Work Characteristics as Determinants of Remote Working Acceptance: Integrating UTAUT and JD-R Models

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Abstract. The spread of remote working exponentially increased in recent years. Since remote working is by definition ICT-enabled, it seems important to identify which organizational and ICT-related factors may influence employees' attitudes towards remote working and remote productivity.

With this aim, we integrated the Unified Theory of Acceptance and Use of Technology model (UTAUT) with technostress literature, using Job demands-resources model (JD-R) as main conceptual framework.

Therefore, we proposed and tested a model of remote working acceptance in which predictors are operationalized in terms of techno-job demands (namely techno-complexity, techno-invasion and techno-overload) and techno-job resources (namely technical support and remote leadership support), to explore their distinctive influence on attitude towards remote working and, in turn, on remote working-enabled productivity.

Data from 836 remote workers from different organizations were collected and analyzed through structural equation modeling.

Results supported empirically the proposed model: both techno-job demands and techno-job resources affected attitude towards remote working which completely mediated the effect of the predictors on remote working-enabled productivity. Practical and theoretical contributions, along with limitations and future research direction, are presented and discussed.

Keywords: Remote working · Technostress · Remote productivity · JD-R Model

1 Introduction

In the last decades, the diffusion of Information and Communication Technologies (ICTs) has led to profound changes in organizational contexts and in the way work is performed by employees [1].

ICT brings several advantages to organizations, such as reducing company costs and fostering productivity [2]. Moreover, technology enables greater autonomy and flexibility so that employees can contribute to business goals anywhere and anytime [3]. However, empirical evidence has shown that it may also have detrimental effects on

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people's psychological and physical health as well on job performance [4, 5]. Indeed, employees have to deal with increasingly complex work environments, new skills to be learned and blurred boundaries between work and personal life. This "dual nature" of technology calls for deeper understanding in the new ways of working [6], since technologies are not only devices used to achieve a task but also the main channel that connects workers with their job role and the organizational context.

In the field of work and organisational psychology, the Job Demands-Resources Model (JD-R [7]) provides a sound theoretical framework to acknowledge the demanding and beneficial aspects of technology.

This framework posits that every organizational context is characterized by two distinctive sets of work features, namely job demands and job resources. On the one hand, job demands include those work-related and organizational factors that entail costs on employees and, thus, activate an energy depletion process. On the other hand, job resources comprise those work-related and organizational factors that facilitate a positive motivational process. As such, job demands and resources are expected to exert opposing effects on employees' health and performance [8]. All in all, the JD-R represents a comprehensive and feasible model to explain the impact of the organizational context on job attitudes (i.e., engagement and burnout) and in turn, on individual and organizational outcomes.

Due to the widespread use of technologies and remote working, some studies have adapted the JD-R model to study the influence of technology-related job characteristics and their negative effects on employees [9, 10]. More specifically, these studies focused on the influence of technostress creators on well-being and performance [11, 12], such as the necessity of keeping up with constant technological updates, the intensification of work pace and the invasiveness of work in one's private life due to technological tools [13]. Although technology fosters remote working, our understanding of how techno-related demands and resources shape workers' attitudes towards it and the perceived benefits on one's own productivity is still limited. Indeed, understanding what determines the attitude towards remote working and its consequences represents a pivotal issue from both theoretical and practical points of view [14].

From a different perspective, the study of the determinants of attitude towards technological tools has been extensively investigated by technology acceptance models [15]. Those theories are aimed to understand how and why people accept or reject technological tools or systems. As such, aspects referring to the technology's characteristics (e.g., ease of use [16]) or individuals' traits (e.g., personal innovativeness [17]) have been taken into account as predictors of attitudes and intention to use. Nevertheless, the role of contextual and organizational variables, which may influence employee adoption of technological tools, has been to date neglected [18].

Among technology acceptance models, the Unified Theory of Acceptance and Use of Technology model (UTAUT [19]) is the most comprehensive framework to understand the predictors that shape a positive attitude towards technology. It suggests that technology usage depends on the perceptions and expectations that people have on technological tools, as well as the facilitating conditions that contribute to the behavioural intention to use it and to the actual adoption of the system.

However, a recent meta-analysis [20] has challenged technology acceptance and UTAUT models claiming that the literature on the topic has reached its peak, and therefore there is a need to investigate new theoretically relevant predictors and outcomes, new application contexts and new theoretical backgrounds aimed at understanding the processes behind technology acceptance.

Based on the assumption that remote working is ICT-enabled, emergent studies have been employing predictors from acceptance models to explore what determines a positive attitude towards remote working [21, 22].

The present cross-sectional study tries to answer the call for further theory-driven research on the topic [23–25], by proposing a conceptual systematization of predictors and outcomes of attitudes towards remote working that integrates JD-R and UTAUT models.

Specifically, the present research aims to contribute to the literature in several ways:

1. Emphasizing the role of organizational context and job characteristics for the acceptance of remote working, operationalizing predictors in terms of (techno) job demands or (techno) job resources;
2. Contributing to the technostress literature by exploring the influence of key technostress creators (namely "techno-job demands") on attitude towards remote working and in turn, on remote working-enabled productivity;
3. Expanding the contribution of the JD-R model to explain new outcomes, moving from traditional attitudinal dimensions (i.e., engagement/burnout) to attitude towards remote working and remote working-enabled productivity;
4. Exploring the mediating role of attitude towards remote working between (techno) job demands and (techno job resources) and remote working-enabled productivity.

1.1 The Present Study

As mentioned above, the idea behind the Job Demands-Resources model is that each job has characteristics that can be classified as demands or resources, that may influence employees' well-being and job attitudes, as well as organizational outcomes [26].

In the case of remote working and technology adoption, some ICT-related job features may represent a job resource whereas others may represent a job demand.

In this regard, previous studies have identified several technostress creators which are responsible for a variety of negative outcomes such as fatigue, lower job satisfaction, work overload and reduced productivity [27]. Among them, Techno-complexity (TCOM) refers to those ICT's characteristics that make the user feel inadequate regarding their digital skills. In fact, employees are required to constantly refresh their skills due to frequent updates that characterize technology systems. In the long term, this can lead to increased frustration and stress [28]. Techno-overload (TOV) deals with the overexposure to information channelled by ICT tools that must be managed. It also compels employees to work longer and faster, challenging their ability to handle workload and maintain an adequate level of efficiency [29]. Techno-invasion (TINV) refers to the invasiveness that technology brings outside of work, leading the person to always stay connected to job-related tasks. Being "always on" leads to negative health outcomes and ultimately, to an impairment of individual performance [30]. As such, technostress literature suggests that these inherent aspects of ICTs systems may influence their acceptance

and adoption beyond the usage potential of technological artefacts (e.g., usefulness [31]; performance expectancy [32]). From this standpoint, we claim that techno-job demands may have an influence on the attitude towards remote working, since technology represents the *conditio sine qua non* this working modality can be implemented. To be sure, when employees perceive technologies as creators of demanding experiences like higher work overload, the erosion of work-life boundaries and the urgency to tune their skills to more complex technological tools, they may be less likely to enjoy working remotely or less likely to experience such a solution as comfortable and effective. The higher the techno-job demands (TJD), encompassing TCM, TOV and TIN, the more negative will be the attitude towards remote working. Therefore, we formulated the following hypothesis:

H1: Techno-job demands are negatively related to Attitude towards remote working.

However, there are some organizational characteristics that go in the opposite direction and act as important job resources. In fact, since companies are also affected by the opportunities and challenges of technological innovations, they are called to create the contextual facilitating conditions to make remote working sustainable, productive and a desirable solution for employees [33]. We believe that remote leadership support and technical support are likely to represent crucial organizational factors in this process. In the first case, leadership processes are transforming due to the diffusion of technology within work contexts, thus leaders play an increasingly decisive role in technology acceptance and usage [34, 35]. As such, we believe the same applies to remote working adoption. In this context, technology mediates the employer-employee relationship that must be reframed in accordance with the worker's characteristics and needs. According to how this turns out, we believe that the experience of working remotely can be facilitated. At the same time, the literature has outlined other crucial resources in dealing with technology and the stress it generates, named technostress inhibitors [36], such as literacy facilitation, innovation support and technical support. Specifically, technical support is defined as the assistance provided to employees in the context of their use of ICTs tools, which is also considered a facilitating condition in the UTAUT model in determining technology adoption and usage behaviour [37]. For this reason, we claim that the availability of both technical support given by the organization as well as the perceived support from the leader when working remotely, promotes a better work experience for employees, fostering a positive attitude towards remote working. Indeed, when employees are facilitated in using remote tools (e.g., timely support in solving technical problems) and perceive that the leader is supportive and engaged in make remote working effective, they may be more aware of the advantages of this working arrangement, as well as the resources to manage it if necessary. Taken together, the higher the techno-job resources (TJR) encompassing technical support and remote leadership support the more positive will be attitude towards remote working. As such, we formulated the following hypothesis:

H2: Techno-job resources are positively related to Attitude towards remote working.

The relationship between attitudes and behaviour is well-known [38]. Indeed, having a positive disposition toward a target situation can help to understand the consequent behaviours. For instance, recalling the technology acceptance model literature, people with a more positive attitude towards technology (e.g., ease of use, useful) are more

likely to actually use the system [6, 16, 19]. Extending those results to remote working, we argue that when employees present a positive attitude towards working remotely (e.g., they think it is a good, comfortable and enjoyable working solution) they may perceive an increase of their productivity due to remote working, that is, achieving their goals more effectively and efficiently. Hence, the following hypothesis was investigated:

H3: Attitude towards remote working is positively related to Remote working-enabled productivity.

Moreover, since the type of perception people have of technologies affects the frequency and quality of ICT use as a function of the degree of acceptance [6, 9], we claim that the same applies for remote working. Indeed, being embedded in a supportive environment from both a technical and relational perspective in the use of technologies or being exposed to a technologically demanding context, may shape the perception of productivity in remote working in opposite ways, depending on the attitude people have toward this working arrangement. Specifically, when employees perceive that they have more TJR at their disposal to work remotely, they may be likely to experience this arrangement as positive and thus, draw performance advantages. Instead, the perception of higher TJD may be associated with a lower positive attitude towards working remotely, thereby perceiving it as hindering their performance.

Specifically, we assume that the attitude towards remote working may act as a mediating mechanism able to link techno-job demands and techno-job resources with remote working-enabled productivity.

Based on this, the following research hypotheses were investigated:

H4a: Attitude towards remote working mediates the effect between Techno-job demands and Remote working-enabled productivity.

H4b: Attitude towards remote working mediates the effect between Techno-job resources and Remote working-enabled productivity.

Specifically, we expect a total mediation, since we claim that the influence that TJD and TJR have on the considered outcome is via ATRW.

Figure 1 represents the overall hypothesized model which characterizes the present study.

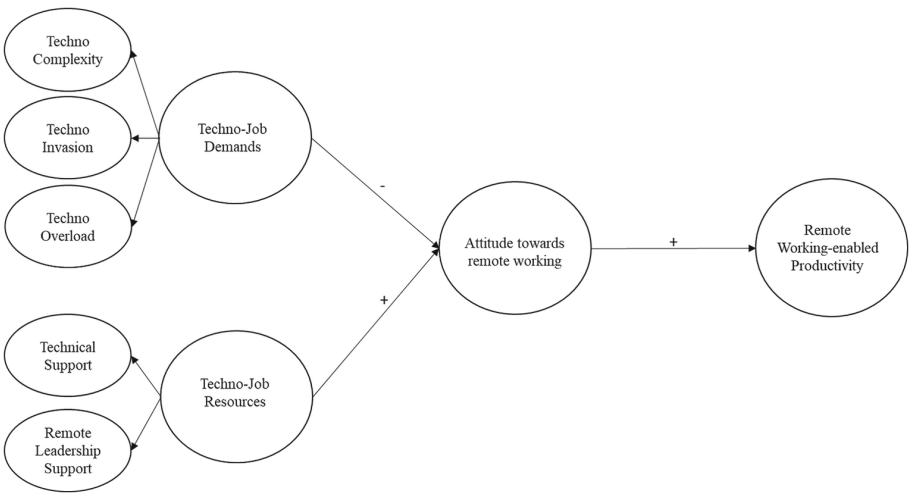

Fig. 1. The hypothesized model. *Note*: Solid lines are used to represent hypothesized direct effect.

2 Materials and Methods

Sample and Procedure. A total sample of 836 remote workers from different organizations took part in the study, of which 456 (54.5%) were females and 380 (45.5%) were males. Regarding age, 50.4% were at least 30 years old while 45.5% ranged from 31 to 60 years old. Few participants (4.2%) were older than 60 years old. Concerning the level of education, most of the sample (32.4%) had a high school diploma, 31.2% had a master's degree, 24.5% had a bachelor's degree, 10% had a post-graduate degree and 1.8% had a junior high school diploma. Most of the sample (60.6%) had a permanent contract and worked in the manufacturing industry sector (30.3%). The study was conducted via an anonymous online self-report questionnaire. Participation in the study was completely voluntary.

2.1 Measures

Techno-Job Demands. Techno-job demands (TJD) were measured with 9 items, using the Italian translation of the technostress creators scale [39]. Specifically, techno-complexity (TCOM) measured the individual's difficulties in dealing with the complexity associated with ICTs; Techno-invasion (TINV) measured the degree to which one's job invades one's private life through technology; Techno-overload (TOV) measured the perception of working longer and faster due to ICTs.

An example item for each dimension includes: "I do not find enough time to study and upgrade my technology skills"; "I have to stay in touch with my work even during holidays, evenings and weekends because of technology"; "Technology requires me to work much faster". Scales were measured through a 5-point Likert scale ordered from 1 (Totally disagree) to 5 (Totally agree). Cronbach's Alpha for TCM, TIN and TOV was respectively 0.79, 0.77 and0.83. The total techno-job demands scale reliability was 0.85.

Techno Job Resources. Techno-job resources (TJR) assessed technical support and remote leadership support. Technical support (TSUP) was measured using 3 items adapted by Tarafdar et al. [40] and Fisher et al. [41]. The dimension measures employee support activities to solve users' ICT related problems (e.g. *"Our organization offers support for the solution of any technological problem"*). The participants rated their agreement on a 5-point Likert scale ranging from 1 (Totally disagree) to 5 (Totally agree). The Cronbach's Alpha was 0.90. Remote Leadership Support (RLS) assessed the perception of leader's behaviours aimed at facilitating the efficacy of remote working. All of the 3 items used were generated ad hoc for this research context, since the literature does not provide any reliable measures to date. Items are the following: *"My manager makes the best use of remote channels and tools to promote exchanges between co-workers"*; *"My manager facilitates teamwork to effectively achieve common goals remotely*"; and *"My manager keeps motivated their remote co-workers by acknowledging their characteristics and needs"*. Items were measured through a 5-point Likert scale

from 1 (Totally disagree) to 5 (Totally agree). The Cronbach's Alpha was 0.87. The total techno-job resources scale reliability was 0.83.

Attitude Towards Remote Working. Attitude towards remote working (ATRW) was measured by using 3 items from Venkatesh et al. [19] and adapted to the specific context of remote working.

They assessed the individual's positive feelings about performing the target behaviour as exemplified by items such as: *"Working remotely is a good idea"*. A 5-point Likert scale from 1 (Totally disagree) to 5 (Totally agree) was used and the Cronbach's Alpha was 0.93.

Remote Working-Enabled Productivity. To measure the perceived increase of productivity due to remote working (RWEP), 3 items adapted by Tarafdar and colleagues [42] were used. Each item assesses the perception of individual productivity through working remotely by a 5-point Likert scale from 1 (Totally disagree) to 5 (Totally agree). An example item is *"Working remotely helps me to accomplish more work than would otherwise be possible"*. Cronbach's Alpha was 0.90.

2.2 Data Analysis

As preliminary analysis, a Confirmatory Factor Analysis (CFA) was conducted on Mplus 8.4 [43] to verify the factorial structure of predictors (TJD and TJR) as latent dimensions, using the Maximum Likelihood (ML) as estimator.

In line with the literature on JD-R model [44], we hypothesized a second-order structure for techno-job demands and techno-job resources dimensions.

To determine whether the hypothesized second-order model (M5) showed the best fit to the data, the following five alternative models were tested.

More precisely, we compared the hypothesized model (M5) with the followings:

1. A first alternative model (M1) with a single factor structure. This model implements Harman's single factor test [45], where all predictor items load on a single factor. This test allows the determination of whether most of the variance can be accounted for by one general factor, representing the influences of method bias on observed item covariances [46].
2. A model with two first-order factor model (M2) representing techno-job demands (TJD) and techno-job resources (TJR), where all the techno-stressors items loaded on the first factor while items related to technical support and remote leadership support loaded on the second factor.
3. An alternative model with four correlated factors (M3) where TCOM, TINV and TOV items loaded on their respective factors (namely TJD) while TSUP and RLS items loaded on the same latent variable.
4. A competing alternative model with five first-order correlated factors (M4) where TCOM, TINV, TOV, TSUP and RLS items are treated as separate factors.
5. The hypothesized model (M5) with five first-order correlated factors (TCM, TINV, TOV, TSUP, RLS) and two second-order factors (TJD and TJR).

The best measurement model was evaluated through fit indices and significant differences in chi-square values [47]. Then the hypothesized measurement and structural models were tested via Structural Equation Modeling (SEM) and a mediation analysis was performed.

To examine the goodness of it, different fit indices were used: the $\chi 2$ goodness-of-fit statistic; the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), the Tucker–Lewis index (TLI) and the comparative fit index (CFI). The appropriateness of the model fit was established with (1) $\chi 2$ statistic values; (2) TLI and CFI values greater than .90 [48]; (3) RMSEA values lower than .08 [49]. Since the $\chi 2$ statistic is dependent on sample size and larger samples tend to result significant (i.e. if the $\chi 2$ is significant at $\rho < .05$ we accept the alternative hypothesis that there is a significant difference between the model and the data), additional fit statistics were used [50]. In order to statistically compare the alternative models, fit indices and significant differences in $\chi 2$ values ($\Delta \chi 2$; p. $< .001$) were evaluated [51]. To test the mediation hypothesis, specific indirect effects procedure was used as implemented in "Model Indirect" in Mplus 8.4. In addition, to evaluate the statistical significance of direct and indirect effects, bootstrapping method was performed, employing 5.000 bootstrap samples with the replacement from the full sample to construct bias-corrected 95% Confidence Intervals (CI) [52]. In particular, the mediation model is significant if zero is not contained within the intervals.

Gender, education, and age were included as control variables within the model, in accordance with previous technostress studies [e.g. 27, 36].

3 Results

As displayed in Table 1, the CFA clearly demonstrated that M1-M2-M3 models did not adequately fit the data. On the other hand, M4 (e.g., with five correlated first-order factors) was the first model to have a good fit, resulting as statistically better than the previous nested models and supporting the factorial distinctiveness of each dimension.

The M5, which relates the first-order factors (TCM, TINV, TOV, TSUP and RLS) to the second-order factors (TJD and TJR), fit the data adequately. According to $\Delta \chi 2$, there was no significant deterioration of the fit, thus, although more conceptually complex, the hypothesized model turned out to be empirically tenable.

The factor loadings of M5 were all statistically significant from zero and greater than 0.30, confirming the appropriateness of the hypothesized measured model. Specifically, the first-order factor loadings ranged from 0.48 to 0.93, while the second-order factor loadings ranged from 0.48 to 0.79.

Table 1. Results of confirmatory factor analysis and alternative model comparisons

Models (M)	χ^2	df	RMSEA	CFI	TLI	CI 95%	SRMR	$\Delta\chi^2$
M1: one-factor model (all 15 items)	3800.45**	90	0.22	0.40	0.30	0.21 0.23	0.17	
M2: two-factors model	2435.64**	89	0.18	0.62	0.55	0.17 0.18	0.12	1364.816 (df = 1) p. < .001
M3: four-factors model	1674.20**	84	0.15	0.74	0.68	0.14 0.16	0.11	761.435 (df = 5) p. < .001
M4: five-factors model	236.23**	80	0.05	0.97	0.96	0.04 0.06	0.03	1437.971 (df = 4) p. < .001
M5: hypothesized two second-order factors model	237.99**	84	0.05	0.97	0.96	0.04 0.05	0.03	1768.00 (df = 4) p. = 0.77

Notes. ** $p < 0.001$; $\chi 2$ = chi-square statistic; CFI = comparative fit index; TLI = Tuker–Lewis fit index; RMSEA = root mean square error of approximation; CI = confidence interval; df = degrees of freedom.The $\Delta\chi 2$ shows comparison of nested models in progressive order from M1 to M5

Table 2. Shows the correlations, means, standard deviation and internal consistencies of the study variables. The associations between the constructs were significant and in the expected direction. In particular, techno-job resources showed a positive correlation with attitude towards remote working and remote working-enabled productivity, while techno-job demands presented a negative relation with attitude towards remote working and remote working-enabled productivity.

Finally, attitude towards remote working showed a positive and significant relationship with remote working-enabled productivity.

Table 2. Descriptive statistics and zero-order correlations

	M (SD)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Age	2.11 (1.30)	–						
(2) Sex	1.55 (.49)	−.17**	–					
(3) Edu	3.15 (1.04)	.13**	.64**	–				
(4) TJD	2.28 (0.70)	−.08*	−.01	−.04	(0.85)			
(5) TJR	3.52 (.70)	.02	−.03	.06	−.21**	(0.83)		
(6) ATRW	3.95 (.94)	.11**	−.01	.01	−.32**	.33**	(0.93)	
(7) RWEP	3.57 (.93)	.12**	.00	.07*	−.21**	.26**	.62**	(0.90)

Notes. * p < 0.05 ** p < 0.01; M = mean; SD = standard deviation; coefficient alpha reliability estimates are presented in brackets along the diagonal; TJD = techno-job demands; TJR = techno-job resources; ATRW = attitude towards remote working; RWEP = remote working-enabled productivity; Edu = education

3.1 Model Results

The hypothesized measurement model showed an adequate fit to the data ($\chi 2$ 606.18 $p < .001$; CFI = 0.97, TLI = 0.97, RMSEA [95% CI] = 0.04 [0.04 0.05], SRMR = 0.04), as well as the structural mediational model fit ($\chi 2$ 606.18 $p < .001$, CFI = 0.96, TLI = 0.95, RMSEA [95% CI] = 0.04 [0.04 0.05], SRMR = 0.04). As displayed in Fig. 2, techno-job demands were negatively associated with attitude towards remote working ($\beta = -.24$ $p < .001$), while techno-job resources presented a positive relation with attitude towards remote working ($\beta = .41$ $p < .001$), confirming respectively H1 and H2. Techno-job demands and techno-job resources were negatively correlated ($\beta =$ -.36 $p < .001$). Hypothesis H3, concerning the direct effect between attitude towards remote working and remote working-enabled productivity was also supported. Indeed, ATRW was positively ($\beta = .67$ $p < .001$) related with RWEP.

The model explained 29% of the variance in attitude towards remote working and 48% in remote working-enabled productivity. The indirect effect for techno-job demands to RWEP was -.16 (bootstrap CI 95% = −.23 and −.08), while for techno-job resources to RWEP was .27 (bootstrap CI 95% = .19 and .36) confirming both H4a and H4b. To ascertain that the relationships between TJD, TJR and RWEP were fulling mediated by ATRW, we tested an alternative partial mediation model including the direct effects of techno-job demands and techno-job resources on RWEP. However, the relations were not statistically significant, therefore the model positing a total mediation of ATRW seems to be a more parsimonious picture of the data. Along with the presented variables, age, gender and education were included as covariates within the model. In particular, age was negatively related to techno-job demands ($\beta = -.15$ $p < .001$), while education was positively related to techno-job resources ($\beta = .11.$ $p = .018$).

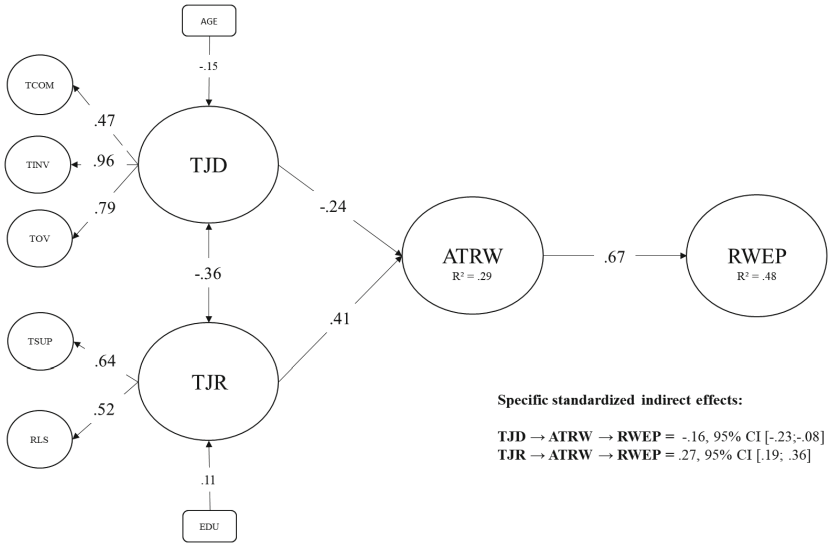

Fig. 2. Figure reports the standardized regression coefficients and the variance explained of the hypothesized structural model, controlled for gender, age and educational level. *Note*: All structural paths were significant, $p < 0.001$. TCOM = Techno-complexity; TINV = Techno-invasion; TOV = Techno-overload; TJD = Techno-job Demands; TSP = Technical support; RLS = Remote leadership Support; TJR = Techno-job resources; ATRW = Attitude towards remote working; RWEP = Remote working-enabled productivity; Edu = Education. R^2 = r-square.

4 Discussion

Overall, the results confirmed the hypothesized relationships between techno-job demands (techno-complexity, techno-invasion, techno-overload), techno-job resources (technical support and remote leadership), attitude towards remote working and remote working-enabled productivity.

In accordance with the JD-R model, techno-job demands and techno-job resources showed opposite associations with attitude towards remote working. More specifically, the higher the perceived techno-job demands, the more negative the attitude towards remote working. On the other hand, the higher the perceived techno-job resources, the more positive the attitude towards remote working.

We explain this result because high techno-job demands, such as being invaded during leisure time by e-mails or perceiving to be obligated to handle more work in a shorter period of time or forced to acquire new technological skills to work, may reduce the likeability and comfort of remote working. This is in line with previous studies underlining the impact of technostress creators on remote workers' performance and well-being [53].

On the contrary, perceiving high techno-job resources provided by the organization, such as the availability of technical support when problems arise as well as the support and encouragement of leaders when working remotely, may facilitate a positive employee experience of such ways of working. This result extends previous findings

which emphasizes the role of the leader and the support given by the organization in facilitating effective performance in virtual work environments [54, 55].

Furthermore, we found that this resulting attitude is a key explanatory mechanism of the influence of both techno-job demands and techno-job resources on remote working-enabled productivity due to remote working. This result is of particular interest because it means that the influence of techno-job demands and techno-job resources on remote working-enabled productivity is uniquely conveyed through the individual's attitude towards remote working.

In line with the JD-R model [56], this outcome can be interpreted as the result of a motivational process in which the degree of ICT-related hindrance demands and facilitating resources leads employees to perceive themselves as more (or less) productive, consequently to how they experience working remotely. Furthermore, extending the predictions of the literature on technology acceptance to remote work, the results support the relevance of individual attitudes as a mechanism for turning the perception of technology into remote productivity outcomes.

Finally, two socio-demographic variables were significant. Specifically, people with a higher level of education tend to perceive more techno-job resources within their work context. We can hypothesise that people with a high degree of specialization are likely employed in work contexts that offer more support both technically and in the professional and digital development of the worker. Furthermore, younger people feel the impact of techno-job demands more strongly than older individuals. This result is in contrast with most of the literature that showed that older people are more exposed to technostress [57, 58]. However, other evidence in the literature has shown the contrary [59, 60] and others have observed that there is no generational difference [61, 62]. It should be noted, however, that in our study, the interpretative significance of the second-order factor of techno-job demands is mainly connoted by the invasion dimension. We can hypothesise that this component is more influential on the younger generations, for whom there is a higher need to define work and private life boundaries [63].

4.1 Practical and Theoretical Implications

From a theoretical perspective, the present research tested a conceptual model of remote working acceptance framed in the organizational context. As the latter is enabled by the use of technology, our model accounted for the perceptions of ICT-organizational and job-related factors to understand how employees approach remote working and perceive themselves as more or less productive under such an arrangement.

To this end, we used the JD-R model as main theoretical framework to define the predictors of remote working acceptance, namely, techno-job demands and techno-job resources. In particular, to specify the content of techno-job demands and techno-job resources, we started from Tarafdar's research on technostress creators (e.g., techno-complexity, techno-invasion, techno-overload) and inhibitors (e.g., technical support). Indeed, while the former refers to the hindering characteristics of technology, the latter concerns organizational factors that can help employees dealing with technostress. Furthermore, we used the UTAUT model to understand the process underlying the emergence of remote working acceptance. Indeed, the UTAUT suggested that technology

acceptance is a process in which technology usage is determined by how people perceive and approach ICTs systems. In line with the UTAUT model and Tarafdar's contributions, this model posits that the behavioural intention and the effective usage of technology increases as a function of the available facilitating conditions. As such, we applied such assumptions in remote working settings with attitude towards remote working as a mechanism that channels the perceptions of technology in remote productivity outcomes.

To the best of our knowledge, this is the first contribution proposing an integration among these theoretical frameworks, applying it specifically to remote working.

Moreover, in doing this we extended the range of considerable predictors in these theoretical perspectives. With respect to the UTAUT, we extended the facilitating conditions beyond technical support (e.g., by considering remote leadership as a form of social support) and also considered the potential hindering factors (e.g., techno job demands), shaping the model's application to organizational contexts.

Regarding the JD-R model, we considered a new job attitude from those usually investigated [64] which in this case refers to a positive attitude towards remote working and the resulting perceived remote productivity.

From an applicational standpoint, our results offer relevant insights for designing interventions aimed at supporting the viability of the increasing use of remote working in organizations. Indeed, according to our study, organizations are called to promote an optimal balance between techno-job resources (i.e., technical support and remote leadership) and techno-job demands (i.e., techno-overload, invasion and complexity) to which workers are exposed to in remote working. Such a balance, in which the perceived techno-job resources exceed the demands, seems to be important in maintaining employees' positive attitude toward remote work, thereby helping them to perceive themselves as more productive in this working arrangement. First, the organization may primarily invest in developing techno-resources, given their greater association with attitude and perceived remote productivity. This could be concretely accomplished by activating organizational actions aimed at designing or at strengthening the technical systems to support the remote worker, ensuring technical feedbacks as timely and effectively as possible in resolving technological problems that the remote workers may encounter. Furthermore, leaders may be targeted with training and development paths designed to develop a variety of skills in managing employees remotely. On the one hand, training could focus on increasing the skills of leaders in adapting to the technological medium to effectively manage remote collaboration and feedback processes. On the other hand, leaders could be trained in learning how to recognize employees digital and work needs and coach them to face remote working challenges.

Second, organizations may take action to reduce perceptions of techno-job demands.

Regarding the perceived complexity of using and learning new technologies, organizations could improve the technological experience of employees, such as by implementing user-friendly work tools, as well as by providing periodic training sessions to update remote workers in terms of digital knowledge and skills [65]. Moreover, to reduce techno-overload and invasion (indicative of work intensification at the expense of recovery time on and off the job, as well as a deconstruction of work-life boundaries; [66]), organizations and managers may foster a culturally sensitive approach to employees'

needs and human sustainability in order to keep them motivated and productive. For example, by discouraging formal and informal practices or expectations towards remote employees of working beyond negotiated hours due to their higher job flexibility [67, 68].

4.2 Limitation and Future Direction

The study presents several limitations that deserve consideration.

First of all, the cross-sectional nature of the data, requires us to be careful in interpreting influence relationships among variables of the study. To ascertain the direction of the observed effects, longitudinal research designs are needed and should be the objective of future studies.

Second, all measures were self-reported. However, they refer to perceived work characteristics and individual attitude that only the employee may evaluate. On the other hand, our outcome, namely remote working-enabled productivity, measuring the perceived increase of productivity due to remote working could be biased. Future studies should include an objective or other-report indicator of employees' remote productivity.

Third, we did not collect information on the intensity of remote working. Future studies could investigate to what extent the number of days or hours in remote working affect the tested model.

Fourth, although we developed a model with a focus on the organizational and techno-related components, we did not include other important predictors that should be investigated further. In particular, it is necessary to examine the role of (techno) personal resources (e.g. e-work self-efficacy [33]) and its specific effects on the attitude towards remote working and in turn on performance.

Finally, we focused only on remote working technology. Further investigations should explore the applicability of the model with other types of technological artefacts (e.g. collaborative robotics, artificial intelligence).

5 Conclusion

By integrating the JD-R and UTAUT models, this paper investigated how techno-related facilitating and hindering factors on the job are related to attitudes towards remote work and remote working-enabled productivity. In particular, the present research highlighted the mediating role of employee's attitude towards remote working in the relationships between perceptions of positive and negative job characteristics associated with technologies, as facilitating or demanding factors, and remote working-enabled productivity. These results provide useful insights on the implications of techno-job demands and techno-job resources in influencing the acceptance of remote working, which could be of particular interest for future research and practical application within organizations.

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