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Research Article

Resilience Carries the Stronger Indirect Association: Perceived Digitalisation and Work-Related Mental Well-Being among Private-Sector Bank Employees in India

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Abstract

Purpose: This study examines which personal resources account for the association between bank employees' experience of digitalisation and their work-related mental well-being. Using the job demands–resources model and conservation of resources theory, it compares digital competency and resilience as parallel and serial mediators.

Design/Methodology: Survey data from 425 employees of four private-sector banks in northern India were analysed with partial least squares structural equation modelling, with supplementary confirmatory factor analysis, interaction and multigroup analyses.

Findings: Digital job resources were strongly associated with digital competency (β = .830) and resilience (β = .827) but not directly with well-being. The indirect association through resilience was significant (β = .399) and larger than the non-significant association through digital competency (β = .078). The serial indirect association through competency and then resilience was significant (β = .243). Because the data are cross-sectional and self-reported, with highly intercorrelated constructs, these associations are not causal evidence.

Implications: Digital upskilling alone is unlikely to be sufficient for employee well-being during digital transformation and may be most useful when paired with resilience-building practices.

Originality: The study compares a capability-based and a regulatory personal resource within one model and separates the resource and challenge sides of digitalisation.

INTRODUCTION

The bank branch has changed more than any other service workplace in India. The COVID-19 pandemic accelerated the shift of routine transactions to mobile channels, and private-sector banks have digitised account opening, know-your-customer procedures, loan processing and performance tracking (Amankwah-Amoah et al., 2021). Digital transformation is therefore a lived experience for employees as well as a strategic change. The technostress tradition treats information and communication technologies mainly as job demands that cause strain and reduce satisfaction and productivity (Day et al., 2012; Ragu-Nathan et al., 2008; Tarafdar et al., 2007), and a systematic review associates techno-stressors with negative health and work outcomes (Borle et al., 2021). Among Indian bankers, technostress has been linked to lower engagement and less innovative work behaviour (Jain et al., 2025). A second line of research argues that the same technologies can be appraised as challenges and resources and produce techno-eustress (Tarafdar et al., 2019), and that techno-eustress and technostressors have different consequences (Califf et al., 2020). The more useful question is therefore not whether digitalisation helps or harms employees in general, but which personal resources account for its association with well-being.

Two resources are especially relevant for bank employees. Digital competency is the capability to use digital technologies at work, together with the organisational support and autonomous motivation that surround it (Oberländer et al., 2020). Resilience is employees' self-evaluated capacity to adapt to and recover from difficulties at work (Näswall et al., 2019; van der Meer et al., 2018). Evidence on each has accumulated separately: technology self-efficacy and organisational ICT support are associated with less technostress and strain (Day et al., 2012; Tarafdar et al., 2007), and resilience is linked to mental health (Hu et al., 2015) and performance under pressure (Cooke et al., 2019). A documented search of journal articles (Supplementary Note S1) found studies linking digitalisation to employee resilience (Zahoor et al., 2024) and digital capability to well-being but, to our knowledge, none that compared the two indirect associations directly, tested a serial path from competency to resilience, or separated the resource and challenge sides of digitalisation. Organisations nonetheless invest mainly in digital competency, often assuming that employees who are capable with new systems will also cope better with them.

This study addresses that gap with survey data from employees of four large private-sector banks in northern India. Grounded in the job demands–resources (JD-R) model (Bakker & Demerouti, 2017) and conservation of resources (COR) theory (Hobfoll, 1989; Hobfoll et al., 2018), it examines digital competency and resilience as parallel and serial mediators between perceived digital job resources and work-related mental well-being. The place of personal resources in the JD-R model is still debated (Schaufeli & Taris, 2014; Xanthopoulou et al., 2007), and comparing two resources of different kinds within one model offers a way to ask whether the role a personal resource plays depends on its kind. Because the data are cross-sectional, mediation is used in its statistical sense only.

The study makes three contributions. First, it compares a capability-based and a regulatory personal resource within one model and tests whether competency relates to well-being through resilience. Second, it separates the resource and challenge sides of perceived digitalisation and examines whether resilience buffers digital challenges, adding evidence on the roles of personal resources in the JD-R model. Third, it provides evidence from Indian private-sector banking, a fast-growing sector with rapid digital adoption and intense performance pressure.

THEORETICAL BACKGROUND AND HYPOTHESES

Theoretical lens: personal resources in JD-R and COR

The JD-R model distinguishes job demands, which require sustained effort and are associated with strain, from job resources, which support goal attainment and engagement (Bakker & Demerouti, 2007). Scholze and Hecker (2023) extended it to digitisation by separating digital job demands, such as pressure to keep pace with new systems, from digital job resources, such as tools that simplify retrieval and coordination. Personal resources, added later, are positive self-evaluations linked to resiliency that refer to a person's sense of their ability to control and affect their environment (Xanthopoulou et al., 2007). Their role remains unsettled. Schaufeli and Taris (2014) identify at least five ways in which personal resources have been incorporated, including as direct predictors, moderators and mediators, and conclude that there is as yet no single best way to include them. When Xanthopoulou et al. (2007) tested three of these roles in one sample, personal resources mediated the association between job resources and engagement but did not buffer the association between job demands and exhaustion.

COR theory explains why mediation is the more plausible role in our setting. People strive to obtain, retain and protect valued resources, and resources travel together in caravans (Hobfoll, 1989; Hobfoll et al., 2018). A work environment rich in digital job resources should therefore be associated with stronger personal resources, which in turn are associated with better well-being. Personal resources should also be related to each other: the mastery that digital competency supplies is a plausible source of the confidence to adapt that resilience reflects (Compeau & Higgins, 1995; Hobfoll et al., 2018). We therefore model digital job resources as the predictor, digital competency and resilience as mediators, and a path from competency to resilience. The pace and challenges of change, which JD-R would classify as demands (Scholze & Hecker, 2023), are modelled as a separate predictor of well-being and used to test the alternative, buffering role of resilience (Section 4.5).

The two personal resources differ in kind. Digital competency enables employees to carry out digital tasks, whereas resilience is a regulatory resource for adjusting to and recovering from disruption, whatever its source. In the transactional model of stress (Lazarus & Folkman, 1984), whether digital change is appraised as a threat or a challenge depends on people's perception of their ability to deal with it, which resilience as measured here reflects.

Digital job resources and personal resources

Digital competency refers to the integrated knowledge, skills, attitudes and motivation required to carry out digital tasks at work (Oberländer et al., 2020) and is closely related to computer self-efficacy, which develops largely through mastery experiences (Compeau & Higgins, 1995). Because digital job resources supply mastery experiences, training and support, employees who perceive more digital job resources should report higher digital competency. We define resilience as employees' self-evaluated capacity to adapt to and recover from difficulties, expressed in confidence in oneself and in one's ability to cope adaptively (van der Meer et al., 2018). So defined, it is a personal resource in the JD-R sense, a positive self-evaluation rather than a fixed trait or an observed behaviour, and it develops through manageable challenge and support at work (Näswall et al., 2019). Where digital changes are purposeful and supported, repeated successful adaptation should strengthen bank

employees' confidence in handling change. In Chinese banks, supportive leadership and co-worker support were associated with resilience, more strongly under high performance pressure (Cooke et al., 2019).

H1: Digital job resources are positively associated with employees' digital competency.

H2: Digital job resources are positively associated with employees' resilience.

Digital job resources, personal resources and mental well-being

Mental well-being combines hedonic elements with eudaimonic elements such as purpose and positive functioning (Ryan & Deci, 2001). In connected workplaces, an important part of it is digital well-being, an optimal balance between the benefits and drawbacks of constant connectivity (Vanden Abeele, 2021). Digital demands can erode such well-being (Ragu-Nathan et al., 2008), but JD-R theory treats job resources as functional in their own right (Bakker & Demerouti, 2017). Digital job resources may therefore be associated with well-being directly, not only through personal resources. Digital competency should support well-being by narrowing the gap between what systems require and what employees can deliver: confident users are less likely to experience digital tasks as overload and more likely to experience autonomy and mastery (Ryan & Deci, 2001), and low technology self-efficacy is a recognised antecedent of technostress (Tarafdar et al., 2007). Self-evaluations of one's capacity to cope are among the most consistent correlates of mental health (Hu et al., 2015).

H3: Digital job resources are positively associated with employees' mental well-being.

H4: Digital competency is positively associated with employees' mental well-being.

H5: Resilience is positively associated with employees' mental well-being.

Indirect associations through digital competency and resilience

Digital job resources should therefore be associated with well-being partly through the personal resources employees bring to their work. The two indirect associations are not equivalent: competency addresses the demands of digital tasks, whereas resilience addresses the broader consequences of change, such as workload, performance pressure and uncertainty. If well-being depends more on regulating these consequences than on performing digital tasks well, the association through resilience should be larger (Fig. 1).

H6: Digital job resources are indirectly associated with mental well-being through digital competency.

H7: Digital job resources are indirectly associated with mental well-being through resilience.

H8: The indirect association between digital job resources and mental well-being through resilience is larger than that through digital competency.

COR theory's caravan principle further implies that capability supports regulation: mastering new systems is a source of the confidence to adapt (Section 2.1).

H9: Digital job resources are indirectly associated with mental well-being through digital competency and resilience in sequence.

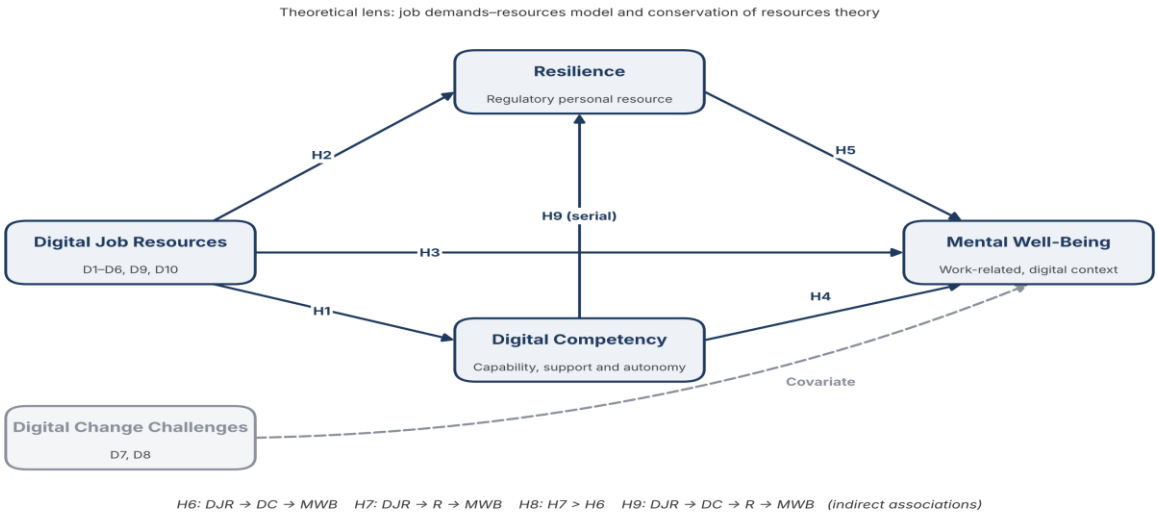

Figure 1. Conceptual research model.

Note. DJR = digital job resources; DC = digital competency; R = resilience; MWB = mental well-being (work-related, digital context). Digital change challenges (D7, D8) enter as a second predictor of well-being and in the interaction model (Section 4.5). Source: authors' elaboration.

METHOD

Design, sample and procedure

A cross-sectional survey was conducted among employees of four large private-sector banks (HDFC Bank, ICICI Bank, Axis Bank and Kotak Mahindra Bank) in branches in Haryana and the Tri-City region (Chandigarh, Mohali and Panchkula). In the absence of a sampling frame, a purposive referral approach was adopted: a Google Forms questionnaire was distributed through the researchers' professional networks in the banking sector, and contacts were asked to pass the link to suitable colleagues. Around 500 potential respondents were approached and 450 questionnaires were received; after screening 25 flagged questionnaires, 425 usable responses remained. No response rate can be reported because the link was passed on through intermediaries. An a priori power analysis for the most complex regression (four predictors of well-being) indicated a minimum sample of 244 (Faul et al., 2009).

Respondents were assured of confidentiality; names were not required and were excluded from the analysis dataset. Participation was voluntary, and submission was treated as implied informed consent. Formal ethics committee approval was not sought (see Declarations). A pilot with 60 respondents showed satisfactory reliability and validity, so no items were changed and the pilot responses were retained. Because they are not identified in the archived dataset, a model excluding them could not be estimated (Section 5.3).

Measures

The questionnaire contained demographic questions and 42 statements rated from 5 (strongly agree) to 1 (strongly disagree), with no reverse-coded items; all items, sources and loadings are listed in Supplementary Table S3.

Digitalisation was measured with 10 items adapted from the Digital Transformation Scale (Pettersson et al., 2024). Following Scholze and Hecker (2023) and the exploratory factor analysis (Section 3.3), we separated two constructs. Digital job resources (8 items: D1–D6, D9, D10) describe the use of digital tools to plan, organise and retrieve work, the degree to which digital technology has changed work and thinking about organisational development, and the strategic integration of digital tools. Digital change challenges (2 items: D7, D8; $r = .55$, Spearman–Brown reliability = .71) describe the challenges and pace of digital change. We expected them to function as digital job demands; Section 4.3 shows that they did not.

Digital competency (12 items; DC1–DC12) comprised organisational support for digital competence development (DC1–DC4), adapted from the technology knowledge component of the TPACK instrument (Schmidt et al., 2009) with the referent shifted to the bank's support; autonomy and motivation in using digital tools (DC5–DC8), adapted from the autonomy-satisfaction items of the Basic Psychological Need Satisfaction and Frustration Scale (Chen et al., 2015); and digital task integration and competence (DC9–DC12), developed for this study. The construct thus captures capability together with its surrounding support and motivation, not pure technical skill. Because the three groups could not be separated empirically (Section 3.3), it was modelled as one first-order reflective construct, and the groups were examined separately in an exploratory model (Section 4.6).

Resilience (10 items; R1–R10) was adapted from the Resilience Evaluation Scale (van der Meer et al., 2018), which measures self-evaluated resilience through self-confidence and adaptive-coping self-efficacy; items were reworded to refer to difficulties in digital work. Mental well-being (10 items; MWB1–MWB10), adapted from Büchler et al. (2020) and reworded so that higher scores indicate better self-regulation, captured psychological balance under constant connectivity. It therefore measures work-related well-being in a digital context, close to digital well-being, rather than general mental health. Two items were excluded from the primary measure: MWB10 describes an organisational practice rather than the respondent's own state, and MWB1 describes comfort with technology and cross-loaded on resilience in the initial analysis. These exclusions were post hoc and risk capitalising on chance (Simmons et al., 2011), so results with all ten items are also reported (Table 4), and conclusions are drawn only from results that hold across specifications. Gender, age and work experience served as controls in a robustness model.

Data screening and dimensionality

The 425 retained responses had no missing values on substantive items. Items were negatively skewed and Cramér–von Mises tests rejected normality for all indicators ($p < .001$), supporting a variance-based estimator. Parallel analysis (Horn, 1965) retained one factor per scale. An exploratory two-factor solution for digitalisation nevertheless showed D7 and D8 loading mainly on a second factor (.57 and .79), so they were modelled as a separate construct. A three-factor solution for digital competency did not reproduce the questionnaire groups.

Analytical approach

The model was specified following SmartPLS 4 defaults (Ringle et al., 2024) (reflective Mode A constructs, path-weighting scheme, stop criterion of 10^{-7}) and estimated with an open-source Python implementation of the PLS algorithm. PLS-SEM suits models with parallel and serial indirect paths and non-normal data (Hair et al., 2022). Significance was assessed with percentile confidence intervals from 5,000 bootstrap subsamples

(2,000 for alternative and exploratory specifications). The measurement model was evaluated through loadings, Cronbach's alpha, composite reliability (ρA, ρC), average variance extracted (AVE), the Fornell–Larcker criterion (Fornell & Larcker, 1981), cross-loadings and the heterotrait–monotrait ratio (HTMT) with bootstrapped intervals (Henseler et al., 2015), classified following Rönkkö and Cho (2022). Discriminant validity was also tested by maximum-likelihood confirmatory factor analysis (CFA), comparing the measurement model with models that constrained each pair of correlations to unity or merged constructs, with fit judged against Hu and Bentler (1999). The structural model was evaluated through VIF, path coefficients, R^2, f^2, PLSpredict (10 folds, 10 repetitions) and the cross-validated predictive ability test (CVPAT) (Liengaard et al., 2021; Shmueli et al., 2019). Indirect associations were assessed following Zhao et al. (2010) and compared by bootstrapping their differences. H6–H8 were tested in the parallel model and H9 in a serial model that added a path from digital competency to resilience.

Common method variance was examined with Harman's single-factor test and full collinearity VIFs (Kock, 2015). Six alternative specifications tested robustness against the primary serial model (Table 4), an interaction model tested whether resilience buffers digital change challenges or digital job resources using the two-stage approach (Becker et al., 2018), and an exploratory model allowed the three competency groups to predict both resilience and well-being. Before multigroup comparisons across gender, work experience and job role, measurement invariance was assessed with the three-step MICOM procedure (Henseler et al., 2016); path differences were then tested with permutation-based multigroup analysis (Sarstedt et al., 2011), both with 1,000 permutations. Because cross-sectional data cannot establish the order in which variables occur (Spector, 2019), all indirect associations are interpreted as statistical.

RESULTS

Sample profile and common method variance

Of the 425 respondents, 66.4% were men; mean age was 34.3 years (SD = 6.9) and mean experience 9.4 years (SD = 7.0). Sales employees formed 48.7% of the sample (Supplementary Table S1), and men were more often in sales roles than women (59.9% vs 26.6%). In Harman's test, the first factor explained 47.9% of the variance, below the 50% threshold, but its eigenvalue (19.18) far exceeded the second (1.70). Full collinearity VIFs were 3.85 (digital job resources), 2.24 (digital change challenges), 5.15 (digital competency), 5.75 (resilience) and 2.58 (well-being), three above the 3.3 threshold (Kock, 2015). Common method variance is therefore likely present: all constructs were self-reported at one time, with no reverse-coded items and mostly positive wording, so the observed correlations are probably inflated. Between 12.9% and 19.3% of respondents had the maximum average on each multi-item construct, and 31.1% on the two-item challenges construct. Such ceiling effects can attenuate or distort associations, and distribution through professional contacts may have encouraged socially desirable responding (Podsakoff et al., 2012).

Measurement model

All loadings were significant ($p < .001$) and ranged from .653 to .881; items loading between .60 and .70 were retained (Hair et al., 2022). Internal consistency was adequate (α = .710–.933; ρC = .873–.943), AVE exceeded .50 for all constructs, and construct means were high (4.08–4.27; Table 1).

Table 1. *Measurement model: reliability, convergent validity and descriptive statistics (n = 425)*

Construct	Items	Loadings	α	ϱA	ϱC	AVE	M (SD)
Digital job resources	8	.676–.819	.892	.897	.914	.571	4.27 (0.70)
Digital change challenges	2	.880–.881	.710	.710	.873	.775	4.11 (0.86)
Digital competency	12	.667–.823	.924	.927	.935	.547	4.19 (0.69)
Resilience	10	.743–.837	.933	.934	.943	.624	4.08 (0.78)
Mental well-being	8	.653–.763	.871	.873	.899	.527	4.09 (0.68)

Note. α = Cronbach's alpha; ϱA and ϱC = composite reliability; AVE = average variance extracted; M (SD) = mean and standard deviation of the unweighted item average (1–5 scale). Mental well-being uses MWB2–MWB9.

Discriminant validity was weaker (Table 2). Latent correlations were high (.653–.874) and the Fornell–Larcker criterion was not met for the pairs among digital job resources, digital competency and resilience, or for resilience and well-being. All HTMT upper confidence limits were below 1, but seven of the ten lay between .90 and 1, a moderate problem in the classification of Rönkkö and Cho (2022) (Supplementary Fig. S1). HTMT point estimates among digital job resources, digital competency and resilience were .898–.937, so these constructs share substantial variance. Every item loaded most highly on its own construct.

The CFA supported distinctiveness (Supplementary Table S2). The five-factor model fitted acceptably ($\chi^2(730) = 1577.7$, CFI = .921, TLI = .915, RMSEA = .052); constraining any pair of correlations to unity worsened fit ($\Delta\chi^2(1) = 24.4–285.1$, all $p < .001$); and rival structures fitted worse, whether digital competency and resilience were merged ($\Delta\chi^2(4) = 81.9$, $p < .001$; CFI = .913), the two digitalization constructs were merged ($\Delta\chi^2(4) = 45.5$, $p < .001$; CFI = .917) or a single factor was specified (CFI = .876, RMSEA = .065). The constructs are thus distinguishable but share much variance, so each mediator's unique contribution is estimated with limited precision; the poor fit of the single-factor model also argues against method variance as the sole explanation.

Table 2. *Discriminant validity: Fornell–Larcker criterion and HTMT ratios*

Construct	DJR	DCC	DC	R	MWB
Digital job resources (DJR)	.756	.841 [.763, .918]	.903 [.869, .937]	.898 [.860, .932]	.764 [.695, .829]
Digital change challenges (DCC)	.672	.880	.849 [.776, .921]	.862 [.791, .935]	.830 [.752, .909]
Digital competency (DC)	.830	.690	.740	.937 [.910, .962]	.786 [.716, .847]
Resilience (R)	.827	.702	.874	.790	.845 [.789, .895]
Mental well-being (MWB)	.679	.653	.710	.762	.726

Note. Diagonal: square root of AVE. Below the diagonal: latent variable correlations. Above the diagonal: HTMT ratios with 95% percentile bootstrap intervals (5,000 subsamples). Following Rönkkö and Cho (2022), upper limits of .90–1.00 indicate a moderate problem and .80–.90 a marginal one.

Structural model and hypothesis testing

Inner VIFs for the predictors of well-being were 3.84 (digital job resources), 2.13 (digital change challenges), 5.13 (digital competency) and 5.15 (resilience); both mediators marginally exceed the critical value of 5 (Hair et al., 2022), which inflates the standard errors of their paths. The parallel model explained 69.0% of the variance in digital competency, 68.4% in resilience and 61.2% in well-being.

Digital job resources were strongly associated with digital competency ($\beta = .830$, $p < .001$) and resilience ($\beta = .827$, $p < .001$), supporting H1 and H2, but not directly with well-being ($\beta = .061$, $p = .446$), so H3 was not

supported (Table 3). Resilience was associated with well-being (β = .483, p < .001; f^2 = .117), supporting H5, but digital competency was not (β = .094, p = .273), so H4 was not supported. Digital change challenges were positively associated with well-being (β = .209, p < .001; f^2 = .053). Their content fits the challenge demands of the challenge–hindrance distinction, which are associated with positive outcomes (Califf et al., 2020); same-direction, positively worded items may also contribute.

The indirect association through resilience was significant (β = .399, 95% CI [.289, .520]), supporting H7; because the direct path was not significant, the pattern corresponds to indirect-only mediation (Zhao et al., 2010). The indirect association through digital competency was not significant (β = .078, 95% CI [−.063, .220]), so H6 was not supported. The difference between the two was significant (Δ = .321, 95% CI [.109, .539]), supporting H8 (Supplementary Fig. S2).

In the serial model (Fig. 2), digital competency was strongly associated with resilience (β = .604, p < .001; f^2 = .559), and the serial indirect association through competency and then resilience was significant (β = .243, 95% CI [.167, .334]), supporting H9. Once this path was added, the indirect associations through resilience alone (β = .157 [.101, .224]) and through competency alone (β = .076 [−.068, .217]) no longer differed significantly (Δ = .081 [−.081, .250]). The associations involving resilience together accounted for 84% of the total indirect association (.400 of .476) and exceeded the competency-only association (Δ = .324 [.115, .543]).

Table 3. *Direct, indirect and total associations*

Hypothesis / path	β	SD	t	p	95% CI	f^2	Decision
Parallel model							
H1: DJR → DC	.830	.015	55.10	<.001	[.801, .861]	2.221	Supported
H2: DJR → R	.827	.017	47.85	<.001	[.791, .859]	2.160	Supported
H3: DJR → MWB	.061	.080	0.76	.446	[−.097, .214]	.002	Not supported
H4: DC → MWB	.094	.086	1.10	.273	[−.076, .264]	.004	Not supported
H5: R → MWB	.483	.071	6.77	<.001	[.348, .626]	.117	Supported
DCC → MWB	.209	.047	4.43	<.001	[.117, .299]	.053	—
H6: DJR → DC → MWB	.078	.072	1.09	.275	[−.063, .220]	—	Not supported
H7: DJR → R → MWB	.399	.059	6.72	<.001	[.289, .520]	—	Supported (indirect-only)
Total indirect	.478	.075	6.38	<.001	[.335, .631]	—	
Total (DJR → MWB)	.538	.045	11.94	<.001	[.450, .626]	—	
H8: Difference (H7 − H6)	.321	.109	2.96	.003	[.109, .539]	—	Supported
Serial model							
DC → R	.604	.047	12.80	<.001	[.510, .697]	.559	—
H9: DJR → DC → R → MWB	.243	.043	5.68	<.001	[.167, .334]	—	Supported
DJR → R → MWB	.157	.032	4.93	<.001	[.101, .224]	—	
DJR → DC → MWB	.076	.072	1.06	.290	[−.068, .217]	—	

Note. DJR = digital job resources; DCC = digital change challenges; DC = digital competency; R = resilience; MWB = mental well-being. n = 425; 5,000 bootstrap subsamples; percentile confidence intervals. In the serial model, R^2 = .689 (DC), .797 (R) and .612 (MWB); the paths to MWB are as in Fig. 2.

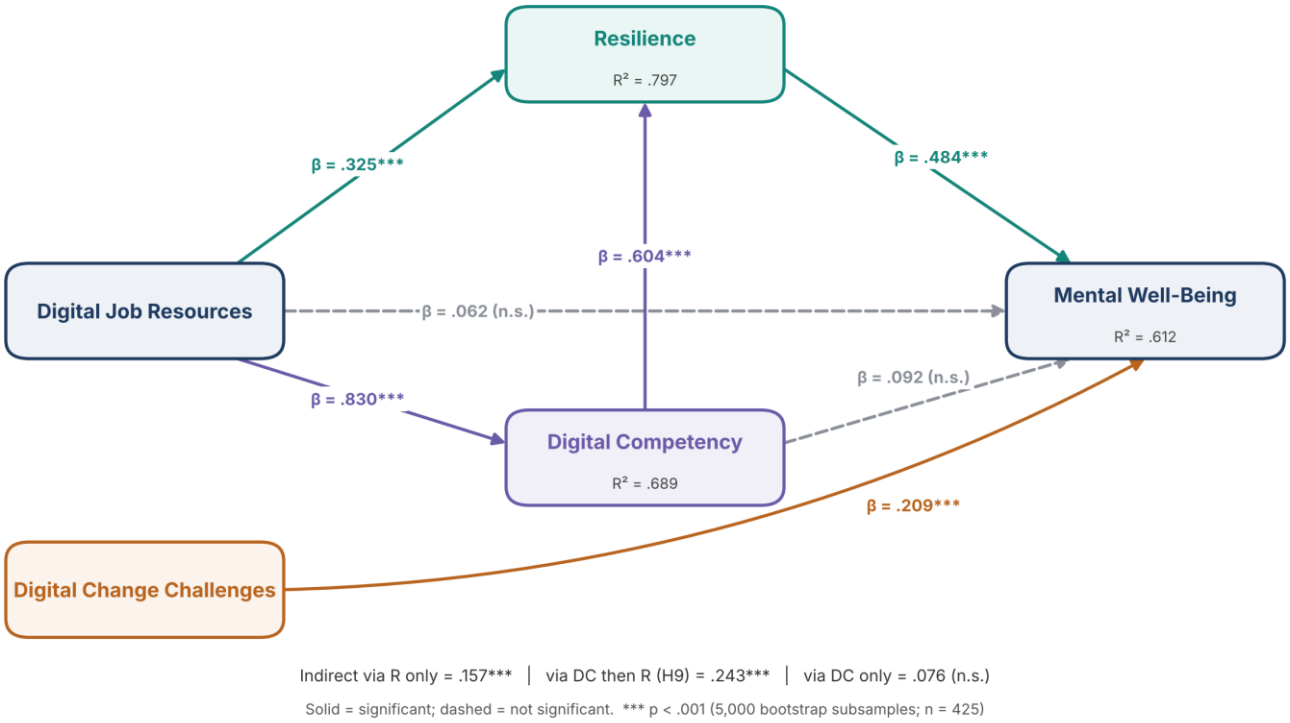

Figure 2. Estimated serial model.

Note. Standardized coefficients (n = 425; 5,000 bootstrap subsamples). Source: authors' analysis.

Predictive power and robustness

All Q^2predict values were positive (digital competency = .684; resilience = .680; well-being = .510). The PLS-SEM model produced lower RMSE than a linear benchmark for 12 of 30 endogenous indicators, including six of eight well-being indicators, indicating medium predictive power for the key target construct (Shmueli et al., 2019). In the CVPAT it outperformed the indicator-average benchmark (average loss difference = −.336, t = 10.87, p < .001) and performed on a par with the linear benchmark (.004, t = 0.73, p = .465).

Across the alternative specifications of the serial model (Table 4; Supplementary Fig. S3), the indirect associations involving resilience were significant and exceeded the competency-only association in every specification. The competency-only indirect association was significant only when competency was restricted to its task-competence items (β = .117 [.007, .211]). With the original 10-item digitalization scale, a small direct association with well-being appeared (β = .209 [.040, .379]), which therefore reflects the two challenge items. No demographic control was associated with well-being.

Table 4. *Alternative specifications of the serial model: indirect associations with mental well-being*

Specification	n	Via DC only	Via R only	Via DC then R	Involving R minus DC only	R^2
(1) Primary serial model	425	.076 [−.071, .208]	.157 [.102, .228]	.243 [.166, .338]	.324 [.127, .553]	.612
(2) + Controls (a)	415	.068 [−.086, .206]	.157 [.097, .229]	.248 [.164, .346]	.337 [.113, .587]	.614
(3) Original 10-item digitalization	425	.079 [−.071, .214]	.192 [.131, .272]	.235 [.161, .332]	.348 [.151, .585]	.599
(4) Without MWB2	425	.082 [−.067, .217]	.154 [.098, .224]	.238 [.162, .329]	.310 [.113, .543]	.605
(5) All 10 MWB items	425	.092 [−.034, .200]	.168 [.113, .235]	.259 [.188, .346]	.335 [.163, .536]	.728
(6) DC = DC9–DC12 only	425	.117 [.007, .211]	.215 [.144, .311]	.163 [.106, .233]	.262 [.088, .460]	.617
(7) Without challenges construct	425	.115 [−.023, .238]	.180 [.121, .250]	.277 [.199, .371]	.341 [.153, .572]	.592

Note. Standardized indirect associations with 95% percentile bootstrap intervals (2,000 subsamples). (a) Excludes records with implausible age or experience values, which are used as controls.

Alternative model: resilience as a buffer

To test whether resilience buffers rather than accounts for the association between digitalization and well-being, we added challenges × resilience and digital job resources × resilience interaction terms to the predictors of well-being (Supplementary Table S4). Digital change challenges were positively associated with well-being (β = .243, 95% CI [.150, .341]), so there was no negative association for resilience to buffer. The challenges × resilience interaction was positive (β = .164 [.044, .296]; f^2 = .025): the association of challenges with well-being was not significant at low resilience (−1 SD: .080 [−.059, .207]) and was substantial at high resilience (+1 SD: .407 [.231, .593]; Supplementary Fig. S4). The digital job resources × resilience interaction was not significant (β = −.034 [−.181, .107]). Resilience therefore showed no buffering role for digital job resources, but was associated with a more positive response to the challenging side of digital change, consistent with challenge appraisal (Califf et al., 2020; Lazarus & Folkman, 1984; Tarafdar et al., 2019).

Exploratory decomposition of digital competency

Treating organizational support (DC1–DC4), autonomy (DC5–DC8) and task competence (DC9–DC12) as separate constructs (Table 5) yielded adequate reliability (ρC = .864–.895; AVE = .614–.682) but high mutual HTMT values (.913–.965), so this model is exploratory. All three groups were associated with resilience, but only task competence was directly associated with well-being. The serial indirect associations through each group and then resilience were all significant, as was the indirect association through resilience alone, whereas the simple indirect associations through support and autonomy were not. Collinearity was acceptable for the resilience equation (VIF 2.90–3.63) but high for resilience as a predictor of well-being (VIF = 5.16).

Table 5. *Exploratory model with separated digital competency groups (n = 425)*

Direct path	β [95% CI]	Indirect association with MWB	β [95% CI]
DJR → Support	.738 [.682, .790]	DJR → Support → MWB	−.060 [−.143, .030]
DJR → Autonomy	.771 [.728, .814]	DJR → Autonomy → MWB	.020 [−.096, .140]
DJR → Task competence	.781 [.736, .824]	DJR → Task competence → MWB	.126 [.019, .228]
DJR → R	.324 [.229, .425]	DJR → Support → R → MWB	.060 [.027, .101]
Support → R	.172 [.082, .257]	DJR → Autonomy → R → MWB	.078 [.039, .131]
Autonomy → R	.213 [.119, .311]	DJR → Task competence → R → MWB	.101 [.054, .156]
Task competence → R	.271 [.156, .386]	DJR → R → MWB	.154 [.097, .224]
DJR → MWB	.058 [−.089, .207]		
DCC → MWB	.210 [.115, .302]		
Support → MWB	−.082 [−.195, .040]	R^2 (R)	.797
Autonomy → MWB	.026 [−.125, .180]	R^2 (MWB)	.619
Task competence → MWB	.162 [.025, .292]		
R → MWB	.476 [.336, .625]		

Note. Support = DC1–DC4; Autonomy = DC5–DC8; Task competence = DC9–DC12. Percentile bootstrap intervals (2,000 subsamples). Exploratory, post hoc specification; the three competency groups are highly intercorrelated.

Measurement invariance and multigroup comparisons

Measurement invariance of composites was tested before groups were compared (Supplementary Table S5). Compositional invariance held for all constructs across gender and job role, establishing partial invariance. Across experience groups it failed for digital job resources, so comparisons involving that construct are not interpreted; no path differed across experience groups in any case (all $p \geq .18$).

Multigroup comparisons (Table 6) showed differences by gender and role. The resilience–well-being path and the indirect association through resilience were stronger for men than for women ($p = .015$ and .032), and the direct path from digital job resources was larger for women ($p = .020$). For sales employees the association ran almost entirely through resilience, whereas in other roles (operations, credit risk and human resources) the direct path was larger ($p = .014$) and the resilience path weaker ($p = .011$). Within-group bootstrap intervals showed that only the indirect association through resilience was significant among men ([.336, .600]), sales employees ([.323, .580]) and employees in other roles ([.034, .408]), whereas among women only the association through competency was significant ([.017, .449]).

Because men were concentrated in sales, we repeated the gender comparison within roles. Within non-sales roles (113 men, 105 women), where full invariance held, men and women did not differ on any path (all $p > .27$). Within sales, no gender difference was significant (all $p > .10$), but the 38 women in sales are too few for reliable estimates.

Table 6. *Permutation-based multigroup comparisons*

Path	Group 1	Group 2	Difference	p
Gender: men (n = 282) vs women (n = 143)				
DJR → MWB	−.055	.316	−.372	.020
DCC → MWB	.214	.176	.038	.690
DC → MWB	.053	.265	−.212	.277
R → MWB	.571	.191	.380	.015
Indirect via DC	.044	.226	−.182	.255
Indirect via R	.455	.168	.287	.032
Role: sales (n = 207) vs other roles (n = 218)				
DJR → MWB	−.141	.262	−.403	.014
DCC → MWB	.186	.200	−.014	.898
DC → MWB	.069	.192	−.123	.509
R → MWB	.620	.247	.373	.011
Indirect via DC	.054	.163	−.108	.489
Indirect via R	.442	.218	.224	.076
Gender within non-sales roles: men (n = 113) vs women (n = 105)				
DJR → MWB	.126	.394	−.268	.278
DCC → MWB	.182	.211	−.029	.828
DC → MWB	.204	.195	.009	.961
R → MWB	.338	.157	.181	.469
Indirect via DC	.172	.168	.005	.977
Indirect via R	.295	.140	.156	.480

Note. Standardized coefficients per group (parallel model); p-values from 1,000 permutations of group membership. Abbreviations as in Table 3. Experience comparisons are reported in the text.

DISCUSSION

Resilience carried a substantial and consistent indirect association between perceived digitalization and work-related mental well-being, whereas no unique indirect association through the full competency construct could be detected beyond its shared variance with resilience. The serial model suggests why: competency was strongly associated with resilience, and the largest indirect association ran through competency and then resilience.

Once the two challenge items were separated, digital job resources showed no direct association with well-being. The positive association of the challenge items runs against the demand-centred framing of technostress research (Ragu-Nathan et al., 2008; Tarafdar et al., 2007) and is more consistent with the view that digital change can be appraised as a challenge (Califf et al., 2020; Tarafdar et al., 2019). The interaction model sharpens this reading: the association was substantial among more resilient employees, who may appraise the pace and difficulty of digital change as manageable challenges rather than threats (Lazarus & Folkman, 1984), and not significant among less resilient ones. This reading should be held cautiously: the challenges construct rests on two items, the interaction is small, digitalization was perceived rather than objective, and several well-being

items refer to self-regulation in digital work, so part of the overlap may reflect a shared digital context (Borle et al., 2021).

The resilience finding is consistent with COR theory's proposition that resource-rich environments are associated with well-being through the psychological resources they help to build (Hobfoll et al., 2018) and with JD-R research in which personal resources mediated, rather than buffered, the associations of job resources (Xanthopoulou et al., 2007). Competency and resilience address different problems: capability, support and autonomy equip employees to perform digital work, but in banking, well-being may depend less on the tasks than on the change, pressure and uncertainty that accompany them, which are managed through regulatory resources. In the exploratory decomposition, support and autonomy were associated with resilience rather than directly with well-being, which fits the resource-caravan principle, whereas task competence was also directly associated with well-being, which suggests that mastery may carry a distinct benefit. Combining the three in one construct may have diluted the association of mastery itself, consistent with the small but significant indirect association when competency was restricted to DC9–DC12 (Table 4, model 6). Because the decomposition was specified post hoc with overlapping constructs, these patterns are hypotheses for future research.

Digital competency and resilience share most of their variance ($r = .874$; HTMT = .937), so the model estimates their combined contribution more reliably than it apportions it. The non-significant unique path from competency to well-being means only that no association could be detected beyond what competency shares with resilience, not that competency is unrelated to well-being.

The indirect association through resilience was strongest among sales employees and among men, whereas among women only the association through digital competency was significant. Gender and role were confounded, however: 60% of men but 27% of women worked in sales, and within non-sales roles men and women did not differ on any path. The gender difference therefore largely reflects role composition.

The role difference fits evidence that the support–resilience link is stronger under high performance pressure (Cooke et al., 2019): where digital change is tied to sales targets, the capacity to absorb change may matter most. For women, one post hoc explanation is that capability matters more where it is less taken for granted: reviews of ICT use report that men tend to express more confidence in their technical skills (Han, 2024), and under COR theory, gains in a resource are most consequential where that resource is less secure (Hobfoll et al., 2018). Demands outside work may also play a part, as examined in research on work-life balance among married female employees in Indian insurance (Nandal & Madhu, 2023). Our main conclusion, that resilience carries the larger indirect association, holds most clearly for sales employees and for men and may not apply equally to women or to non-sales roles.

Theoretical implications

First, our results suggest that a capability-based and a regulatory resource can carry different indirect associations within the same model, and that capability may be associated with well-being largely through regulation, most clearly in performance-intensive roles. Second, resilience did not buffer the association of digital job resources with well-being, but it was associated with a more positive response to digital change challenges. This suggests that the roles listed by Schaufeli and Taris (2014) can coexist for different features of the same work environment, and it extends the techno-eustress perspective (Tarafdar et al., 2019). Third, the

strong associations between digital job resources and both personal resources ($\beta \approx .83$) are consistent with resource caravans but raise the question of whether a higher-order "digital adaptation" resource better represents them.

Practical implications

For bank management and HR, reskilling is a recognised route to workforce agility (Nandal & Nain, 2026), but digital upskilling should not be assumed to be sufficient for well-being on its own. Training remains essential for performance and competency was strongly associated with resilience, but the larger indirect association ran through employees' capacity to absorb continuous change. Banks can pair technology rollouts with resilience-building programmes (Robertson et al., 2015), bearing in mind that their average effects are small and fade over time and that one-on-one formats such as coaching are the most effective (Vanhove et al., 2016). Because supportive leadership and co-worker support are associated with resilience in banking (Cooke et al., 2019), resilience support may also be embedded in everyday management through phased implementation, realistic targets during transitions, peer and coaching networks and protected recovery time.

The highest return is likely where digital change meets sales targets. Line managers can monitor strain during major system changes, and HR teams can track resilience and well-being alongside digital-skill metrics. Because these associations may not hold where tools are poorly designed or targets rise with each new system, banks should monitor digital demands as closely as digital adoption.

Limitations and future research

First, the cross-sectional design precludes causal inference; resilient employees may, for example, perceive digitalization more favourably, so longitudinal, diary or intervention designs are needed. Second, the data share a single source, occasion and response format, with no reverse-coded items, so method variance probably inflated the associations. Future studies can reduce this by measuring the constructs in separate waves, including a marker variable, mixing positively and negatively keyed items, and obtaining supervisor ratings or system-use records for at least one construct (Podsakoff et al., 2012; Spector, 2019).

Third, discriminant validity among the antecedents was only moderately supported: the competency scale combines capability, support and autonomy, the resilience and well-being scales are framed in digital terms, and the digital change challenges construct rests on two items. Resilience was measured as a self-evaluation; behavioural, work-specific measures such as the Employee Resilience Scale (Näswall et al., 2019) may relate differently to digital resources. Shorter, clearly differentiated scales and a general well-being measure are needed (Rönkkö & Cho, 2022). Fourth, the purposive sample came from four private-sector banks in one region, no response rate could be computed, pilot responses could not be separated in the data, and ceiling effects may distort the associations. Fifth, the exclusion of MWB1 and MWB10, the separation of D7 and D8, the serial path, the interaction model, the separated-competency model and the within-role comparisons were decided after the initial analysis or in response to review. Generalisation to public-sector banks, other regions and other services should be tested with probability samples, as should the reverse sequence in which resilience supports competency development.

CONCLUSION

Among 425 private-sector bank employees in India, perceived digital job resources were strongly associated with digital competency and resilience but not directly with work-related mental well-being. Resilience showed the larger and significant indirect association, and competency was associated with well-being largely through resilience. Resilient employees also responded more positively to the challenges of digital change. For banks, the evidence points to building employees' capacity to adapt and recover alongside their ability to operate new systems, especially in sales roles, while longitudinal and intervention research tests whether these associations are causal.

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Data Availability Statement	The data that support the findings of this study are available from the corresponding author upon reasonable request.
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