Frontline employee expectations on working with physical robots in retailing

Peer-reviewed author version

WILLEMS, Kim; Verhulst, Nanouk; De Gauquier, Laurens & BRENGMAN, Malaika
(2023) Frontline employee expectations on working with physical robots in retailing.
In: Journal of Service Management, 34 (3), p. 467-492.

DOI: 10.1108/JOSM-09-2020-0340
Handle: http://hdl.handle.net/1942/38678

Frontline Employee Expectations on Working with Physical Robots in Retailing

----- *JOSM, 27 July 2022, authors' copy* -----

Purpose

Service robots have increasingly been utilized in retail settings, yet empirical research on how frontline employees (FLEs) might deal with this new reality remains scarce. This mixed-methods study examines how FLEs expect physical service robots to impact job characteristics and affect their job engagement and well-being.

Design and Methodology

First, explorative interviews (Study 1; N = 32) were conducted to investigate how FLEs currently experience job characteristics and how they believe robots might impact these job characteristics and job outcomes. Next, a survey (Study 2; N = 165) examined the relationship between job characteristics that retail FLEs expect to be impacted by robots and their own well-being and job engagement.

Findings

While the overall expectations for working with robots are mixed, retail FLEs expect that working with robots can alleviate certain job demands, but robots cannot help to replenish their job resources. On the contrary, most retail FLEs expect the pains and gains associated with robots in the workspace to cancel each other out, leaving their job engagement and well-being unaffected. However, of the FLEs that do anticipate that robots might have some impact on their well-being and job engagement, the majority expect negative effects.

Originality

This study is unique in addressing the trade-off between expected benefits and costs inherent to job demands-resources (JD-R) theory while incorporating a transformative service research (TSR) lens. By integrating different streams of research to study retail FLEs' expectations about working with robots and focusing on robots' impact on job engagement and well-being, this study offers new insights for theory and practice.

Keywords: service robots; frontline employee; JD-R model; retail; transformative service research; well-being, physical robot

Introduction

Service robots are a booming business, and their total market size is predicted to hit a turnover of USD 103 billion by 2026 (Markets and Markets, 2020). Additionally, in retail, service robots are increasingly being introduced. The service robot market in retail has been valued at USD 7.1 billion in 2022 and is expected to grow to USD 55.8 billion by 2028 (Coherent Market Insights, 2021). Service robots, or "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 909), can perform both back-office tasks, such as picking warehouse orders, and front-office tasks, such as welcoming customers (Niemelä et al., 2017). Thus, integrating service robots can generate great value for the retail industry by improving productivity (De Panafieu *et al.*, 2016), customer experiences (Hollebeek *et al.*, 2021), and sales (Brengman et al., 2021).

Retail managers and retailers are ready to start working with service robots; some have even begun experimenting with them (De Gauquier et al., 2021). Managers often see implementing robots as an opportunity for employees (Shi et al., 2016), yet the shift toward robotization in retail can affect frontline employees (FLEs) dramatically, creating opportunities while introducing additional challenges (Kunz et al., 2019; Lu et al., 2020; Meyer et al., 2020). Therefore, it is crucial to understand the impact of technological innovations such as service robots from an employee's perspective (Subramony et al., 2021; Trenerry et al., 2021). The topic "technology and the changing nature of work" tops the list of service research priorities put forward by Ostrom et al. (2021, p. 329). While much knowledge is already available on how customers respond to robots in retail settings, far less is known about how retail FLEs respond to robots (Xiao and Kumar, 2021; De Keyser and Kunz, 2022).

The jobs of retail FLEs often do not require much education and usually come with many physical, mental, and emotional demands without the proper resources to allow FLEs to both perform and feel well at their jobs (e.g., Crawford *et al.*, 2010; Voorhees et al., 2020). This toxic combination feeds the phenomena of absenteeism, burnout, and turnover among retail FLEs (Tuckey et al., 2017). While robots may be (part of) the solution if they are properly introduced in retail work environments (Xiao and Kumar, 2021; Huang et al., 2019), whether retail FLEs see it this way remains an open question. Do retail FLEs actually expect working with robots to alleviate their job demands and replenish their job resources? How do they feel this will impact their well-being and job engagement? Consequently, to successfully engage with robots in the frontlines of retail, it is essential to understand FLE expectations *upfront* prior to the introduction of such robots (cf. Trenerry et al., 2021).

Nevertheless, to date, most service robot research has been conceptual or centers on the customers' perspective (e.g., De Keyser and Kunz, 2022; Finsterwalder and Kuppelwieser, 2020). De Keyser and Kunz (2022) mentioned that since 2016, only 10 papers in top-tier service journals have examined FLE perspectives (versus 153 from a consumer perspective). Thus, research on the impact of robotization on FLEs in retail is still nascent (Xiao and Kumar, 2021; Meyer et al., 2020).

[Insert Table 1 about here please]

Table 1 reveals that much of the existing empirical work on physical robots (1) lacks a clear theoretical lens, (2) does not focus on FLE-related outcomes (such as job satisfaction, well-being, or engagement), and (3) is often qualitative. Furthermore, (4) studies that focus on service robots in the context of retail are scarce and often center on AI or virtual applications, rather than on physical robots (Xiao and Kumar, 2021). In this paper, we aim to contribute to this pressing and scantly addressed research topic in several ways (cf. Table 1 for an overview of how our study differs from previous ones). First, this paper foregrounds FLE-related outcomes by drawing from the growing body of literature regarding transformative service research (TSR; cf. Anderson and Ostrom, 2015; Russell–Bennett et al., 2020). More specifically, robotic TSR (RTSR) is defined by Henkel et al. (2020, p. 1132) as "the integration of social robot and transformative service research that focuses on well-being-relevant outcomes of consumer and employee interactions with social robots" and aims at improving the well-being of individuals, society, and ecosystems in the context of social robots. Thus, rather than focusing on traditional output parameters (e.g., productivity, sales), we use a TSR lens to examine whether (and how) robots on the frontlines can go hand-in-hand with employee well-being and job engagement (as suggested by Ostrom et al., 2021 and Dobrosovestnova and Hannibal, 2021).

To do so, we adopt an organizational psychology lens, using the job demands-resources (JD-R) model, which other studies have suggested is useful to study the impact of robots on the frontlines (De Keyser and Kunz, 2022; Schepers and Streukens, 2022), but has not yet been utilized for this purpose. Combining the JD-R theory and RTSR to study FLEs offers an important contribution to the available literature, and the findings may be useful for informing human resource management in both supporting organizational decision-making and improving internal communications (Bhargava et al., 2021). Finally, our study uses a mixed-methods approach to shed light on how FLEs anticipate changes to their job characteristics (demands as well as resources) when considering working with robots, as well as the impact of these robots on their job engagement and well-being.

Theoretical Background

An RTSR lens on retail employee well-being.

As retailing is a typical for-profit service industry, retail ecosystems generally are not centered around transformative goals (Rosenbaum et al., 2011), nor are retailers always held accountable for the effect they have on the well-being of people (Gardiazabal and Bianchi, 2021). Well-being has likewise largely remained relegated to the background in the literature on services (De Keyser and Larivière, 2014) until TSR emerged. In TSR, indicators of increasing and decreasing well-being are the fundamental subjects of analysis (Kuppelwieser and Finsterwalder, 2016). TSR has mainly focused on service contexts with primarily transformative (rather than financial) goals, such as health care (Russel-Bennett et al., 2020). Indeed, while retailers tend to invest much in commercial forecasting, anticipation of the impact of their business activities and decisions on the well-being of individuals (such as employees) and ecosystems is often far less of a concern for them (Gardiazabal and Bianchi, 2021). However, doing good by caring for the well-being of FLEs can put the service-profit chain to work (Heskett *et al.*, 2008) and go hand-in-hand with performing well financially (Troebs et al., 2018).

Employee well-being is linked to organizational performance measures such as productivity, employee turnover, and job satisfaction (e.g., Keeman et al*.,* 2017) but also affects health care at the national level (Goh et al*.,* 2015). Studying retail FLEs is particularly essential since the retail sector employs over 10% of the labor force in advanced economies (Huang *et al.*, 2019), and retail FLEs often have challenging jobs with low pay, yet high pressure and stress (e.g., Crawford *et al.*, 2010; Voorhees et al., 2020). Overall, working conditions on the retail frontlines are poor, and there is little access to structural resources that may support employees' well-being and career growth, resulting in high levels of employee turnover (Tuckey et al., 2017). Thus, there is much room for improvement in the design of shopfloor jobs to enhance organizational performance, resilience, and employee well-being (Huang *et al.*, 2019).

Introducing robots into retail settings can impact employee well-being in distinctive ways. For example, physical health could improve because the need to carry heavy objects might decrease, while perceived social support could decrease due to collaboration with robots instead of human co-workers. Existing studies on FLEs' perceptions of working with robots have often been framed either as opportunities (Huang and Rust, 2018; Wirtz *et al.*, 2018) or as threats (e.g., Frey and Osborne, 2017). A notable exception is Meyer et al. (2020), who accounted for both sides of the debate by interviewing retail FLEs on the perceived impact of a robot while actually working alongside one. The present study connects with the nascent stream of RTSR (Henkel et al., 2020), and our central objective is to improve our understanding of retail FLEs' well-being in light of the impactful business decision of introducing physical service robots in the workspace.

An essential concern in TSR is the need to determine how technologies can better support employee performance rather than engender stress and anxiety (Ostrom et al., 2021; Dobrosovestnova and Hannibal, 2021). However, genuinely caring for employees' well-being requires (human resource) managers to think in a transformative manner, *prior* to making a decision to implement a particular technology, such as robots, in the workspace. Rather than (post-hoc) aiming to optimize employee adoption of robots, a key to success is to understand how FLEs expect (hope or fear) their job to change when envisioning working with robots (cf. Trenerry et al., 2021). Unlike related work on retail employee experiences of actually working with robots (cf. Meyer *et al.*, 2020), the present paper therefore focuses particularly on FLEs' expectations about working with robots on the shopfloor.

Job demands-resources model

To study employee well-being, it is necessary to understand such employees' job characteristics in the first place. The JD-R model allows expectations about changes to various job characteristics to be studied, facilitating the translation of these expectations into prognoses about changes to employee well-being and engagement.

Stemming from organizational psychology, this theoretical framework classifies these characteristics into job demands and job resources, both of which can be stressors and motivational factors (Bakker et al., 2007; Demerouti and Bakker, 2011). The JD-R model is unique because it includes both positive and negative job characteristics and can be applied across occupational settings. The JD-R model's central assumption is that every job is characterized by a specific set of demands and resources. Bakker *et al.* (2007, p. 312) define job demands as "physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological effort or skills and are therefore associated with certain physiological and/or psychological costs." Examples of job demands include high work pressure, dangerous physical environments, and demanding emotional interactions. Job resources are defined as "aspects of the job that are functional in achieving work goals and/or reduce job demands and the associated physiological and psychological costs and/or stimulate personal growth, learning, and development" (Bakker *et al.*, 2007, p. 312). Examples of job resources include working under a respectful manager, working with pleasant colleagues, and experiencing feelings of autonomy.

Job resources and demands underlie two core psychological processes that impact organizational outcomes (e.g., employee well-being, turnover intention, engagement)—namely, strain and motivation (Demerouti and Bakker, 2011). Essentially, the JD-R model posits that excessively stringent job demands cause exhaustion and strain, while job resources stimulate motivation and buffer against exhaustion and stress. High job demands, combined with low job resources, can considerably diminish employee well-being and performance (Reijseger et al., 2017).

The expected impact of physical robots on retail FLE job characteristics

Service robots can perform both back-office tasks (e.g., warehouse tasks) and front-office tasks (e.g., talk to customers; Niemelä et al., 2017). This paper focuses on physical service robots and both types of tasks because the responsibilities of retail FLEs often include both. It is important to know that any characteristic of a robot can be considered a factor that impacts demands and resources. The academic literature and the popular press have cited numerous examples of the way robots can affect various aspects of a job positively and negatively (Bertacchini et al., 2017; Niemelä et al., 2017; Pantano, 2014). For instance, robots can unburden retail FLEs from time-consuming, labor-intensive, and repetitive tasks, leaving more time for meaningful tasks (De Panafieu et al., 2016; Huang and Rust, 2018). Apart from decreasing job demands, the implementation of robots can also increase job resources, such as feelings of task significance (Ivanov et al., 2020). JD-R theory indicates that salespeople who have access to technological tools (i.e., job resources) are less likely to, for example, perceive studying customer data as too complex and time-consuming (Rapp et al., 2008).

The introduction of robots to shopfloors may, however, also exert a negative impact on job resources. Working with a robot can be very different from working with a human colleague. Friendly and supportive co-workers are typically an important job resource. The dismantling of this emotional support system may adversely affect organizational outcomes (Niemelä et al., 2017). Furthermore, the introduction of robots into an organization may induce higher stress levels, at least initially (Wisse and Sleebos, 2016). It can also intimidate: some employees may experience decreased feelings of job security (Tuomi et al., 2021).

The affected job demands and resources are likely to impact key FLE outcomes, such as engagement and well-being (Bakker and Demerouti, 2007). These parameters can, in turn, affect other stakeholders and key performance indicators (e.g., higher returns, profitability, productivity, customer satisfaction; cf. Keeman et al., 2017). In sum, it is essential to recognize the anticipated strains and resources that employees expect to be confronted with when working with robots to gain a better understanding of where the co-creation value of robot–employee teams lies (Kaartemo and Helkkula, 2018). Accordingly, we formulate two research questions:

> RQ1: What are the overall expectations of retail FLEs for how the introduction of a physical robot might change their job and well-being?
>
> RQ2: How do retail FLE expect the introduction of a physical robot to change (a) the particular demands of their jobs and (b) their particular job resources?

Empirical Research

This research uses a mixed-methods approach and sequentially integrates an exploratory qualitative study (Study 1) and a quantitative study (Study 2; Harrison and Reilly, 2011). The qualitative approach of Study 1 was chosen to explore FLEs' expectations for working with service robots. The aim was not to build hypotheses but to provide a contextual understanding of retail FLE jobs and valid JD-R operationalizations for Study 2 (both in terms of wording and in terms of job specifications; Bryman, 2006; Harrison and Reilly, 2011). The approach of Study 1 also serves to explore the anticipated impact of robots in this context. Study 2 used these retail FLE-specific job demands and resources as inputs in an online survey (N = 165; cf. operationalization table – Table 3), focusing on whether and how the introduction of physical robots would affect their job characteristics and well-being. The FLEs in both studies had no prior experience of working alongside robots, which remains the case for most retail FLEs in 2022. In the sections that follow, the methods and results of both studies are described. In the discussion section, the relevant findings of both studies are integrated to harness the synergies between the depth and breadth of both methods (Johnson *et al.*, 2007).

Study 1: Interviews

Design, data collection, data analysis

We conducted 32 semi-structured interviews (22 female, age range: 23–60y) across eight different retail sectors (bookstores, DIY, gardening, and pets, electronics, fashion, general food, health and beauty, pharmacies, toys and games). A convenience sampling scheme was used. The participants had no prior experience with working with robots and were recruited by three research assistants through their own personal networks and by calling specific stores in the retail sectors under study. The sampling stopped when saturation was reached. These research assistants also conducted the interviews and transcribed the recordings. The interviews took place in a quiet room at the FLEs' workplaces and took about 60 minutes.

The interview guide used a funnel structure, and interviewers were trained to use probes to encourage participants to engage in conversation. The interviews had three parts. First, general questions on job responsibilities and the perceived value of robots (e.g., "What could a robot mean for you at the store?") were asked. Second, pictures of robots performing tasks in front- and back-office settings were shown. The FLEs were asked to keep in mind different kinds of robots and their various qualities, as well as how the robots could impact their jobs. Third, the JD-R conceptualization was used to further probe for participants' anticipation of how robots could impact specific job demands and resources (e.g., "How can a robot impact your current workload?"). Further details on the interviews are available upon request. The transcripts were analyzed in NVivo, utilizing a deductive approach with content analysis coding based on the JD-R model's concepts as a predetermined framework to classify the quotes (Mayring, 2015). In addition to job demands and job resources, links to organizational outcomes (e.g., well-being, customer satisfaction, motivation) were also coded.

The analysis was conducted by a single coder. To minimize subjectivity and bias, the coding manual was discussed with the co-authors and updated based on the feedback.

Findings

Our interviews showed that the JD-R model was useful as a theoretical framework to explore the impact of robot operationalization. We coded 226 reflections on job demands with "workload issues" (n = 59) mentioned most frequently, while "unsafe working environment" was rarely mentioned (n = 4). For job resources, 206 reflections were coded, with "job security" (n = 53) mentioned the most, while "autonomy" was mentioned just once. The frequency of the mentions is considered indicative of their salience and relative importance (Krippendorf, 2004; see Table 2), yet topics that are mentioned infrequently may nonetheless be important (Buetow, 2010). In Table 2, an overview of the key insights from the interviews is provided.

[Insert Table 2 about here please]

Job demands. The interviewees made it clear that robots are well equipped to help decrease the physically demanding aspects of their jobs (e.g., repetitive movements, lifting, workload):

If a robot could do a part of our tasks, it would be less severe. I always have that rushed feeling (pharmacy FLE).

We must lift a lot and reach above our heads, which is not good for our bodies. Especially for the back. We get a lot of training on how to do this, but in practice, we do not apply it. Especially when you need to be fast (health & beauty store FLE).

Retail jobs have high mental and emotional demands. Our interviewees expected the impact of robots on these demands to be somewhat positive. For example, robots can handle difficult customers, keep track of inventory, ensure that shelves are filled, take over repetitive tasks, or fix FLEs' forgetfulness or mistakes. As several FLEs explained:

It is always possible that you forget something, and if a robot could pass this on, you would be more confident about yourself` (toys & games store FLE).

He can help with the technical information of the products; that would be handy. For example, different speeds or comparisons of machines so we do not have to search for them. That would be very welcome. (DYI store FLE).

On Tuesdays and on Fridays, electronics are delivered to our store. If the robot knows this and says, "I will put it in the system," that would make our job easier. Now we open the box and scan items. Next, the quote goes in a folder. This is something the robot can do (electronics store FLE).

However, FLEs also expect that robots might create an extra burden for them:

I think that when the customer has a problem, that you really have to listen to, and that a robot will have a negative impact and make the customer even more agitated (electronics store FLE).

Job resources. The interviewees were rather pessimistic about job security and interpersonal support. Decreases in feelings of job security were reported by 26 out of the 32 interviewees.

Robots are getting better and better. It might be the case that 100 years from now, there will be such good robots that we are no longer needed and that they are capable of taking over everything we do. That is a bit anxiety of for everyone in a job that may no longer be needed in a couple of years from now. A robot is nice as long as it isn't more important than you are yourself (pharmacy FLE).

However, approximately a third of the FLE (11 out of 32) had the opinion that it is unlikely that service robots would be capable of replacing the support that a (human) supervisor or co-worker can provide:

> *I think a robot might be too impersonal. […] it will not be able to motivate me personally* (supermarket FLE).

Nevertheless, FLEs also mentioned several positive expectations linked to their job resources. For instance, many FLEs expected that robots would allow them to spend more time on significant tasks, such as interacting with customers:

> *Of course, tasks will be taken over… That is the purpose of robots. That will allow us to focus on more important things* (electronics store FLE).

Organizational outcomes. During the interviews, several insights about organizational outcomes linked to FLEs that might result from changes in job demands and resources surfaced, as well as the impact on customers. FLEs believed that robots would lead to stronger engagement and less stress because they help decrease work pressure:

> *If there was a robot that could help me, especially in times of chaos, […] I would experience that moment as less stressful and feel more committed* (bookstore FLE).

Furthermore, FLEs expect that their well-being might improve because robots can assume mentally tiresome, repetitive, or dangerous tasks. For example, an electronics store employee charged with several supervision tasks mentioned:

> *I will no longer have to repeat everything a hundred times. It [the robot] would put me more at ease.*

However, some FLE fear that robots might take over too many tasks, leading to a decrease in feelings of job autonomy, which could, in turn, lower job satisfaction:

I would be annoyed, I think […], he [the robot] would want to do everything by himself (electronics store FLE).

Some FLEs also fear that if co-worker support is taken away (i.e., the human co-worker being replaced by robots), overall well-being would also decrease:

You would start to feel lonely […] as human contact would no longer be needed (bookstore FLE).

Furthermore, FLEs mentioned 60 times that robot implementation may lead to customers a losing human and personal touch, which can, in turn, have detrimental impacts on organizational outcomes.

I think that the customer who has a persistent problem needs a real conversation. […] It [the robot] could make the customer even more nervous (electronics FLE).

Study 2: Survey

Research design

Participants for Study 2 were contacted in Spring 2021 through Facebook community groups for Belgian retail employees. Only FLEs that occupied frontline roles and had no prior experience of working with robots could participate. The online survey was answered by 165 Belgian retail FLEs (62% female, ages 19–62, $M_{age} = 32$) working in eight retail sectors (cf. Study 1). After providing informed consent, participants went through five sections in the survey: (a) introduction, (b) evaluating their current job, (c) evaluating robot introduction at their job, (d) general opinions on robot introduction, and (e) socio-demographic characteristics.

First, FLEs received a short introduction to robots and their most common retail applications (cf. Appendix). The second and third parts of the survey contained matrix-type survey questions, allowing participants to indicate whether and to what degree each job characteristic statement applied to their current job (i.e., left side of the matrix; e.g., 1 = never;

7 = very often) and how service robots would change that particular aspect of their employment (i.e., right side of the matrix; e.g., 1 = deteriorate; 4 = status quo or no effect; 7 = improve). The specific statements relating to job demands, job resources, and job outcomes were derived from the general JD-R literature (e.g. Demerouti and Bakker, 2011), as well as retail FLE context-specific findings obtained from Study 1. See Table 3 for the items and subcategories of demands and resources. Finally, we asked some questions about participants' general opinions on the introduction of robots to their jobs and about their socio-demographic characteristics.

Analyses

Several principal component analyses were conducted on the initial pools of items that pertained to job demands, job resources, and job outcome parameters. Items were removed iteratively, according to Hair et al.'s (2018) eigenvalue criterion and an inspection of factor- and cross loadings. A satisfactory factor solution consisting of four job demands was reached: (1) physically heavy work, (2) difficult customer conversations, (3) work pressure, and (4) mentally repetitive tasks. Five job resources were identified: (1) career opportunities and job security, (2) participation in decision-making, (3) task significance, (4) feedback, and (5) role clarity in the team. Finally, two outcomes—namely, employee well-being and employee engagement—surfaced.

Based on the retained pool of items, the psychometric properties of the latent constructs' measurement model were further examined with SmartPLS 3.0 (Ringle et al., 2015). Unidimensionality was confirmed for all constructs in line with Karlis *et al.*'s (2003) criterion. Internal consistency reliability was satisfactory for all constructs, as evidenced by Cronbach's alpha and composite reliability values. Convergent validity was established at the level of individual items based on outer loadings' size and bootstrapped statistical significance, and with the average variance extracted criterion at the latent construct level. Discriminant validity was confirmed for all constructs with Fornell-Larcker's (1981) criterion and with Henseler et al.'s (2015) heterotrait-monotrait ratio of correlations. As the final scales in Table 3 show, all resulting model operationalizations were reliable and valid. Moreover, we used procedural and statistical methods to control for common method bias (Podsakoff *et al.*, 2003). The anonymity of the respondents was assured, and anchor points from the 7-point scale-type items differed, depending on whether participants rated their current job situation or the expected impact of robot deployment. Furthermore, a Hartman's single-factor test was conducted, and variance-inflation-factor values for all sets of predictor constructs were inspected. On these different grounds, it can be concluded that collinearity among the predictor constructs does not appear to be an issue, and there is no obvious reason to suspect common method bias. Further details can be obtained from the authors upon request.

[Insert Table 3 about here please]

Findings

RQ1. What are the overall expectations of retail FLEs for how the introduction of a physical robot might change their job and well-being? When FLEs were asked to reflect on the overall anticipated effects of working with robots, the results were mixed. The mean expected impact of the introduction of robots on well-being (M = 3.83; SD = 1.27; $t(164)$ = −1.07; p = .09 > .01) and job engagement (M = 3.92; SD = 1.14; $t(164)$ = −.80; p = .43 > .01) was slightly negative (i.e., below the status quo of score "4" on the 1–7 scale) but statistically insignificant (cf. Table 4). Asking FLEs to reflect directly on potential shifts in their job engagement and well-being, in other words, revealed no statistically significant effects. While the median values for both constructs were also equal to 0 (i.e., no anticipated change due to robots), an inspection of the spread (cf. Table 4) does reveal that a relatively larger proportion of respondents expect a negative effect of robots on their well-being at their job (i.e., 35.7% versus 25.5% who expect an improvement). For engagement, the effect was similar (29.3% versus 24.2%). Most respondents, however, expected no noteworthy change, neither in well-being (38.8%), nor in terms of job engagement (46.5%).

We also asked respondents about their overall attitudes toward the use of robots in their jobs. We used the following 7-point Likert scale-like items: (1) “To what extent are you a proponent of the introduction of service robots to the retail store where you work?” (1 = completely against; 7 = completely supportive), (2) “Balancing advantages and disadvantages, what is your overall expectation about the introduction of robots to the retail store where you work?” (1 = mainly disadvantages; 7 = mainly advantages), and (3) “To what extent do you fear losing your job with robots being introduced in retail stores?” (1 = totally not; 7 = very much). Overall, expectations were mixed and scattered (cf. Table 4). While the mean scores on all three questions differed significantly from the scale’s midpoint, the difference was rather small, and the central tendency of the responses was neutral. A closer look at the spread of responses, however, revealed that a relatively larger proportion of respondents were optimistic about robots in the workspace compared to the proportion of those rather against them for all three items. In total, 47.1% (almost half) of the surveyed retail FLEs were, on average, proponents of robots in the workspace, while 46.5% indicated that they see more advantages than disadvantages in working with robots. Furthermore, the plurality (i.e., 41.9%) of respondents indicated that they do not fear losing their job when robots enter into play. When examining the complement of this positive picture, still over a quarter of retail FLEs in our sample (i.e., 25.8%) saw more disadvantages than benefits in working with robots, and a staggering 37.5% of our sample indicated that they (have) fears of losing their jobs to robots.

[Insert Table 4 about here please]

RQ2. How do retail FLE expect the introduction of a physical robot to change (a) the particular demands of their jobs and (b) their particular job resources? Respondents were also asked to evaluate specific demands and resources in their current jobs, in an "as is" baseline evaluation (i.e., without robots), before they were invited to reflect on the impact of the introduction of robots into their workplaces. Table 5 offers descriptive statistics of this baseline, as well as the mean and spread of expectations about the effects of introducing robots on the retail frontlines. To examine how retail FLEs expect service robots to impact the demands of their jobs, one-sample t-tests were conducted. The mean expected impact was calculated as the difference from the scale midpoint of 4, which corresponds to "status quo" or no anticipated effect (cf. Table 5). Results show that for three of the four job demands observed, a significant alleviating impact is expected: (1) physical heavy work ($M = -1.43$, $SD = 1.45$, $t(164) = -16.80$, $p < .01$), (2) work pressure ($M = -1.22$, $SD = 1.08$, $t(164) = -14.52$, $p < .01$), and (3) mentally repetitive tasks ($M = -1.45$, $SD = 1.45$, $t(164) = -12.88$, $p < .01$).

The same analyses were conducted to determine how retail FLEs expect service robots to impact job resources. The one-sample t-tests showed that FLEs anticipated that service robots would have a significant deteriorating impact on (1) career opportunities and job security ($M = -0.90$, $SD = 1.16$, $t(164) = -10.01$, $p < .01$) and (2) participation in decision-making ($M = -0.22$, $SD = .71$, $t(164) = -3.93$, $p < .01$).

[Insert Table 5 about here please]

To understand the relative contribution of these particular job demands and job resources in explaining FLEs' well-being and job engagement, two path model estimations were conducted in SmartPLS 3.0. The coefficient of determination (R^2) values were .48 for the outcome "well-being" and .43 for "engagement," indicating the models' weak to moderate predictive power. For employee well-being, two job demands were significantly negatively related to well-being: heavy physical work ($\beta = -.20$; $BCCI_{95\%} = [-.36; -.02]$) and repetitive mental tasks ($\beta = -.17$; $BCCI_{95\%} = [-.30; -.02]$). Three resources were significantly positively affected: job security and career opportunities ($\beta = .34$; $BCCI_{95\%} = [.20; .47]$), clearly defined roles ($\beta = .20$; $BCCI_{95\%} = [.07; .31]$), and participatory decision-making ($\beta = .15$; $BCCI_{95\%} = [.02; .06]$).

Turning to employee engagement, again, two job demands and three job resources were statistically significantly associated. The job demands affecting engagement involved mentally repetitive tasks ($\beta = -.23$; $BCCI_{95\%} = [-.36; -.10]$), which are negatively related, and work pressure ($\beta = .17$; $BCCI_{95\%} = [.01; -.31]$), which is positively related. The three job resources with a significantly positive association with employee engagement are identical to those that relate positively to well-being: job security and career opportunities ($\beta = .23$; $BCCI_{95\%} = [.08; .36]$), role clarity ($\beta = .22$; $BCCI_{95\%} = [.06; .38]$), and participation in decision-making ($\beta = .17$; $BCCI_{95\%} = [.02; .29]$). Figure 1 presents the overall picture for the outcomes (a) well-being and (b) job engagement. Note that all f^2 values fall between .02 and .15, implying small effect sizes. Table 6 presents path coefficients and bias-corrected confidence intervals generated by a 5,000-resample bootstrapping procedure.

[Insert Figure 1 about here please]

[Insert Table 6 about here please]

Discussion

This study is the first to adopt an RTSR lens to examine how retail FLEs experience their job and how they expect working with physical robots to impact their job demands and resources. As such, this study is rare in its focus on employees as key stakeholders and in its interdisciplinary theoretical lens to better anticipate effects on employee well-being. The mixed-methods approach of this research allowed in-depth explorations, along with JD-R conceptualizations of how retail FLE-specific job demands and resources are expected to be impacted. The subsequent survey adds value to the existing literature by directly investigating FLEs' overall expectations on changes in job engagement and well-being, as well as indirectly examining their expectations via the combination of changes in particular job demands and resources. In the following section, we discuss our findings related to our research questions, considering existing related literature.

Physical robots and retail FLEs' job demand expectations

The results show that FLEs expect robots to reduce three of the four job demands that we studied (cf. RQ2 and Table 5). In particular, *job challenges* seem to be reduced, while *job hindrances* are not expected to be affected. While the former are energy-depleting and stimulating, yielding opportunities for growth, the latter are mainly energy-depleting and are often an emotional drain on employees (Van den Broeck et al., 2010). First, a robot could assist them with *heavy physical work*. This was also a recurring topic for 75% of the interviewees, indicating an expected positive impact on issues related to physically heavy tasks (cf. also Vänni and Korpela, 2015; Table 1). FLEs also think that robots could decrease demands such as *repetitive mental tasks* and *relieve work pressure* (cf. also Wolbring and Yumakulov, 2014; Table 1).

However, the demanding part of handling difficult customer conversations was on average *not* expected to be alleviated by robots (cf. Study 2). The interviewees (cf. Study 1) even indicated that robots might worsen customer communication (cf. also Vatan and Dogan, 2021). While FLEs expect that robots cannot replace having a human touch, there may be a role to play for robots (albeit, according to our findings of Study 1, virtual assistants than rather physical robots) in complementing human FLEs (Henkel et al., 2020).

Physical robots and retail FLE job resource expectations

Subsequently, robots' expected effect on job resources is overall negative. *All* studied job resources were expected to erode when FLEs had to work with robots. For example, FLEs expect *lower job security* and fewer career opportunities, which are essential sources of job engagement and well-being (cf. Vatan and Dogan, 2021; Table 1). Brougham and Haar (2018) also found that higher awareness of robots (and artificial intelligence more generally) goes together with lower career satisfaction for employees. Meyer and colleagues' (2020) interviews with retail employees revealed that they perceived robots as threats, in part because of a loss in (job) status. Our study confirms the fact that many retail FLEs fear being replaced by robots. Moreover, we found that FLEs also expect robots to reduce their *participation in decision-making*. For example, they fear that the presence of a robot may reduce their ability to decide when to work.

The introduction of robots: An expected zero-sum game for FLEs?

While working with robots was found to have no *direct* expected impact on job outcomes (cf. RQ1), FLEs did anticipate that demands and resources would be affected (cf. RQ2). Turning to an inspection of the spread in responses in Study 2, some interesting insights emerged. While the majority of FLE respondents expect more advantages than disadvantages from working with robots and thus consider themselves proponents of robots rather than being anti-robots, a staggering 37.5% of them still admitted fearing losing their job to robots. This could be a reason for the finding that relatively more FLE respondents expect their well-being to suffer, rather than to benefit, from robots at work (i.e., 35.7% vs. 25.5%). Perceiving robots as a threat to one's job is an issue that has been surfacing in several other studies (e.g., Vatan and Dogan, 2021; Meyer et al., 2020). This (mis)perception seems crucial to remediate if retail FLEs are to embrace robots at work.

Additionally, the path modeling approach linking job demands, resources, and outcomes reveals interesting results that *indirectly* show that the expectations of retail FLEs are not overwhelmingly positive. First, employee well-being can be explained by job demands and resources. Both job demands that significantly affect well-being (i.e., physically heavy work and mentally repetitive tasks) are expected to decrease, along with two of the three job resources that significantly affect well-being (i.e., career opportunities and job security; participation in decision-making). Combining these insights regarding decreased job demands (and particularly the fact that these can be considered job *challenges*, which require energy but are usually also stimulating), and decreased job resources, the overall picture becomes rather negative. Second, for job engagement, the conclusion is similar. Both job demands (i.e., work pressure and mentally repetitive tasks) that affect FLE job engagement are expected to decrease when working with robots, as are two of the three job resources (i.e., career opportunities and job security; participation in decision-making). Again, both challenging demands and job resources are decreased, leading to an overall detraction from job engagement.

Managerial Implications

The literature on organizational behavior has shown that internal communications that match reality are critical and foster commitment, while disconfirmation of expectations can lead to lower well-being and higher employee turnover (cf. realistic job reviews; Roth and Roth, 1995). To pinpoint the central elements of communications about robot introduction and what to keep in mind when formulating a human resources (HR) plan, it is vital to understand what FLEs expect from robots from the outset. Focusing on expectations is relevant to expectation management because expectations set standards (Oliver, 1977). For example, if employees expect a robot to perform a certain task easily but this expectation is not met, their beliefs are disconfirmed, and they may become disgruntled. Consequently, from a bottom-up perspective, managers should care for employee expectations in co-designing relevant robot applications. From a top-down perspective, management should ensure that employees have a realistic idea of what (not) to expect from working with robots.

For the *bottom-up approach*, retail employees often feel uninvolved in robot use cases (Meyer *et al.*, 2019). The JD-R model is an ideal HR management tool to stimulate a (R)TSR reflex, as it supports identifying potential well-being hazards posed by new technology at work. Administering an adapted JD-R scale as has been done in the present study can help managers to understand their employees better, and the resulting insights can prove a great conversation starter prior to the introduction of novel technologies. Group-level results can be discussed on a team or individual level to support change management and facilitate a smooth transition. Furthermore, listening to employees and incorporating their feedback into the decision-making process can improve the acceptance of changes (e.g., Latack and Foster, 1985), while advancing important outcomes such as job satisfaction, productivity, and commitment (Bhatti and Qureshi, 2007).

Fear of losing one's job to a robot, for example, seems to be quite prevalent among service FLEs (cf. also Study 2). Identifying such misconceptions can help retail (HR) managers act on them. Internal communication campaigns can be used to highlight how robots complement (rather than replace) human FLEs and illustrate how robots can alleviate job demands (e.g., physical heavy work; repetitive tasks). Other than retail (HR) management, robot developers also benefit from understanding FLE user expectations. As retail FLEs appear to expect robots to reduce their participation in decision-making in their job, for example, developers can address this concern. They could, for example, program robots with a certain degree of freedom and with options built-in, rather than having robots making all decisions for employees.

Regarding the need for *top-down expectations management*, the findings of our study indicate that a substantial proportion of retail FLEs do not have pronounced positive or negative expectations on how working with robots would influence their well-being. This indefinite opinion (cf. Study 2, RQ1) can have several implications. On one hand, the hopes of retail FLEs are not (overly) high, limiting possible disappointment due to robots not living up to their hopes (cf. Gartner's trough of disillusionment; Blosch and Fenn, 2018). On the other hand, many retail FLEs do not seem to currently have overly negative prejudice toward robots that would first need to be overcome. However, retail FLEs may not know enough about the phenomenon at present to be able to anticipate its effects. Alternatively, they might be indifferent toward the idea of working with robots, considering it perhaps only a short-lived fad rather than a reality that is here to stay. Examining which of such assumptions is valid would provide valuable input in further optimizing internal communications.

Limitations and Suggestions for Further Research

This study is not free of limitations. Studying expectations about collaborating with robots is an important (first) step because expectations set standards. In particular, in regions where few robots are used in retail, such as western Europe, examining expectations about working with robots is relevant. There are three particularly crucial next steps to further extend this study's findings in this respect. First, a longitudinal approach could prove valuable in studying the gap between expectations and actual experience. This would be enriching for both management practice and theory, as it would capture the whole process that employees undergo when exposed to robots. Second, a cross-sectional comparison of employees' perceptions of working with robots across countries that exhibit differences in robot density (i.e., the number of robots per 10,000 employees; IFR, 2018) would be useful. For instance, human–robot interaction studies have proven that phenomena like the "uncanny valley" are less of an issue to the Japanese than to westerners (e.g., Kaplan, 2004). Japanese society is more accustomed to robots since they emerged earlier in Japan. A third approach for further gap analysis could be to systematically confront our findings on retail FLE *expectations* with other recent (often exploratory) studies on actual *experiences* (e.g., Meyer et al., 2020; Paluch et al., 2021). Doing so would allow for an assessment of which expectations are confirmed or disconfirmed.

Another potentially fruitful avenue to extend our findings is to examine contingency factors. The influence of robots on job characteristics can depend on robot type, individual differences between employees, and contextual specificities (Belanche et al., 2020; Wirtz et al., 2018). The interviews that Paluch et al. (2021) recently conducted with service FLEs on willingness to collaborate with robots, as well as those by Tuomi et al. (2021) in hospitality, both confirm the need to further investigate moderating variables when studying the appraisal of robots by employees.

A first contingency factor that merits further (confirmatory) research is that of differences in *robot designs and applications*. Those differences may have implications for demands and resources. The employees in our study were asked to think about physical service robots and the tasks that they can perform in *general* terms. As such, our findings do not allow for distinguishing between FLEs' expectations toward different types of robot applications. Additionally, the extent to which and how robots are taking over tasks is likely to impact FLE responses (Kandampully et al., 2021; Xiao and Kumar, 2021). Our study, for example, hints at the fact that retail FLEs would like to have a say when management considers implementing robots on the work floor rather than being forced.

A second contingency factor in need of further research is employee characteristics. Our present study was conducted with Belgian FLEs. The culture of Belgium is characterized by high power distance (Hofstede Insights, 2019). Belgian employees may attach greater importance to their hierarchical superiority to robots than employees elsewhere. In cultures characterized by less power distance, taking orders from a robot may be more acceptable to employees (e.g., Grandey *et al.*, 2010). Beyond culture, the personal characteristics that distinguish FLEs' attitudes toward and expectations for working with robots also merit further investigation (e.g., technology readiness, job experience, education level, and other personal resources).

A third valuable path for further research on contingency factors is to systematically compare differences between retail sectors and to study industries other than retail services. As mentioned in the systematic literature review by Savela et al. (2018), robot acceptance differs across occupational fields such as health care, education, tourism, and business. As such, the findings of the present study cannot be guaranteed to apply (to an equal extent) in every specific retail sector. The use of a theoretical framework such as the JD-R model would be appropriate to guide further comparative examinations. A fourth contextual specificity that could be influential is the zeitgeist. The data for Study 2 were collected in Spring 2021 in Belgium, where bricks-and-mortar retail in non-essential sectors had been closed for several months in 2020 due to the fight against COVID-19. This precaution was unprecedented. It may have made shoppers in the aftermath of these lockdowns more agreeable and grateful for merely having the opportunity to go shopping again.

Finally, our study focuses on studying employee well-being as a general concept, yet well-being is a multi-faceted concept (with physical, psychological, and social dimensions; Edgar et al., 2017; Dodge et al., 2012). Future research could, for instance, focus on whether the physical safety value that robots can bring to FLEs (cf. Berry *et al.*, 2020; Schepers and

Streukens, 2022) was heightened in pandemic times (and how long in its aftermath such effects may persist). Additionally, further research into the expectations and experiences of retail FLEs on working with robots, along with the distinct categories of job demands and resources (e.g., job hindrances and job challenges), would provide inspiring input for better introducing and developing robots for the retail service frontline.

References

Allan, B.A., Duffy, R.D., and Collisson, B. (2018), "Task significance and performance: Meaningfulness as a mediator", *Journal of Career Assessment,* Vol. 26 No. 1, pp. 172-182.

Anderson, L., and Ostrom, A.L. (2015), "Transformative service research: advancing our knowledge about service and well-being", *Journal of Services Research*, Vol. 18 No. 3, p. 243.

Bakker, A.B., and Demerouti, E. (2007), "The job demands-resources model: State of the art", *Journal of Managerial Psychology,* Vol. 22 No. 3, pp. 309–328.

Bakker, A.B., Hakanen, J.J., Demerouti, E., and Xanthopoulou, D. (2007), "Job resources boost work engagement, particularly when job demands are high", *Journal of Educational Psychology*, Vol. 99 No. 2, pp. 274–284.

Belanche, D., Casaló, L.V., Flavián, C., and Schepers, J. (2020), "Service robot implementation: a theoretical framework and research agenda", *The Service Industries Journal*, Vol. 40 No. 3–4, pp. 203–225.

Berry, L. L., Danaher, T. S., Aksoy, L., and Keiningham, T. L. (2020), "Service safety in the pandemic age". *Journal of Service Research,* Vol. 23 No. 4, pp. 391-395.

Bertacchini, F., Bilotta, E., and Pantano, P. (2017), "Shopping with a robotic companion", *Computers in Human Behavior*, Vol. 77, pp. 382–395.

Bhargava, A., Bester, M., and Bolton, L. (2021), “Employees’ Perceptions of the Implementation of Robotics, Artificial Intelligence, and Automation (RAIA) on Job Satisfaction, Job Security, and Employability”, *Journal of Technology in Behavioral Science*, Vol. 6 No. 1, pp. 106–113.

Bhatti, K.K., and Qureshi, T.M. (2007), "Impact of employee participation on job satisfaction, employee commitment and employee productivity", *International Review of Business Research Papers*, Vol. 3 No. 2, pp. 54-68.

Blosch, M., and Fenn, J. (2018). “Understanding Gartner’s Hypecycles”, Available at: https://www.gartner.com/en/documents/3887767 (accessed 15 January 2022).

Brengman, M., De Gauquier, L., Willems, K., and Vanderborght, B. (2021), “From stopping to shopping: An observational study comparing a humanoid service robot with a tablet service kiosk to attract and convert shoppers”, *Journal of Business Research*, Vol. 134, pp. 263–274.

Brougham, D., and Haar, J. (2018), “Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees’ perceptions of our future workplace”, *Journal of Management & Organization*, Vol. 24 No. 2, pp. 239–257.

Bryman, A. (2006), “Integrating quantitative and qualitative research: how is it done?”, *Qualitative Research,* Vol. 6 No. 1, pp. 97–113.

Buetow, S. (2010), “Thematic analysis and its reconceptualization as ‘saliency analysis’”, *Journal of Health Services Research & Policy*, SAGE Publications Sage UK: London, England, Vol. 15 No. 2, pp. 123–125.

Christ-Brendemühl, S., and Schaarschmidt, M. (2020), "The impact of service employees’ technostress on customer satisfaction and delight: A dyadic analysis", *Journal of Business Research*, Vol. 117, pp. 378-388.

Coherent Market Insights (2020), “Retail robots market analysis”, available at: https://www.coherentmarketinsights.com/market-insight/retail-robots-market-4535 (accessed 15 January 2022).

Crawford, E.R., LePine, J.A., and Rich, B.L. (2010), “Linking job demands and resources to employee engagement and burnout: a theoretical extension and meta-analytic test.”, *Journal of Applied Psychology*, Vol. 95 No. 5, pp. 834.

Deci, E.L., and Ryan, R.M. (1985). *Intrinsic Motivation and Self-determination in Human Behavior,* Plenum Press, New York, NY.

De Gauquier, L., Brengman, M., Willems, K., Hoang-Long, C., and Vanderborght, B. (2021), “In or Out? A Field Observational Study on the Placement of Entertaining Robots in Retailing”, *International Journal of Retail & Distribution Management*, Vol. 49 No. 7, pp. 846–874.

De Keyser, A., and Lariviere, B. (2014), “How technical and functional service quality drive consumer happiness: moderating influences of channel usage”, *Journal of Service Management*. Vol. 25 No. 1, pp. 30-48.

De Keyser, A., and W.H., Kunz (2022), “Consuming, Working, and Living with Service (Ro)Bots: A TCCM analysis”, *Forthcoming in Journal of Service Management*.

De Panafieu, O., Teisseyre, N., De La Fosse, G., Kharlamov, A., Bonnet, A., and Laville, A. (2016), “Think, act beyond mainstream: Robots and retail”, Think Act Beyond Mainstream, Roland Berger, available at: https://www.rolandberger.com/publications/publication_pdf/roland_berger_tab_robots_retail_en_12.10.2016.pdf (accessed 15 January 2022).

Demerouti, E., and Bakker, A.B. (2011), “The Job Demands–Resources model: Challenges for future research”, *Journal of Industrial Psychology*, Vol. 37 No. 2, pp. 1–9.

Dobrosovestnova, A., and Hannibal, G. (2021), "Working Alongside Service Robots: Challenges to Workplace Identity Performance", in Nørskov, M., Seibt, J., Quick, O.S. (Eds.), *Culturally Sustainable Social Robotics: Proceedings of Robophilosophy 2020*, IOS Press, Vol. 335, p. 148.

Dodge, R., Daly, A., Huyton, J., and Sanders, L. (2012), "The challenge of defining wellbeing", *International Journal of Wellbeing*, Vol. 2 No. 3, pp. 222-235.

Edgar, F., Geare, A., Saunders, D., Beacker, M., and Faanunu, I. (2017), "A transformative service research agenda: A study of workers' well-being", *The Service Industries Journal*, Vol. 37 No. 1, pp. 84–104.

Finsterwalder, J., and Kuppelwieser, V.G. (2020), "Equilibrating resources and challenges during crises: a framework for service ecosystem well-being", *Journal of Service Management*, Vol. 31 No. 6, pp. 1107–1129.

Fornell, C., and Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, Vol. 18 No. 1, pp.39-50.

Frey, C.B., and Osborne, M.A. (2017), "The future of employment: How susceptible are jobs to computerisation?", *Technological Forecasting and Social Change*, Vol. 114 No. 6, pp. 254-280.

Gardiazabal, P., and Bianchi, C. (2021), "Value co-creation activities in retail ecosystems: well-being consequences". *Journal of Services Marketing,* Vol. 35 No. 8, pp.1028-1044.

Goh, J., Pfefer, J., and Zenios, S.A. (2015), "Workplace stressors & health outcomes: health policy for the workplace", *Behavioral Science and Policy,* Vol. 1 No. 1, pp. 43-52.

Grandey, A., Rafaeli, A., Ravid, S., Wirtz, J., and Steiner, D.D. (2010), "Emotion display rules at work in the global service economy: the special case of the customer", *Journal of Service Management,* Vol. 21 No. 3, pp. 388-412.

Hair, J.F., Black, W.C., Babin, B., Anderson, R.E., and Tatham, R.L. (2018), *Multivariate data analysis,* Cengage, London, UK.

Harrison, R.L., and Reilly, T.M. (2011), “Mixed methods designs in marketing research”, *Qualitative Market Research,* Vol. 14 No. 1, pp. 7–26.

Henkel, A.P., Čaić, M., Blaurock, M., and Okan, M. (2020a), “Robotic transformative service research: deploying social robots for consumer well-being during COVID-19 and beyond”, *Journal of Service Management,* Vol. 31 No. 6, pp. 1131–1148.

Henkel, A.P., Bromuri, S., Iren, D., and Urovi, V. (2020), "Half human, half machine – augmenting service employees with AI for interpersonal emotion regulation", *Journal of Service Management*, Vol. 31 No. 2, pp. 247- 265.

Henseler, J., Ringle, C.M., and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135.

Heskett, J. L., Jones, T.O., Loveman, G.W., Sasser, W. E.,and Schlesinger, L.A. (2008), “Putting the service-profit chain to work”, *Harvard Business Review*, Vol. 72 No. 2, pp. 164-174.

Hofstede Insights (2019). “Country Report Belgium”, available at: https://www.hofstede-insights.com/country/belgium/ (accessed 15 January 2022).

Hollebeek, L.D., Sprott, D.E., and Brady, M.K. (2021), “Rise of the Machines? Customer Engagement in Automated Service Interactions”, *Journal of Service Research,* Vol. 24 No. 1, pp. 3-8.

Hoonakker, P.L., Carayon, P., Brown, R.L., Cartmill, R.S., Wetterneck, T.B., and Walker, J.M. (2013), "Changes in end-user satisfaction with Computerized Provider Order Entry over time among nurses and providers in intensive care units", *Journal of the American Medical Informatics Association*, Vol. 20 No. 2, pp. 252-259.

Huang, M.-H., and Rust, R.T. (2018), “Artificial intelligence in service”, *Journal of Service Research*, Vol. 21 No. 2, pp. 155–172.

Huang, Q., Xing, Y., and Gamble, J. (2019), “Job demands–resources: a gender perspective on employee well-being and resilience in retail stores in China”, T*he International Journal of Human Resource Management,* Vol. 30 No. 8, pp. 1323–1341.

Ivanov, S., Seyitoğlu, F., and Markova, M. (2020), “Hotel managers’ perceptions towards the use of robots: a mixed-methods approach”, *Information Technology & Tourism*, Vol. 22 No. 4, pp. 505–535.

Johnson, R.B., Onwuegbuzie, A.J., and Turner, L.A. (2007), “Toward a definition of mixed methods research”, *Journal of Mixed Methods Research*, Vol. 1 No. 2, pp. 112–133.

Kaartemo, V., and Helkkula, A. (2018), “A systematic review of artificial intelligence and robots in value co-creation: current status and future research avenues”, *Journal of Creating Value*, Vol. 4 No. 2, pp. 211–228.

Kandampully, J., Bilgihan, A., Bujisic, M., Kaplan, A., Jarvis, C.B., and Shukla, Y.S., (2021), “Service transformation: How can it be achieved?”, *Journal of Business Research*, 136, pp.219-228.

Kaplan, F. (2004), “Who is afraid of the humanoid? Investigating cultural differences in the acceptance of robots”, *International journal of humanoid robotics*, Vol. 1 No. 3, pp. 465-480.

Karasek, R., Brisson, C., Kawakami, N., Houtman, I., Bongers, P., and Amick, B. (1998), "The Job Content Questionnaire (JCQ): an instrument for internationally comparative assessments of psychosocial job characteristics", J*ournal of Occupational Health Psychology*, Vol. 3 No. 4, 322-355.

Karlis, D., Saporta, G., and Spinakis, A. (2003), "A simple rule for the selection of principal components", *Communications in Statistics-Theory and Methods*, Vol. 32 No. 3, pp. 643-666.

Keeman, A., Näswall, K., Malinen, S., and Kuntz, J. (2017), “Employee wellbeing: evaluating a wellbeing intervention in two settings”, *Frontiers in Psychology*, Vol. 8, April, pp. 1-14.

Kim, S., and Wang, J. (2018), "The role of job demands–resources (JDR) between service workers’ emotional labor and burnout: New directions for labor policy at local government", *International Journal of Environmental Research and Public Health*, Vol. 15 No. 12, p. 2894.

Krippendorf, K. (2004), *Content Analysis. An Introduction to Its Methodology*, Sage Publications, Newbury Park, CA.

Kunz, W.H., Heinonen, K., and Lemmink, J.G. (2019), “Future service technologies: is service research on track with business reality?”, *Journal of Services Marketing,* Vol. 33 No. 4, pp. 479-487.

Kuppelwieser, V.G., and Finsterwalder, J., (2016), Transformative service research and service dominant logic: Quo Vaditis?. *Journal of Retailing and Consumer Services*, Vol. 28, pp.91-98.

Latack, J.C., and Foster, L.W. (1985), "Implementation of compressed work schedules: Participation and job redesign as critial factors for employee acceptance", *Personnel Psychology*, Vol. 38 No. 1, pp. 75-92.

Lu, V.N., Wirtz, J., Kunz, W.H., Paluch, S., Gruber, T., Martins, A., and Patterson, P.G. (2020), “Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps?”, *Journal of Service Theory and Practice,* Vol. 30 No. 3, pp. 361–391.

Markets and Markets (2020), “Service robotics market”, available at: https://www. marketsandmarkets.com/Market-Reports/service-robotics-market-681.html (accessed 20 December 2021).

Mayring, P. (2015), Qualitative content analysis: Theoretical background and procedures. In *Approaches to qualitative research in mathematics education* (pp. 365-380). Springer, Dordrecht.

Meyer, P., Jonas, J.M., and Roth, A. (2020), “Frontline Employees’ Acceptance of and Resistance to Service Robots in Stationary Retail - An Exploratory Interview Study”, *Journal of Service Management Research*, Vol. 4 No. 1, pp. 21–34.

Mingotto, E., Montaguti, F., and Tamma, M. (2020), "Challenges in re-designing operations and jobs to embody AI and robotics in services. Findings from a case in the hospitality industry", *Electronic Markets*, Vol. 31, pp. 493-510.

Nasr, L., Burton, J., Gruber, T., and Kitshoff, J. (2014), "Exploring the impact of customer feedback on the well- being of service entities : A TSR perspective*", Journal of Service Management*, Vol. 25 No. 4, pp. 531-555.

Niemelä, M., Heikkilä, P., Lammi, H., and Oksman, V. (2017), “Shopping mall robots–opportunities and constraints from the retailer and manager perspective”, in Kheddar, A., Yoshida, E., Ge, S.S., Suzuki, K., Cabibihan, J.-J., Eyssel, F., & He, H. (Eds.), *9th International Conference on Social Robotics,* Springer, Cham, pp. 485–494.

Oliver, R.L. (1977), “Effect of expectation and disconfirmation on postexposure product evaluations: An alternative interpretation”, *Journal of Applied Psychology*, Vol. 62 No. 4, pp. 480–486.

Ostrom, A.L., Field, J.M., Fotheringham, D., Subramony, M., Gustafsson, A., Lemon, K.N., Huang, M.H., and McColl-Kennedy, J.R. (2021), "Service Research Priorities:

Managing and delivering service in turbulent times", *Journal of Service Research,* Vol. 24 No. 3, pp. 329-353.

Paluch, S., Tuzovic, S., Holz, H.F., Kies, A., and Jörling, M. (2021), “My colleague is a robot”–exploring frontline employees' willingness to work with collaborative service robots”, *Journal of Service Management*. DOI 10.1108/JOSM-11-2020-0406

Pantano, E. (2014), “Innovation drivers in retail industry”, *International Journal of Information Management,* Vol. 34 No. 3, pp. 344–350.

Parker, S.K., and Grote, G. (2020), "Automation, algorithms, and beyond: Why work design matters more than ever in a digital world", *Applied Psychology*, https://doi.org/10.1111/apps.12241.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology,* Vol. 88 No. 5, 879-903.

Rapp, A., Agnihotri, R., and Forbes, L.P. (2008), “The sales force technology–performance chain: The role of adaptive selling and effort”, *Journal of Personal Selling & Sales Management*, Vol. 28 No. 4, pp. 335–350.

Ringle, C.M., Wende, S., and Becker, J.M. (2015), SmartPLS 3, available at: http://www.smartpls.com (Accessed 17 September 2021).

Rosenbaum, M., Corus, C., Ostrom, A., Anderson, L., Fisk, R., Gallan, A., Giraldo, M., Mende, M., Mulder, M., Rayburn, S.W., Shirahada, K., and Williams, J. (2011), “Conceptualisation and aspirations of transformative service research”, *Journal of Research for Consumers, Vol. 19*, pp. 1-6.

Roth, P.G., and Roth, P.L. (1995), “Reduce turnover with realistic job previews”, *The CPA Journal*, Vol. 65 No. 9, pp. 68.

Russell–Bennett, R., Mulcahy, R., Letheren, K., McAndrew, R., and Dulleck, U. (2020), "The transformative service paradox: the dilemma of wellbeing trade-offs", *Journal of Service Management*, Vol. 31 No. 4, pp. 637–663.

Savela, N., Turja, T., and Oksanen, A. (2018), "Social acceptance of robots in different occupational fields: A systematic literature review", *International Journal of Social Robotics*, Vol. 10 No. 4, pp. 493–502.

Schepers, J.J.L., and Streukens, S. (2022), "To serve and protect: A typology of service robots and their role in physically safe services", *Journal of Service Management*, forthcoming.

Shi, C., Satake, S., Kanda, T., and Ishiguro, H. (2016), "How would store managers employ social robots?", in: Bartneck, C., Nagai, Y., Paiva, A., & Šabanović, S. (Eds.), *11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, IEEE, Christchurch, New Zealand, pp. 519–520.

Subramony, M., Groth, M., Xinyu, J., Hu, X., and Wu, Y. (2021), "Four Decades of Frontline Service Employee Research: An Integrative Bibliometric Review", *Journal of Service Research,* Vol. 24 No. 2, pp. 230-248.

ter Hoeven, C.L., and van Zoonen, W. (2015), "Flexible work designs and employee well-being: Examining the effects of resources and demands", *New Technology, Work and Employment*, Vol. 30 No. 3, pp. 237–255.

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z.S., Lim, S.S., Lu, H.Y., and Oh, P.H. (2021), "Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors", *Frontiers in Psychology*, Vol. 12, pp. 822.

Troebs, C.C., Wagner, T., and Heidemann, F. (2018), "Transformative retail services: elevating loyalty through customer well-being", *Journal of Retailing and Consumer Services,* Vol. 45, pp. 198-206.

Tuckey, M.R., Boyd, C.M., H.R. Winefield, Bohm, A., Winefield, A.H., Lindsay, A., and Black, Q. (2017), “Understanding stress in retail work: Considering different types of job demands and diverse applications of job resources”, *International Journal of Stress Management,* Vol. 24 No. 4, pp. 368–391.

Tuomi, A., Tussyadiah, I.P., and Stienmetz, J. (2021a), “Applications and implications of service robots in hospitality”, *Cornell Hospitality Quarterly,* Vol. 62 No. 2, pp. 232–247.

Tuomi, A., Tussyadiah, I.P., and Hanna, P. (2021b), “Spicing up hospitality service encounters: the case of Pepper™”, *International Journal of Contemporary Hospitality Management,* Vol. 33 No. 11, pp. 3906-3925.

Van den Broeck, A., De Cuyper, N., De Witte, H., and Vansteenkiste, M. (2010). “Not all job demands are equal: Differentiating job hindrances and job challenges in the Job Demands–Resources model”, *European Journal of Work and Organizational Psychology*, Vol. 19 No. 6, pp. 735-759.

Vänni, K.J., and Korpela, A.K. (2015), “Role of social robotics in supporting employees and advancing productivity”, in: Tapus, A., André, E., Martin, J.C., Ferland, F., and Ammi, M. (Eds.), *International Conference on Social Robotics,* Springer, Vol. 9388, Springer, Cham, pp. 674-683.

Vatan, A., and Dogan, S. (2021), "What do hotel employees think about service robots? A qualitative study in Turkey", *Tourism Management Perspectives,* Vol. 37, https://doi.org/10.1016/j.tmp.2020.100775.

Voorhees, C.M., Fombelle, P.W., and Bone, S.A. (2020), “Don’t forget about the frontline employee during the COVID-19 pandemic: Preliminary insights and a research agenda on market shocks”, *Journal of Service Research*, Vol. 23 No. 4, pp. 396-400.

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S., and Martins, A. (2018), “Brave new world: service robots in the frontline”, *Journal of Service Management*, Vol. 29 No. 5, pp. 907–931.

Wisse, B., and Sleebos, E. (2016), “When Change Causes Stress: Effects of Self-construal and Change Consequences”, *Journal of Business and Psychology*, Vol. 31 No. 2, pp. 249–264.

Wolbring, G., and Yumakulov, S. (2014), “Social robots: views of staff of a disability service organization”, *International Journal of Social Robotics*, Vol. 6 No. 3, pp. 457–468.

Xiao, L., and Kumar, V. (2021), “Robotics for customer service: A useful complement or an ultimate substitute?", *Journal of Service Research*, Vol. 24 No. 1, pp. 9-29.

Zhang, S., and Liu, Q. (2019), "Investigating the relationships among teachers’ motivational beliefs, motivational regulation, and their learning engagement in online professional learning communities", *Computers & Education*, Vol. 134, pp. 145–155.

Tables

Source	Sector[1]	Theoretical lens	Research aim(s) / Outcomes	Method	Key findings
Paluch et al., 2021[a]	V	Appraisal theory & autonomy and control	Willingness to work with a collaborative service robot	Interviews	- Identifies key factors that enable and restrict FLE willingness to collaborate with robots - The interaction between robots & FLE is a multistage process - Appraisal of robots by FLE depends on the FLE, robot, & job attributes - 4 FLE personas: supporter, embracer, resister & saboteur
Tuomi et al. 2021[b]	H	Theories on uncanny valley, task level view, technology acceptance	Expected implications of integrating Pepper	Interviews Observation	- Robots are believed to be able to take over routine and unpleasant tasks - Dealing with customer complaints could involve a robot or an FLE -robot team - FLE do not see robots as real human colleagues - Adoption of humanoid robots in hospitality is influenced by contextual, social, interactional & psychological factors, and extrinsic & intrinsic drivers of adoption
Vatan & Dogan 2021[b]	H	No theoretical lens	Perceptions and emotions related to robots in hospitality	Interviews	- The word Robot elicited negative emotions - Robots can provide benefits for FLE (e.g., reduce workload) - Robots can create problems (e.g., worse communication with the customers. increased unemployment, …)
Meyer et al. 2020[c]	R	Theories on Acceptance and reducing resistance to service robots	Understanding the factors that promote acceptance and reduce resistance toward robots	Interviews	- Robots are perceived as a threat (e.g., loss of status) and potential support - Key aspects to promote acceptance and reduce resistance toward robots; the need for enablement, empowerment, engagement
Mingotto et al. 2020[b]	H	Roles frameworks	Effects on the changing roles of FLE	Action research	- Robots can act as an augmentation - Emergence of the (key) role of the AI supervisor
Brougham & Haar, 2018[b]	V	STARA (smart technology, artificial intelligence, robotics & algorithms) awareness & career planning theory	Impact on organizational commitment, satisfaction, turnover, depression, etc.	Survey	- Higher STARA awareness decreases organizational commitment & career satisfaction and increases turnover intentions & depression feelings
Vänni & Korpela, 2015[b]	E/H	No theoretical lens	Willingness to collaborate with a robot when sick	Survey	FLE expect that a robot improves productivity when ill
Wolbring & Yumakul, 2014[b]	HC	No theoretical lens	Perceptions toward different robot applications	Survey	- Robots can be used for routine tasks, but robots cannot replace the human touch - Concerns about safety, interactions feeling artificial
This paper	R	J-DR model RTSR lens	Expectations toward working with robots	Interviews Survey	- Robots are expected to reduce many job demands - Robots are expected to erode several job resources - The net effect on job engagement and well-being is equivocal: anticipated changes in job demands and -resources seem to cancel each other out

Table 1: Overview of empirical studies on employees and working alongside robots in service settings. *Note: The table was created based on (a) a WoS search on robot and employees as reported in De Keyser et al., 2022, (b) a supplementary search in Scopus with (Robot(s) + employee(s) + service(s) as search terms, and (c) enriched with empirical papers suggested by peers. Only papers with empirical research and (if possible) a focus on physical service robots are retained. Legend: (1) E=Education, F=finance, H=*hospitality including hotels, food services, restaurants, etc., *HC=healthcare, R=Retailing, V=*various sectors.

	Frequency mentions	Key insights
Job Demands	**226**	
Mental & emotional		
Customer conversations	36	• Robots can help with dealing with difficult customers • Robots are not suitable for all customer situations and can create more burdens in this way • Robot as entertainment function and informative helpdesk • Lost human touch with customers because robots have no emotion • Robots are too standardized and cannot deal with consumer complexities
Mentally fatiguing	22	• Robots can remember detailed info on products and keep track of stock • Robots can advise employees (e.g., do not forget that these products will expire)
Repetitive tasks (monotony)	45	• Robots can deal with annoying or repetitive tasks (e.g., stock, checking deliveries, cleaning) • Robots can help during busy periods (e.g., pricing during discount periods) • Robots can be used as a control device
Physical		
Heavy objects	40	• Robots can help with lifting heavy objects and heavy physical jobs
Repetitive movements	20	• Robots can take over repetitive physical tasks (e.g., sorting stock in storage and store)
Unsafe environment	4	• Robots can detect dangerous situations or avoid unhealthy situations (e.g., lifting)
Workload	59	• Robots can minimize daily workload and work pressure
Job Resources	**206**	

***Organization* of work**		
Participation in decision making	9	• Robots could help with planning • Robots should not make a decision for FLE
Role clarity	9	• Robots can help to give an overview of which tasks FLE need to do • No significant impact is expected by robot implementation
Level of the organization		
Career opportunities	9	• Robots could train employees for certain tasks
Job security	53	• Lower feelings of job security but not for all parts of the job
Interpersonal and social relations		
Autonomy	1	• Less autonomy because robots would take over too many tasks
Feedback	9	• Robots could give feedback, but it could feel like controlling
Supervisor and co-worker support	28	• Robots cannot replace colleagues or supervisors (e.g., no small talk or get something off your chest) • Robots cannot offer emotional support • Robots cannot joke around or laugh • Robots cannot lead and support like a manager
Level of the task		
Specific skills	23	• Robots can deal with tasks that need more precision (e.g., stock, objective measurements) • Robots can store more information
Task identity & significance	65	• FLE would feel less useful because robots take over too many tasks • Robots can create more time for FLE to do significant tasks (e.g., selling, human touch)
Links to organizational outcomes	**86**	
		• Robot implementation can help to decrease sick leave

	• Robots can help during busy periods, and this can be good for the mindset • Robots can give extra stress • Robots can help FLE to have more time for their core tasks, human touch, customers • Robots taking over certain repetitive/unliked tasks is good for motivation/engagement • Taking tasks away can both decrease and increase motivation (depending on the task) • Robot implementation will lead to losing human and personal touch for the customer and FLE

Table 2: Key insights of Study 1

Constructs and Measured Items	Standard Loadings
JOB DEMANDS	
Physical heavy work *(λ_1 = 2.63; λ_2 = .63; Cronbach's alpha = .82; CR = .86; AVE = .62; based on Karasek et al., 1998 and Study 1 interviews)*	
In my current job…	
… I often have to lift heavy things.	.96
… I often have to assume uncomfortable body positions.	.61
… I often have to repeat the same physical efforts.	.57
… I often have to perform physical efforts.	.92
Difficult customer conversations *(λ_1 = 1.40 ; λ_2 = .61; Pearson's r = .40; p < .01; CR = .78; AVE = .5; based on Kim & Wang, 2018)*	
In my current job…	
… I often have to deal with verbally aggressive customers.	.89
… I often have to deal with difficult customers.	.95
Work pressure *(λ_1 = 1.74; λ_2 = .83; Cronbach's alpha = .63; CR = .77; AVE = .41; based on ter Hoeven & van Zoonen, 2015)*	
In my current job…	
… I often experience high work pressure.	.65
… I often have to work hard.	.71
… I often have to remember a lot of information.	.83
Mentally repetitive tasks *(λ_1 = 1.60; λ_2 = .41; Pearson's r = .60; p <.01 ; CR = .88; AVE = .79; based on Parker & Grote, 2020)*	
In my current job…	
… I often have to do boring tasks.	.93
… I often have to do useless tasks	.85
JOB RESOURCES	
Career opportunities and job security *(λ_1 = 2.11; λ_2 = .99; Cronbach's alpha = .69; CR = .81; AVE = .52; based on Demerouti & Bakker, 2011))*	
In my current job …	
… I have career opportunities.	.79
… I can be promoted.	.72
… I experience job security.	.71
… I have the impression I will still be employed in the future.	.65
Participation in decision making *(λ_1 = 3.62; λ_2 = .44; Cronbach's alpha = .90; CR = .93; AVE = .72; based on Hoonakker et al., 2013; Allan, Duffy, and Collisson, 2018; Karasek et al., 1998, and Study 1 interviews)*	
In my current job …	
… I can make decisions that determine my work.	.81
… I can decide when certain things should be done.	.85
… I have a say when things are being changed at work.	.87
… I have a lot of decision-making freedom.	.83
… I have a lot of say.	.82
Feedback *(λ_1 = 1.33; λ_2 = .67; Pearson's r = .33; p < .01; CR = .79; AVE = .65; based on Parker & Grote, 2020 and Study 1 interviews)*	
In my current job …	
… I get sufficient feedback from my supervisor.	.91
… I get sufficient advice to improve myself in my job.	.70
Role clarity in team *(λ_1 = 1.33; λ_2 = .67; Pearson's r = .33; p < .01; CR = .80; AVE = .66; based on Christ-Brendemühl and Schaarschmidt, 2020, and Study 1 interviews)*	
In my current job …	
… I know clearly which responsibilities I have.	.77

… my colleagues and I work well together.	.86
JOB OUTCOMES	
Job well-being *(λ_1 = 2.09; λ_2 = .53; Cronbach's alpha = .78; CR = .87; AVE = .70; based on Ter Hoeven and van Zoonen, 2015)*	
In my current job …	
… I feel energetic at work.	.80
… I feel content at work.	.87
… I feel successful at work.	.82
Job engagement *(λ_1 = 2.17; λ_2 = .45; Cronbach's alpha = .81; CR = .89; AVE = .72; based on Zhang et al., 2019)*	
In my current job …	
… I always want to give the best of myself at work.	.83
… I feel fulfilled at work.	.86
… I feel committed at work.	.86

Table 3. Measurement model of psychometric properties

Note: Items that originate from Study 1 (interviews) are underlined

	M (SD)	t(164); p-value	Median	Proportion < 4	Proportion = 4	Proportion > 4
To what extent are you a proponent of the introduction of service robots to the retail store where you work?	4.45 (1.72)	3.22; .002	4	21.9%	31.0%	47.1%
Balancing advantages and disadvantages, what is your overall expectation about the introduction of robots to the retail store where you work?	4.26 (1.23)	2.68; .008	4	25.8%	27.7%	46.5%
To what extent do you fear losing your job with robots being introduced in retail stores?	3.60 (2.04)	-2.44; .016	4	41.9%	20.6%	37.5%
To what extent do you expect working with robots to impact on your well-being?	3.83 (1.27)	-1.70 (.09)	4	35.7%	38.8%	25.5%
To what extent do you expect working with robots to impact on your job engagement	3.92 (1.14)	-.80 (.43)	4	29.3%	46.5%	24.2%

Table 4. General attitudes toward working with robots

Note: t-test refers to a comparison of mean scores with the neutral scale midpoint 4.

	Baseline (current job)	Anticipated situation (when working with robots)		
	M(sd)	M(sd)	t(164)	p
Job Demands				
Physical heavy work	4.81 (1.41)	2.57 (1.45)	-16.80	<.001
Difficult customer conversations	4.37 (1.11)	4.23 (1.72)	1.72	.09
Work pressure	5.44 (1.13)	2.78 (1.08)	-14.52	< .001
Mentally repetitive tasks	3.85 (1.45)	2.55 (1.45)	-12.88	< .001
Job Resources				
Career opportunities and job security	4.95 (1.27)	3.10 (1.16)	-10.01	< .001
Participation in decision making	4.56 (1.47)	3.78 (0.71)	-3.93	< .001
Feedback	5.00 (1.34)	4.00 (1.04)	.04	.97
Role clarity in team	5.89 (1.05)	4.03 (0.98)	.36	.72

Table 5. Baseline job demands and -resources and anticipated impact of robots

Note: (1) t-test refers to a comparison of mean scores with the neutral scale midpoint 4; (2) when applying a Bonferroni correction to the obtained p-values, the results remain the same, providing support for the statistical robustness of the findings.

	Employee Well-Being R^2 = .48			Employee Engagement R^2 = .43		
	Stand. Path Coeff.	95% BCCI	f^2	Stand. Path Coeff.	95% BCCI	f^2
Job Demands						
Physical heavy work	**-.20**	**[-.36; -.02]**	**.06**	-.02	[-.16; .15]	<.01
Difficult customer conversations	.03	[-.14; .29]	<.01	-.11	[-.25; .16]	.02
Work pressure	.06	[-.09; .21]	.03	**.17**	**[.01; .31]**	**<.01**
Mentally repetitive tasks	**-.17**	**[-.30; -.02]**	**.07**	**-.23**	**[-.36; -.10]**	**.04**
Job Resources						
Career opportunities and job security	**.34**	**[.20; .47]**	**.06**	**.23**	**[.08; .36]**	**.15**
Participation in decision making	**.15**	**[.02; .06]**	**.03**	**.17**	**[.02; .29]**	**.04**
Feedback	.11	[-.03; .25]	<.01	-.01	[-.15; .12]	.02
Role clarity in team	**.20**	**[.07; .31]**	**.06**	**.22**	**[.06; .38]**	**.07**

Table 6. Path coefficients in predicting employee well-being and engagement

Note: Statistically significant path coefficients (α = .05) = in bold typeface; baseline job ratings are used

Figures

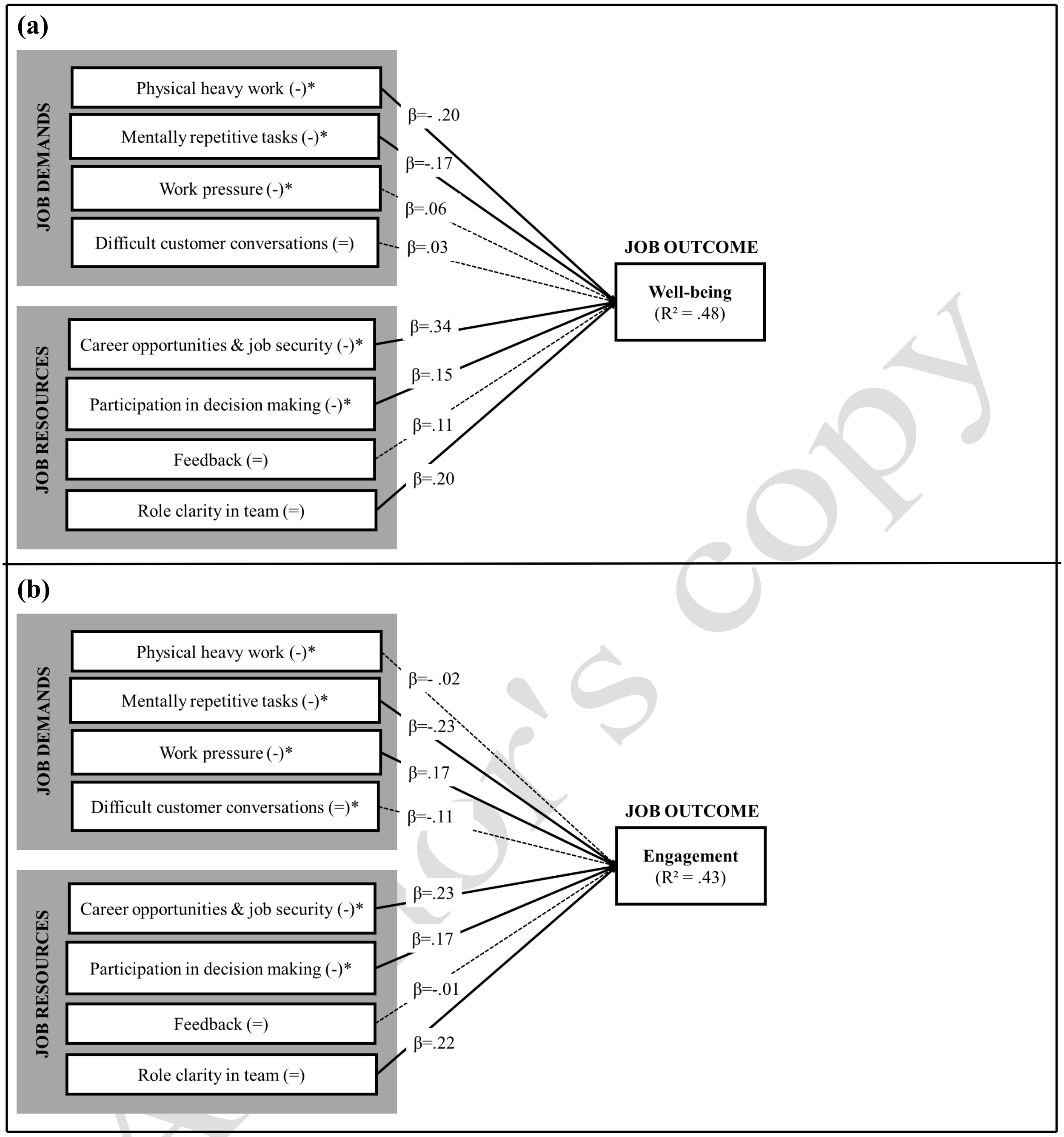


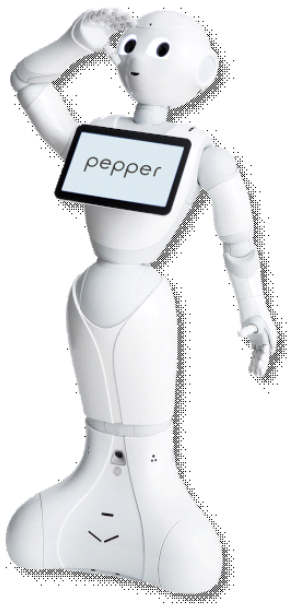
Figure 1. (a) JD-R model on retail FLE well-being; (b) JD-R model on retail FLE job engagement

Note: (-) = expected average effect of introducing robots is statistically significantly (5%) more negative than the current job situation; (+)* = idem but positive; (=) = no statistically significant difference; dashed lines = statistically non-significant relationships (5%).*

Appendix. Introduction to the survey (Study 2)

Retail stores are beginning to introduce robots, but they are not very common yet. We will give you a little more information about these robots.

o Robots can work on front-office tasks (e.g., direct contact with customers and sellers).
o Robots can also work on back-office tasks (e.g., helping staff without interacting with customers).
o Robots can look like humans or animals (e.g., they may have a body or face—see the photo on the left) or non-human objects like machines (e.g., a walking kiosk with a screen—see the photo on the right).



Robots can be used in all types of retail stores (e.g., clothing stores, pharmacies, bookstores, supermarkets, electrical stores, etc.)

For example, the tasks of a robot are as follows:
o Welcoming customers
o Finding products in the store
o Providing product recommendations
o Filling shelves
o Preparing orders
o Etc.

Robots can be used to help store personnel or to take over tasks. Robots are sometimes successful (e.g., when taking over repetitive tasks) and sometimes disappointing (e.g., when extra time is needed to maintain the robot).

When completing this questionnaire, it is important that you keep these examples in mind. All the questions relate to what robots can do in general, as briefly outlined for you here. So, it is not about one specific type of robot or one specific task but about robots in general and your job.

Acknowledgments

The authors would like to thank the research assistants [BLINDED] for their help in collecting the data.