviour striving for experiences of positive affect (e.g. happiness) along with cognitive dimension in the form of an evaluation of job satisfaction (Fisher, 2014). The latter refers to the positive functioning of employees, illustrating aspects such as self-realisation, flourishing and striving to realise one's potential and goals (Grant and McGhee, 2011). Interestingly, the notion of job satisfaction representing the hedonic aspect of well-being previously dominated the examination of the happy-productive hypothesis (Wright and Cropanzano, 2000). Following the emergence of positive psychology, the focus has shifted to consider the role of optimal human functioning expected to add extra value for job performance compared to that of merely experiencing positive feelings.

The eudemonic aspect of well-being inherently concerns striving for fulfilling one's potential in terms of achieving important goals based on a sense of meaningfulness (Grant and McGhee, 2021). Schaufeli and Bakker (2004) characterise WE as a positive and persistent work-related state of mind, comprising the dimensions of vigour, dedication and absorption; as such, it represents the eudemonic aspect of well-being (Fisher, 2014). Schaufeli and Bakker (2004) characterised vigour as possessing a high level of energy and the motivation to persist when facing difficulties. Dedication refers to feelings of enthusiasm and pride in one's work. Absorption means an intense concentration on doing one's job in a situation where time flies while working.

The burnout literature emphasises experiences of negative affect and low levels of energy as defining aspects of well-being (Fisher, 2014). EE, regarded as a core component of burnout (other dimensions of cynicism and personal accomplishment), refers to feelings of being drained and having difficulties giving more to the job emotionally and arises from extended exposure to intense job demands without adequate job resources to respond to them

(Maslasch and Leiter, 2008). It has been shown that EE occurs first in the development of burnout (Alarcon, 2011), suggesting the need to identify more carefully how exhaustion might hinder job performance to target specific interventions promptly. Furthermore, meta-analyses indicate that EE has been most consistently, compared to other aspects of burnout, related to variables characterising organisational attitudes, such as higher turnover intentions, lower commitment and job satisfaction (Lee and Ashforth, 1996; Alarcon, 2011). Furthermore, WE and EE represent state-like characteristics, meaning that they are not susceptible to changes in the short term (Schaufeli *et al.,* 2009).

Job resources

The foundation of the JD-R model lies in distinguishing two different paths that originate from working conditions involving divergent levels of job resources and demands that ultimately lead to opposite organisational outcomes through two independent psychological processes (Bakker and Demerouti, 2017). In a motivational process, job resources are found to relate to positive organisational outcomes through a higher level of WE (Christian *et al.,* 2011). Respectively, in a health impairment process, high job demands along with a lack of job resources expose employees to a sense of EE, although this latter relationship is not always supported by longitudinal studies (Bakker and Demerouti, 2017; Schaufeli *et al.,* 2009). Basically, job resources are those aspects of work that contribute to employees' professional growth and enhance the reaching of work-related goals as well as reduce the negative impacts of excessive job demands (Bakker and Demerouti, 2017).

We base our choice of job resources on the insights from van den Tooren *et al.*'s (2012) study, emphasising the importance of having job resources that match the demands arising from a work situation. First, the significance of learning possibilities may result from the fact that the digitalisation of work puts employees under pressure to continually develop their skills to perform better in their job. Second, having discretion over work-related issues, such as regulating the sequence of work tasks, may be crucial in responding to new technology-related work practices (O'Driscoll *et al.,* 2010). One essential function of job resources is to help overcome demanding situations at work (Bakker and Demerouti, 2017). Furthermore, the JD-R model prompts consideration of occupation-specific work characteristics of employees under study (Bakker and Demerouti, 2017), with both JC and PD representing relevant job resources for employees in the financial industry (Sengupta *et al.,* 2015; Sousa *et al.,* 2012). Empirical evidence further demonstrates the aforementioned resources to be positively related to WE (Bakker and Bal, 2010) and negatively to EE (van Ruyesseveldt *et al.,* 2011; Lee and Ashford, 1996).

JC refers to the extent to which employees can exert control over how to perform work tasks by setting work goals and schedules and participating in decision-making (Morgeson and Humphrey, 2006). Generally, the construct of JC entails two aspects, one that concerns the possibilities of employing specific skills in work settings and the other one relating to decision-making, such as choosing work methods (Häusser *et al.,* 2010). Two underlying reasons could offer an explanation for the role of JC as contributing to WE and buffering the development of EE. First, having control over work might facilitate coping in demanding work situations. That is, employees with high JC could be more capable of solving problems at work and therefore overcome demanding customer service situations (Daniels *et al.*, 2013). Second, JC might contribute to reaching work goals (Nahrgang *et al.,* 2011) by providing employees with more freedom to experiment alternative ways in their work-related efforts and act in a more flexible manner in the face of changing job demands.

In the present study, PD refers to the extent to which employees can use their knowledge and skills and have the possibility to develop new ones (Pejtersen *et al.*, 2010) and as such characterises informal learning opportunities intertwined with workplace practices. Regarding EE, learning opportunities may facilitate coping by providing skills to deal with divergent job demands, implying that employees equipped with more skills and knowledge tend to succeed in work tasks and therefore receive more positive feedback that further enhances their job resources (Demerouti and Bakker, 2017). Regarding WE, learning opportunities within the workplace are expected to enhance personal resources involving aspects such as heightened self-efficacy beliefs and optimism that contribute to employee's capacity to act across diverse work settings and thus enhance their in-role performance (Xanthopoulou *et al.,* 2009). In line with this, work environments that provide possibilities to learn in terms of critical reflection and unlearning (i.e. giving up non-functional work habits) have been shown to advance a sense of WE (Matsuo, 2019).

Productivity and technology-enabled performance (TEP)

Regarding the concept of job performance, Roe (1999) suggested two dimensions: the outcome refers to the actual accomplishment of the work goals, while the process relates to attitudes and actions taken by employees to reach their work goals. In the present study, a definition of TEP derived from technostress studies characterises an attitudinal component of performance that covers the employees' views on how technology may help them carry out customer service through technology (Tarafdar *et al.,* 2015). To date, aspects of technology use are mainly considered either as ICT-related job resources or job demands (e.g. technology overload) within studies based on the JD-R model (Day *et al.*, 2010). In the present study, we approach TEP as an outcome variable capturing the expected positive effects of technology on customer work, and as such, it represents positive organisational outcomes within the JD-R model (Bakker and Demerouti, 2017). In line with this, empirical evidence demonstrates the importance of satisfaction with technology as a source of better sales performance, possibly resulting from improvements that enable the delivery of more superior-quality service (Román and Rodríguez, 2015).

Employee productivity can be regarded as an outcome dimension following Roe's (1999) classification; it concerns in-role performance, focusing on employee behaviour in their core tasks, and can be defined as the ratio of the employee's weighted outcomes to the employee's weighted resource utilisation (Motowidlo and Van Scotter, 1994; Misterek *et al.,* 1992). Estimating employee productivity requires using measures that are independent of an individual's perceptions (Jaramilo and Grisaffe, 2009). One of the hindrances to be tackled derives from the need to target productivity indicators to focal areas of performance that represent the central work tasks of employees. However, objective performance is often measured on an aggregated organisational level instead of executing an employee-level measurement (Nielsen *et al.,* 2017). Furthermore, it is fundamental to consider the inputs of employees, namely working time, which may affect the number of conceivable outputs instead of solely measuring financial gains (c.f. Hakanen and Koivumäki 2014; Xanthopoulou *et al.,* 2009). Consequently, more objective indicators are needed—coupled with multidisciplinary approaches, such as utilising insights from economics—to explore the happy-productive-worker hypothesis more carefully (Bakker and Demerouti, 2017).

A study by Taris and Schreurs (2009) addressed antecedents of organisational productivity, finding that aggregated levels of EE relate to lower organisational performance and weaker customer satisfaction. Exhausted employees appear to cope by decreasing their work demands, leading to a reduction in work-related motivation (Halbesleben and Bowler, 2007), suggesting that employees may be less motivated to find new solutions to challenging situations arising at work and have more negative technology interpretations. In line with this, Bala and Bhagwatwar (2018) report that individuals with low job satisfaction and high EE are less inclined to use a new technology system. However, a review conducted by Taris (2006) reveals that the relationship between EE and self-and other-rated job performance is weak (Taris, 2006).

Additionally, studies reveal that WE is linked both with better job performance and organisational citizenship behaviour, meaning that engaged employees are more willing to help colleagues and advance the success of the whole workgroup in a broader sense (Christian *et al.*, 2011). Furthermore, Xanthpoulou *et al.* (2009) conducted a diary study among fast food restaurant employees, concluding that individuals with a higher level of WE received a greater amount of financial returns. A similar conclusion can be drawn from studies by Christensen *et al.* (2020) and Hakanen and Koivumäki (2014), revealing that engaged employees were more productive at their work measured by number of job outcomes as well as financial gains. The broaden-and-build theory suggests that employees with positive emotions have broader momentary thought-action repertoires, which allows many new possibilities to arise (Fredrickson, 2001). In line with this, engaged employees are shown to be more active and innovative (Hakanen *et al.,* 2008), suggesting that they may perceive technology use in customer service as conducive to their work goals.

Employee well-being mediating the relationship between job resources, productivity and TEP

Meta-analytic evidence supports the premises of the JD-R model that employee well-being serves as a mediator in a relationship between job resources and advantageous organisational outcomes (Lesener *et al.,* 2020). Engaged employees display more customer-oriented behaviour in service delivery (Salanova *et al.,* 2005), which might explain better productivity in terms of financial sales. Resourceful working conditions seem to play a crucial role in motivating and energising employees to pursue their work-related goals (Bakker and Demerouti, 2017). For instance, higher WE may follow as employees who can exert control over their work may have more possibilities to experiment with new technology between work tasks (O'Driscoll *et al*., 2010) and engage in customer-oriented selling (Román and Rodríguez, 2015) as a consequence of being able to adapt their ways of working to meet the needs of customers.

Under the JD-R model, creating a resourceful working environment may also play a role in preventing the development of EE. For instance, weak control over work-related issues may undermine opportunities to experiment with new technology within a stream of work tasks, thereby leading to a reduced sense of self-efficacy in coping with new technology (O’Driscoll *et al*., 2010) and possibly explaining higher EE and subsequent negative perceptions of technology. Further, inadequate learning at work might lead to a loss of resources, such as a shortage of skills hampering the adoption of new technology. Adopting new technology into work practices appears to require competence development to learn new work methods and to give up some old ones (Cegarra-Navarro and Cepeda Carrión, 2013). Moreover, considering that exhausted employees tend to be selective regarding the use of their remaining resources (Halbesleben and Bowler, 2007), striving to protect current resources, for instance, by lowering performance standards and possibly more easily perceiving new technology as a threat.

To sum up, based on previous discussions, we formulated the following hypotheses:

H1: The relationship between JC and TEP is a) positively mediated by WE and b) negatively mediated by EE.

H2: The relationship between PD and TEP is a) positively mediated by WE and b) negatively mediated by EE.

H3: The relationship between JC and employee productivity is a) positively mediated by WE and b) negatively mediated by EE.

H4: The relationship between PD and employee productivity is a) positively mediated by WE and b) negatively mediated by EE.

[Figure 1 near here]

Methods

Samples and data collection

We drew our samples from Nordea, which conducts business in the life insurance and banking sectors in the Nordic countries; our study focused on Nordea Finland. This financial institution consisted of two affiliates: Nordea Life focused on life insurance, and the personal bank covered a business area targeted at the production of services for customers representing households. In study 1, our sample covered respondents from these two affiliates, while in study 2, the sample consisted of bank employees.

The technological application most often used in daily work is the core banking system, which consists of several features to keep a record of a range of banking issues and to serve as a source of knowledge. Furthermore, technological communication tools, such as online video meetings, have become an important means of serving customers. Additionally, employees utilised a collaborative system to consult with their colleagues and get support from the internal service centre regarding specific financial services. The central background variables are presented in Table I.

Study 1

The scope of the survey involved four units from Nordea’s personal bank as well as the entire personnel from its life insurance company. The surveys differed in their target respondents within the affiliates because the bank organisation was considerably larger than the insurance company. Three regional units from the bank focused on serving customers via face-to-face meetings as well as increasingly via online meetings, which concerned a variety of banking issues related to loan applications, savings and investments. One unit concentrated on serving customers entirely online for a wide array of banking needs. The data were collected through an online survey in the summer of 2017.

Employee representatives (n = 10) tested the survey before its actual implementation, which led to a few elaborations on the items concerning demographic details. A response link was sent to 1,020 participants via email, including an informed consent letter that clarified the study’s objectives and ensured the confidentiality of the respondents’ information. The respondents were asked for their informed consent to use both their survey responses and register data on job performance for research purposes. The final sample comprised 643 respondents, yielding a response rate of 63%. There were 545 respondents from the bank and 98 respondents from the insurance company.

Study 2

The study covered three front-office job roles (financial advisers, wealth advisers and 24/7 service advisers), in which outputs were documented. However, the productivity measurement for financial advisers was problematic. The introduction of new customer service models for financial advisers signified that, instead of having a stable assigned customer base, they started serving customers nationwide. As a result, we could not target each employee's output accurately, which led to incomplete information concerning employees' actual outcomes. Thus, we focus on two job roles (wealth advisers and 24/7 service advisers), for which we have reliable data.

Wealth advisers worked in premium branches serving premium customers (i.e. customers with high prosperity), with a range of savings and investment issues. This job role was suitable for performance measurement due to the wealth advisers' rather similar customer base and the comprehensive responsibility they had for their customers. The 24/7 service advisers were working in service centres in which they were serving customers via communication technology with a range of daily banking issues, such as offering consumer loans. There were no differences in the clients among the 24/7 advisers because the customers generally initiated service, and calls were assigned randomly to the service advisers. Altogether, our performance data consisted of 98 wealth advisers and 131 24/7 service advisers. We combined performance data with pseudonymised survey data, yielding 143 respondents, of which 80 were 24/7 service advisers and 63 were wealth advisers.

[Table I near here]

Measuring employee productivity

The productivity scores of each employee were calculated as the ratio of the weighted outputs to working hours. Instead of using ad-hoc weights, we used a data-driven approach to obtain output weights that fit the observations, an approach that has been previously applied to bank branches (Eskelinen and Kuosmanen, 2013). To estimate the output weights from the data, we used CNLS regression, which was introduced to productivity analysis by Kuosmanen (2008). This technique allowed us to adhere to the principles of the production functions of economics (e.g. Coelli *et al.,* 2005).

A fundamental principle of the production functions is that the outputs cannot decrease when the input increases, meaning that the output weights cannot be negative. In this study, we also assumed constant returns to scale. This means, for example, that an employee who worked 11 months full time is expected to have a 10% higher output volume compared to an employee who worked 10 months full time. The employee's productivity score represented the relative deviation from the average performance of the employees in the same job. For example, a score of 1.2 indicated that the employee's aggregated outputs were 1.2 times the outputs of an average peer had they worked the same number of working hours. Using this approach necessitates that employees' inputs (e.g. working time) and outputs (i.e. money or sales quantities) can be measured and that there are enough employees doing the same job. For wealth advisers, the working hours were converted from full-time equivalent working days during the 12 months (3/2017–2/2018) and over 11 months (4/2017–2/2018) for the 24/7 service advisers (excluding long-term absences and employees with under 200 working hours).

For wealth advisers, the outputs encompassed life insurance services (e.g. capital redemption plans, endowments and personal life insurances) and other saving services (e.g. funds and savings deposits). Thus, outputs were measured as quantities of new sales contracts, which is in line with the definition of productivity as the ratio of inputs to outputs. For the 24/7 service advisers, the main indicators of outputs comprised the number of referrals and the sales of consumer loans. Referrals represented customer encounters in which 24/7 service advisers directed a customer to a specialist as a result of customer needs arising during the meeting. Consumer loans are represented by monetary values. There was a limitation in terms of monetary values for loans that 24/7 service advisers could allow, which ensured that comparison between employees was meaningful. We proceeded to estimate the productivity for all wealth advisers and the 24/7 service advisers in performance data (n = 229) because the higher number of observations provided more reliable estimates for productivity. Although productivity scores were estimated separately for job roles, the performance data were pooled after the productivity estimation.

Measures

Work engagement (WE) was measured with an ultrashort, three-item version of the Utrecht Work Engagement Scale (Schaufeli *et al.,* 2017). One example item is ‘At my work, I feel bursting with energy’, which was scored on a seven-point scale, with the response options ranging from 0 = never to 6 = always.

Job control (JC) was measured using four items from the QPS-Nordic Questionnaire (Elo *et al.,* 2000). One example item is ‘Can you influence the amount of work assigned to you?’, which was scored on a five-point scale, ranging from 1 = very seldom/never to 5 = very often/always.

Possibilities for development at work was measured with four items from the Copenhagen Psychosocial Questionnaire (Pejtersen *et al.,* 2010). One example item is ‘Does your work give you the opportunity to develop your skills?’, which was scored on a five-point scale ranging from 1 = very seldom/never to 5 = very often/always. One item was deleted due to low factor loading ($\beta = 0.40$), resulting in a three-item scale.

Technology-enabled performance (TEP) was measured with three items adopted from a scale developed by Tarafdar *et al.* (2015). One example item is ‘Using technology helps me communicate better with customers’, which was scored with a five-point scale, ranging from 1 = totally disagree to 5 = totally agree. These items were chosen as they reflected the expected benefits of technology from the perspective of customer work.

Emotional exhaustion (EE) was measured with three items from the Oldenburg Burnout Inventory (Demerouti and Bakker, 2007). One example is ‘After my work, I usually feel worn out and weary', which was scored with a seven-point scale ranging from 0 = never to 6 = always.

Control variables

Regarding study 1, we controlled for the age based on correlational analysis that older employees have less favourable attitudes towards technology compared with their younger counterparts ($r = -.21$, $p < 0.001$). In study 1, we controlled for the job role classified into the following categories: 1 = supervisor (n = 82), 2 = financial employee (n = 182, including financial experts and wealth advisers) and 3 = frontline employee in the bank (n = 371, including 24/7 service advisers and financial advisers). There were job role differences in TEP $F(2, 633) = 22.07$, $p < 0.001$, as supervisors scored significantly higher than financial experts or frontline employees. In study 2, there were no differences in productivity scores with job role, age or job tenure.

Data analysis

The data were analysed by applying structural equation modelling (SEM) in Amos software version 26, with the maximum likelihood estimation method. SEM was used to study multivariate relationships based on a theoretical model (Hair *et al.,* 2014). We applied a two-step process for SEM (Kline, 2016). First, we examined the model's measurement properties through confirmatory factor analysis (CFA). Then, we examined the structural relationships involved in the hypothesised model. We compared the proposed model with two alternative models to examine our hypothesis: the direct-effect model entailed the direct paths from four variables (EE, WE, PD and JC) to TEP (study 1) or to productivity (study 2). The partial-mediation model entailed both direct and indirect paths from PD and JC to the outcome variable, whereas the hypothesised (full-mediation model) excluded the two direct paths (from JC and PD to the outcome variable) from the partial-mediation model.

As the $\chi 2$ test is sensitive to large sample sizes, we employed a variety of fit indices recommended by Kline (2016): Comparative Fit Index (CFI), Root Mean Square Error of

Approximation (RMSEA) and Tucker-Lewis Index (TLI). We followed the cut-off values presented by Hu and Bentler (1999)—that is, a good model fit is indicated by CFI and TLI values greater than 0.95 and RMSEA values below the level of 0.06. Moreover, the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) were used for the selection of the best-fitting model, with lower scores demonstrating a better fit for the model (Byrne, 2016). We employed bootstrapping to test the significance of the indirect effect of job resources on employee productivity and TEP based on 95% bias-corrected bootstrap confidence intervals (CI), using 1,000 samples (Hayes, 2009). We tested the common method bias using Harman's single factor test to detect possible variability due to the self-report measure (Podsakoff *et al*., 2003). All items were loaded into a single factor in the factor analysis, which revealed that the first factor accounted for 37% of the variance in study 1 and 38% in study 2, both being below the recommended value of 50%. Thus, we concluded that the common method bias was not a serious threat to our study.

Results

Study 1

Preliminary analyses

We first explored the multivariate normality of the study variables, which is a precondition for SEM (Hair *et al.,* 2014). By screening the data, we detected eight outliers excluded from the final sample (n = 636) because of the multivariate nonnormality estimated by Mahalanobis distance. The multivariate kurtosis of the model (Mardia's coefficient critical ratio, cr. 11.89) exhibited values that were not within acceptable thresholds (cr < 5) (Bentler, 2005). Hence, we applied the Bollen-Stine bootstrap and its associated p-value to supplement the chi-square test and bootstrapping to estimate the regression weights (Byrne, 2016). The correlations indicated that WE was positively correlated with TEP ($r = 0.38$, $p < 0.001$), whereas EE was negatively correlated with it (r = -0,38 $p < 0.001$). Furthermore, both the PD ($r = 0.29$, $p < 0.001$) and JC ($r = 0.33$, $p < 0.001$) were positively correlated with TEP.

We conducted a series of CFAs to estimate the distinctiveness of the constructs involved in this study. First, CFA was conducted to estimate the fit of the theorised five-factor model. For this model, the Bollen-Stine corrected bootstrap p-value was statistically significant (χ^2=337.92, df=94), indicating a poor fit to the data ($p < 0.001$). The other fit indices showed an acceptable and significantly better fit to the data: CFI = 0.95, RMSEA = 0.064 and TLI =0.93 than a one-factor model: χ^2= 1843.88, df=104, $p < 0.01$, CFI=0.63, RMSEA =0.162 and TLI=0.58 or a four-factor model (job resources combined): χ^2= 764.75, df =98, $p < 0.01$, CFI=0.86, RMSEA =0.104 and TLI=0.83. Thus, we were assured of the distinctiveness of our constructs.

To evaluate the model's measurement properties, convergent and discriminant validity were investigated. Convergent validity is represented as the items' load on their respective factors, assessed on the magnitude of the factor loadings, as well as the average variance extraction (AVE) and the composite reliability (CR) (Hair *et al.,* 2014). As seen in Table II, the items loaded on their respective latent factors, and all items had factor loadings that exceeded the threshold value of 0.50 (Kline, 2016). Furthermore, each construct's CR exceeded the recommended value of 0.70. The AVE value for JC was below the recommendation (> 0.50). However, its measurement properties have been validated in prior studies (De Cuyper *et al.,* 2011); thus, its value was considered acceptable. As shown in Table III, the requirement for the discriminant validity of the constructs was met as the square root of AVE was greater than the correlation coefficient values with any other variable (Fornell and Larcker, 1981).

[Table II near here]

[Table III near here]

Hypothesis testing

To validate the hypothesised model, we compared the proposed model with alternative models to determine the best-fitting model (Hair *et al.,* 2014). The fit indices of our hypothesised model indicated an acceptable fit to the data (Table IV). The full-mediation model demonstrated better fit indices than the partial-mediation model or direct-effects model due to lower values of AIC and BIC and better values of RMSEA and TLI. The direct-effects model demonstrated the poorest fit to the data. Furthermore, for the sake of parsimony, the hypothesised model (full mediation) was favoured as a direct path from neither of the two job resources to TEP was not statistically significant. As seen in Figure 2, the proposed model's results indicated that both JC ($\beta = 0.36$; $p < 0.001$) and PD ($\beta = 0.41$; $p < 0.001$) were positively associated with WE, whereas only JC was negatively associated with EE ($\beta = -0.59$; $p < 0.001$). Furthermore, WE was positively associated with TEP ($\beta = 0.33$; $p < 0.001$), and EE was negatively associated with it ($\beta = -0.15$; $p < 0.05$).

[Table IV near here]

Next, the hypotheses regarding the indirect effect of job resources on TEP (H1 and H2) were tested. Table V shows that, as for WE, the CIs for both indirect effects of job resources excluded zero, thus supporting H1a and H2a. The bootstrapping estimate for the indirect effect of JC on TEP through EE was 0.09, with a 95% CI excluded zero, supporting H1b. As there was no significant link between PD and EE, H2b was rejected.

[Table V near here]

[Figure 2 near here]

Study 2

Preliminary analyses

We first screened the data to detect deviations from normality assumptions. The multivariate kurtosis of the model (Mardia's coefficient critical ratio, cr. 3.19) was within an acceptable threshold. WE was positively correlated with employee productivity ($r = 0.22$, $p < 0.05$), whereas EE was negatively correlated with it ($r = -0.30$, $p < 0.001$). We then estimated the psychometric properties of the latent variables. The fit indices of the hypothesised model showed a significantly better fit to the data: χ^2=79.48, df=59, CFI = 0.98, RMSEA = 0.049 and TLI = 0.97 than a one-factor model: χ^2= 355.63, df=65 CFI = 0.67, RMSEA = 0.175; and TLI = 0.60 or a three-factor model (job resources combined): χ^2= 176.42, df=62, CFI = 0.87, RMSEA = 0.117 and TLI = 0.84.

Next, convergent validity was evaluated with CR and AVE. The internal consistency of latent variables exceeded the acceptable threshold of CR > 0.70. Table II shows that the items loaded on their respective latent factor and all items except one item concerning WE had factor loadings that exceeded the threshold value of 0.50. All latent constructs, except JC, met the criteria for the AVE value being over 0.50. The assumption of the discriminant validity of the constructs was met, as the square root of AVE was greater than the correlation coefficient values with any other variable (Fornell and Larcker, 1981). (Table III).

Hypothesis testing

We first tested three alternative models to validate the hypothesised model. As shown in Table VI, the fit indices of the three structural models indicated that the fit index of the full-mediation model was better than the two other models. The indices for the full-mediation model indicate good adaptability according to the cut-off criteria (Hu and Bentler, 1999). Thus, the model comparisons demonstrated the hypothesised to better account for the data than two alternative models. As seen in Figure 3, EE was negatively associated with productivity ($\beta = -0.25$; $p < 0.05$), whereas WE was not associated with it ($\beta = 0.09$; ns). Moreover, PD was positively associated with WE ($\beta = 0.51$; $p < 0.001$) and negatively with EE ($\beta = -0.31$; $p < 0.001$), whereas only JC was negatively associated with EE ($\beta = -0.36$; $p < 0.001$) and contrary to expectation, not with WE.

[Table VI near here]

The hypotheses of the indirect effect of job resources on employee productivity (H3 and H4) were tested using bootstrapping with a confidence limit of 95%. Because WE was not associated with employee productivity, hypotheses 3a and 4a, concerning the indirect effect of job resources on employee productivity through WE, were rejected. However, Hypothesis 3b was accepted, as the bootstrapping estimate for the indirect effect of JC on employee productivity via EE was 0.091, with a 95% CI [0.004–0.255]. Hypothesis 4b was rejected, as the bootstrapping estimate for the indirect effect of PD on employee productivity via emotions was statistically insignificant and CI included zero.

[Figure 3 near here]

Discussion

This study sheds light on the role of the job resources as a driver of employee productivity and TEP through employee well-being manifested as EE and WE. Our findings indicated that of the job resources JC was positively related to TEP through WE and EE (Hypothesis 1). However, only WE acted as an intervening variable in the relationship between PD and TEP, thus supporting Hypothesis 2a. Regarding employee productivity, contrary to our expectations, only Hypothesis 3b was supported, as JC was associated through EE with employee productivity, although the indirect effect was small.[1]

[1] It could also be assumed that job resources (JC and PD) would act as moderators by boosting the positive impact of WE and negative effect of EE on productivity and TEP. The analysis was conducted by moderating structural equation modelling using the approach of Ping (1995). We found no statistically significant moderating effect in study 1 or study 2.

Theoretical considerations

TEP as an outcome

First, our study's findings provide the JD-R literature with evidence that job resources are more strongly related to TEP through WE than EE. Hence, this finding is in line with previous research suggesting that WE as a motivational construct seems to trigger positive perceptions of technology as more useful in pursuing better outcomes in customer service (Christian *et al.,* 2011). Second, our study's results support the premises of the JD-R model that wider job characteristics, characterised as job resources, seem to play a role in determining how employees respond to technology-related changes in their work practices through employee well-being (Tarafdar *et al.,* 2017). When employees have control over their work (i.e. are capable of regulating their pace of work and schedules), they may be more inclined to develop new practical ways to use technology with customers during work situations (O'Driscoll *et al.*, 2010). Consequently, this might fuel the development of personal resources, such as self-efficacy beliefs concerning coping with and learning to use new technology, thereby contributing to its easy adoption. It is conceivable that employees may engage in technology-related work practices more easily due to learning possibilities at work that support opportunities for critical reflection and unlearning (Matsuo, 2019), thereby helping employees deal with novel ways of working with technology.

Employee productivity as an outcome

Overall, our study findings are consistent with the JD-R model's assumption concerning the role of EE in determining productivity. As such, this study responds to the calls presented by Bakker and Demerouti (2017), who argued for the use of objective measures on job performance to overcome the methodological weaknesses related to the use of single-source self-reported data. Furthermore, the results support the notion that resource loss fuelling the development of EE seems to play a crucial role in employee productivity (Halbesleben and Bowler, 2007). However, our findings contradict a study by Hakanen and Koivumäki (2014) that underlined the importance of WE in explaining better productivity. Interestingly, evidence suggests that only vigour as an energising aspect of WE would be essential regarding job performance (Christensen, 2020). Similarly, our findings show that an item capturing vigour was more strongly related to productivity ($r = 0.32$, $p < 0.01$) than items concerning absorption ($r = 0.21$, $p < 0.05$) or dedication ($r = 0.04$, ns.) Moreover, the difference between study findings may exemplify varying perspectives taken to measure productivity, also to possibly reflecting the characteristics of the occupational groups used as study populations. However, the extant literature argues against the effect of occupational context by showing the importance of WE covering both blue-collar and white-collar workers (Hakanen and Koivumäki, 2014; Xanthopoulou *et al.,* 2009). Productivity measures used in this study strictly covered work outputs involved in one's job descriptions, and they were not related to financial rewards or financial returns (c.f. Xanthopoulou *et al.*, 2009).

Furthermore, employees with higher JC may have more possibilities to apply various compensation strategies, such as prioritising important work goals, which have been proven to be useful for sustaining job performance when experiencing burnout (Demerouti *et al.,* 2014). It is worth noting that our findings differed from the JD-R model's expectations in one critical aspect: the path from JC to EE was more substantial than that of WE. This may be due to the cross-sectional study design (Bakker and Demerouti, 2017); it may also reflect the role of JC as a factor buffering against the wearing out of energy (Schaufeli *et al.,* 2009), or it may illustrate a domain-specific factor of the financial sector, in which the role of job autonomy is highlighted due to strictly regulated work processes that may threaten it (Parkatti and Tammelin, 2020).

It is worth noting that WE has been related to better extra-role performance, which has been termed organisational citizenship behaviour (Christian *et al.,* 2011). This may imply that engaged employees display more helping behaviour towards colleagues, which raises productivity at the unit level but does not necessarily affect employee productivity as such. Contrasting with this argument, Halbesleben and Bowler (2007) noted that exhausted employees sought to complement their minor resources by exhibiting more organisational citizenship behaviours. Taken together, these suggestions call for more studies using multilevel study designs that consider both employee-and aggregated team-level productivity.

Our study's findings also make a contribution to the JD-R model by perceiving that in addition to classifying organisational outcomes into positive (e.g. organisational commitment) and negative ones (e.g. turnover intentions), there may exist qualitatively divergent outcomes regarding job performance in the sense that some of them may represent more distal outcomes for well-being (e.g. productivity). In contrast, outcomes concerning attitudes may relate more strongly to well-being, as indicated by this paper. However, this may reflect the fact that generally self-reported measures have been found to be related more strongly to employee well-being than objective measures (Nielsen *et al.*, 2017). However, further clarification is needed to better understand whether approaching organisational outcomes in a more detailed way could theoretically benefit the premises of the JD-R model and produce empirically new insights into research, for instance, by examining whether outcomes related to attitudes may serve as predictors of more distal outcomes, such as productivity. In the other study we grasp this suggestion by examining TEP as a possible antecedent of productivity (Authors, manuscript in preparation).

Practical implications

This study claims that creating job resources that foster a sense of WE should be highlighted when undertaking technological developments. First, this means that job roles enacted in digitalised customer service should involve features that support employees' ability to exert control over work-related issues. Being able to adjust working methods to meet customer needs might be needed, as online customer service may require extra effort and competence from the employee to build relationships. Second, the findings indicate the importance of creating learning opportunities that sustain professional development in situations where technology is transforming work practices. Employees' willingness to share their experiences of using technology in customer service should be advanced, considering that learning at work often requires interaction with colleagues. This may need special attention, as technology appears to fuel a culture of surveillance in which employees are compared with one another based on their sales performance, making social relations instrumental (Laaser and Bolton, 2017).

Regarding employee productivity as a managerial implication, our study's findings point to the importance of developing interventions that decrease EE. Our findings reveal that the level of EE, together with JC, explained 10% of variance in productivity scores measured the following year. This is an important notion, considering that the negative impacts of EE have been found to deteriorate first service quality, which reflects the fact that frontline service employees struggle to maintain their productivity level (Singh, 2000). Thus, developing work practices that sustain employees' possibilities to have control over work-related issues should be emphasised, given that employees need to apply their professional expertise and act proactively towards customers.

Study limitations and avenues for future research

First, an important limitation of this study is that it focused solely on the financial sector. Therefore, generalising the results to the entire working population should be regarded with caution. Second, because of our survey data's cross-sectional nature, we could not establish the causal order of the variables in study 1. Thus, future studies would benefit from using longitudinal designs to gain more detailed knowledge about the relationships between job resources, employee well-being and TEP. Furthermore, more detailed knowledge could be attained by asking employees to estimate the actual degree and benefits of using technologies in daily customer service. Using the approach of diary studies, it would be possible to gain in-depth knowledge about whether fluctuations in daily job resources and employee well-being would predict the variations in actual sales performance.

Third, we could not explore reciprocal relationships between employee productivity, EE and job resources over time in study 2. It is possible that more productive individuals might gain more resources as a result of succeeding in work tasks. Based on recent developments in the JD-R model, exhausted employees may not be able to engage in job crafting behaviours (i.e. making proactive changes in work tasks) that have been found to increase job resources (Lesener *et al.,* 2020). Fourth, future studies could use longitudinal study designs to determine more carefully boundary conditions, such as the use of various coping strategies or organisational practices that could buffer the negative impact of EE on productivity. Future studies could also take account of the quality dimension of customer service into study designs, which could represent a relevant aspect of sales performance.

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