

Article

Teachers' Digital Competencies as a Resource in the Job Demands-Resources Model

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Abstract

Against the backdrop of substantial transformations in the education system, including digitalization and increasing societal pluralization, there is growing attention paid to teachers' digital competencies and their role within broader school well-being processes in digitally transforming educational environments. This paper adopts digital competencies as a novel domain-specific personal resource within the Job Demands-Resources (JD-R) framework to examine how both individual and organizational resources shape teachers' professional motivation and organizational commitment. The analysis draws on data from the 'Deisel' project, comprising 550 teachers in Germany. Within this empirical context, this study reveals considerable variation in both teachers' digital competencies and the organizational conditions of schools. In particular, differences in leadership support and collegial collaboration influence whether digital transformation is experienced as an additional burden or as a meaningful resource for professional development. The findings indicate a small but statistically significant indirect association between digital competencies and organizational commitment, operating primarily through reduced psychological strain rather than increased motivation. Prior evidence emphasizing the relevance of school management support and self-efficacy was replicated. These results demonstrate that digital competencies function as a personal resource within the JD-R framework, reducing perceived strain and indirectly strengthening organizational commitment. This study contributes to JD-R research by showing that digital competencies appear to function less as direct motivational drivers and more as domain-specific personal resources that may mitigate the strain associated with technology-related demands in digitally transforming schools.

Keywords: Job Demands-Resources model (JD-R); teachers' digital competencies; teacher well-being



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1. Introduction

Digital transformation has fundamentally changed teachers' professional work. Beyond their pedagogical approaches to new learning environments (OECD, 2025b), teachers are increasingly required to possess the competencies necessary to effectively integrate technology into their teaching practices (Knezek & Christensen, 2016). As schools undergo processes of digitalization, questions of how teachers cope with these transformations and which factors support their occupational well-being become increasingly important. At the same time, the increasing integration of digital technologies into teachers' everyday work has created a complex constellation of new demands and resources. While digital

technologies expand pedagogical opportunities and enable new forms of collaboration, they also increase complexity, intensify communication processes, and may contribute to technostress if not accompanied by sufficient support structures (Lillelien & Jensen, 2025).

Within the Job Demands-Resources (JD-R) framework, research in educational settings has therefore increasingly examined how job demands such as workload stress, emotional strain, role ambiguity, and organizational contexts affect teachers' well-being and professional functioning (e.g., He et al., 2026; Sharma & Sengupta, 2025). More recently, studies addressing digitalization in education have focused particularly on technology-related demands, including technostress, role overload, digital workload, and challenges associated with blended learning environments (e.g., Z. Cheng et al., 2026; Zhang et al., 2026). At the same time, existing studies have primarily focused on organizational and social resources that buffer these demands (e.g., Reintjes et al., 2025a, 2025b; Windlinger & Züger, 2021). Comparatively little attention has been devoted to teachers' digital competencies as a distinct domain-specific personal resource within the JD-R framework. This omission is theoretically important because digital competencies differ from more generalized personal resources. For instance, whereas self-efficacy reflects a broad belief in one's capability to cope successfully with challenges, digital competencies refer to perceived domain-specific knowledge, skills, and capabilities required for dealing with technology-related tasks and demands (Krumsvik, 2011; Quast et al., 2023; Rubach, 2024). Consequently, digital competencies may influence whether digital transformation is perceived primarily as an additional burden or as a manageable and potentially enriching aspect of professional work. Against this background, the present study contributes to the literature in three ways. First, it extends JD-R research in educational settings by conceptualizing teachers' digital competencies as a domain-specific personal resource. Second, it examines whether digital competencies are associated with organizational commitment primarily through motivational processes or through the health-impairment pathway. Third, it compares the relevance of digital competencies with established personal, social, and organizational resources, thereby situating digital competencies within a broader resource constellation relevant to teacher well-being in digitally transforming schools.

2. Literature Review and Hypothesis Development

2.1. Job Demands-Resources Model

This study builds on the Job Demands-Resources (JD-R) model (Demerouti et al., 2001), which is widely regarded as one of the leading frameworks in management and organizational behavior for explaining the relationship between job characteristics, psychological health, and performance outcomes (Galanakis & Tsitouri, 2022). It partitions work-related factors into two core categories: demands and resources. Demands are energy-depleting stressors that may lead to exhaustion (e.g., intense work pressure or challenging student behavior). In contrast, resources function as both motivational drivers and buffers against such demands, including social support from colleagues, high-quality leadership, opportunities for self-regulation, and personal traits like self-efficacy (Bakker & Demerouti, 2007). In its more recent developments, the JD-R model has increasingly incorporated personal resources as additional explanatory mechanisms. Personal resources refer to positive self-evaluations and domain-specific capacities that influence individuals' ability to control and affect their work environment. They may shape how employees appraise job demands, mobilize coping strategies, and maintain motivation under challenging conditions. This extension is particularly relevant in educational contexts, where teachers' professional functioning depends not only on organizational conditions but also on individual capacities to respond to complex and changing work demands. The JD-R model distinguishes between two central processes. The motivational pathway assumes that job and personal

resources foster work engagement, motivation, and commitment. The health-impairment pathway assumes that job demands deplete energy and increase psychological strain, while resources may buffer or reduce these negative consequences. This dual-process logic provides the conceptual basis for examining whether digital competencies primarily strengthen motivation or reduce strain in the context of digital transformation.

In the educational context, the JD-R model is particularly suitable because it captures the complex interplay among individual, team-level, and structural variables. Empirical work has shown that collegial support, transparent communication by school leadership, and perceived autonomy are especially critical resources for teachers' occupational well-being (Keller-Schneider, 2014). Moreover, recent research in education suggests that job resources do not merely buffer the negative effects of demands but can also exert boosting effects, enhancing engagement particularly in already favorable working conditions (Reintjes et al., 2025a). Thus, the model offers a dynamic perspective: high demands can be offset by adequate resources, while resource scarcity may produce strain even when demands are moderate. This makes JD-R especially useful for analyzing educational settings where structural and interpersonal factors are tightly intertwined.

2.2. Job Demands and Resources in Digital Work Contexts

Due to ongoing digitalization, many professional fields have undergone a fundamental transformation, altering the structural and interpersonal dynamics of modern work environments (Colbert et al., 2016; Schwarzmüller et al., 2018). Within digitalized work environments, technology-related demands are frequently conceptualized through the lens of technostress research. Technostress refers to the stress experienced as a consequence of using information and communication technologies and encompasses several distinct dimensions, including techno-overload, techno-complexity, techno-invasion, techno-insecurity, and techno-uncertainty (Tarafdar et al., 2007). These stressors have been associated with lower job satisfaction, increased exhaustion, reduced organizational commitment, and impaired occupational well-being. From a JD-R perspective, technostress can be understood as a specific form of technology-related job demand whose consequences depend on the availability of adequate personal, social, and organizational resources.

Importantly, digital technologies do not function exclusively as job demands. Depending on their design, implementation, and organizational embedding, they may also operate as job resources by facilitating collaboration, increasing access to instructional materials, supporting professional learning, and enabling more flexible forms of communication and teaching (Pansini et al., 2023; Scholze & Hecker, 2023, 2024).

Digital transformation in schools should therefore be understood as an ambivalent process in which the same technological tools may either intensify work demands or support professional agency. This ambivalence makes it necessary to examine which personal and organizational resources determine whether digitalization is experienced as burdensome or beneficial.

This dual character of digital technologies highlights the importance of teachers' digital competencies. If teachers lack the competencies required to use digital tools effectively, digitalization is more likely to be experienced as complexity, overload, and uncertainty. Conversely, stronger digital competencies may reduce the perceived intensity of digital demands and enable teachers to make more purposeful use of technological resources.

2.3. Digital Competencies as Domain-Specific Personal Resources

Digital competencies are increasingly regarded as essential transversal skills necessary for learning in both school and vocational settings, as well as for social participation (SWK, 2025).

The ability to use digital tools for information retrieval, communication, problem solving, and participation is viewed as a core component of future-oriented basic education (Krumsvik, 2011; SWK, 2025). The literature defines digital literacy, information and communication technology (ICT) literacy, digital competencies, and digital skills in various ways, with some terms used interchangeably (Godhe, 2019; Tinmaz et al., 2022). The *International ICT Literacy Panel* (2002) framed ICT literacy across five components, increasing in knowledge and expertise. The *European Commission* (2019) defined digital competencies—originally identified in 2006 as a key lifelong-learning capability—as the confident, critical, and responsible use of digital technologies for learning, work, and societal participation. The *Digital Competence Framework for Citizens* (DigComp; Carretero Gomez et al., 2017; Vuorikari et al., 2022) describes digital competencies across five areas and up to eight proficiency levels. Mattar et al. (2022) review a range of DigComp-based assessment instruments, including self-report measures, knowledge tests, problem-based questions, and performance assessments. In Germany, the DigComp framework serves as a central reference for the national strategy “Education in the Digital World” (KMK, 2016, 2021).

Although frameworks such as DigComp and the KMK strategy were primarily developed to define educational goals and competence standards, they also imply psychologically relevant capacities for coping with technology-related job demands. From a JD-R perspective, digital competencies can therefore be interpreted not merely as instructional skills but as personal resources that facilitate effective task accomplishment under conditions of digital transformation (Krumsvik, 2011; Rubach, 2024). Teachers who possess stronger digital competencies are more likely to perceive technological challenges as manageable, maintain a sense of control when confronted with new technologies, and experience lower levels of uncertainty and frustration. This interpretation provides a conceptual bridge between normative competence frameworks and occupational well-being research. Whereas competence frameworks specify what individuals should know and be able to do in digital environments, the JD-R framework helps explain why such competencies matter from a psychological perspective. Digital competencies increase teachers’ capacity to cope with technology-related demands and can therefore shape both the appraisal of demands and the experience of psychological strain.

It is important to distinguish digital competencies from general self-efficacy. Self-efficacy refers to a generalized belief in one’s ability to cope successfully with a broad range of challenges (Marsh et al., 2019). Accordingly, digital competencies represent a more proximal determinant of teachers’ adaptation to digital transformation processes than generalized self-efficacy. While self-efficacy may foster persistence and confidence across situations, digital competencies provide the specific functional repertoire needed to manage digital tools, evaluate digital information, and integrate technologies into professional practice.

Accordingly, digital competencies influence how technological demands are perceived and managed. Teachers with higher digital competencies are more likely to experience digital transformation as manageable and meaningful, whereas limited competencies may contribute to strain and avoidance. This perspective aligns with the JD-R model, in which personal resources shape both motivational processes and the experience of strain. Accordingly, digital competencies can be understood not only as skills but also as a mechanism linking digital transformation to teacher well-being and professional functioning.

From an intervention perspective, recent systematic reviews (e.g., Avola et al., 2025; Lillelien & Jensen, 2025) suggest that promoting teacher well-being requires a combination of strengthening personal resources—such as resilience, self-efficacy, and emotional regulation—and providing adequate organizational support systems. Notably, digital inter-

ventions themselves may function as both resources and additional demands, depending on their design and implementation (Lillelien & Jensen, 2025).

Theoretically, digital competencies may contribute to both JD-R pathways. They may support the motivational pathway by enabling creative teaching practices and professional agency. However, in contexts of rapid and often externally driven digital transformation, their primary relevance may lie in the health-impairment pathway. Digital competencies can reduce uncertainty, prevent feelings of inadequacy, and lower the perceived complexity of digital tasks. Thus, they may protect teachers from experiencing digital transformation as overwhelming or meaningless, even if they do not necessarily increase work engagement directly.

The increasing relevance of digital competencies becomes particularly apparent in the context of generative artificial intelligence (Galindo-Domínguez et al., 2024; Ng et al., 2023). Beyond conventional technology use, teachers are increasingly required to evaluate AI-generated outputs, formulate effective prompts, verify information quality, identify biases and hallucinations, and make responsible pedagogical decisions regarding AI-supported learning environments. These AI-related competencies may constitute an emerging extension of digital competency frameworks and represent increasingly important personal resources in digitally transformed educational contexts.

2.4. Hypothesis Development

Building on the preceding theoretical arguments, we distinguish between motivational and health-impairment pathways. The motivational pathway links resources to organizational commitment through higher work engagement and motivation. The health-impairment pathway links resources to organizational commitment through reduced psychological strain. We assume that established personal and organizational resources may contribute to both pathways. For digital competencies, however, we expect the strain-reducing mechanism to be particularly relevant because these competencies directly affect teachers' ability to cope with technology-related demands.

Therefore, we aim to integrate teachers' digital competencies in the JD-R model to examine its relevance for teachers' motivation, strain and organizational commitment in comparison to "classic" personal resources, like self-efficacy, perceived autonomy and social resources that are highly relevant for the teaching profession, like school management support and collegial support. Specifically, we argue that digital competencies operate primarily through the health-impairment process. As an instrumental resource, they act as a "demand-shield" that lowers the perceived intensity of digital stressors (e.g., technological complexity; Tarafdar et al., 2007). By facilitating a more efficient handling of digital tasks, these competencies prevent a sense of frustration and professional inadequacy, often experienced as a perceived meaninglessness of work when faced with unmanageable technological requirements. This is supported by research showing that digital competencies are closely related to teachers' ability to perceive the educational value and meaningfulness of technology use (S. L. Cheng et al., 2021). Without sufficient competencies, the use of digital tools may be perceived as a mere administrative burden. While digital competencies may also contribute to the motivational process by enabling more creative teaching, we expect their most significant impact in the context of rapid digital transformation to be the mitigation of strain, which in turn preserves organizational commitment. Drawing on these suggestions, we develop the following hypotheses within the JD-R-Framework (see Figure 1).¹

Effects of digital competencies:

H1a. *Digital competencies have a positive indirect effect on organizational commitment through increased motivation (paths 1 and 2).*

H1b. Digital competencies have a positive indirect effect on organizational commitment through reduced strain (paths 5 and 4).

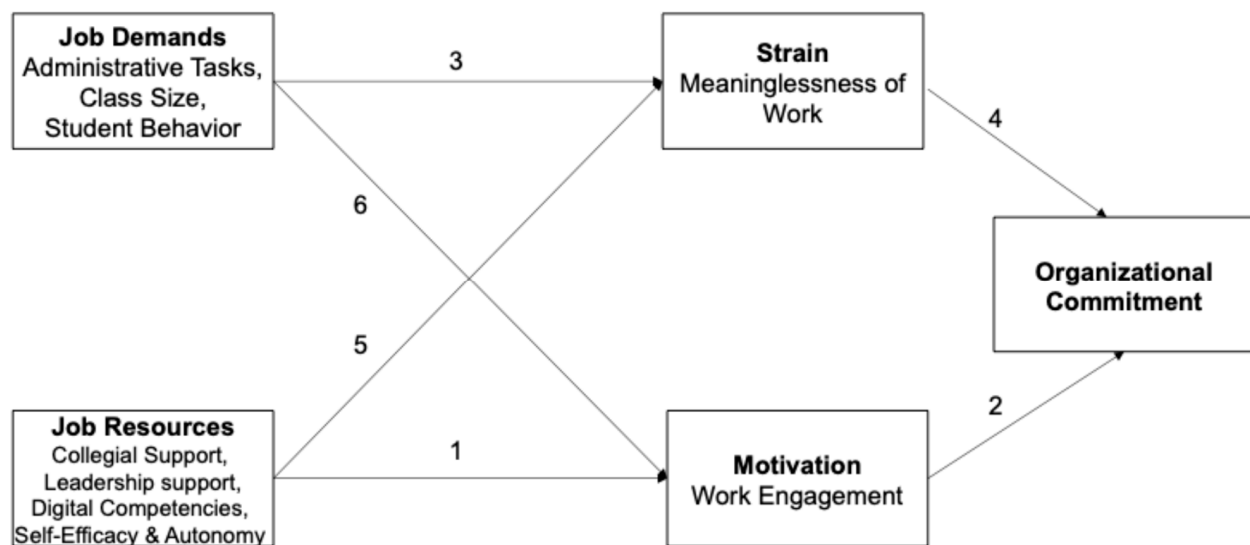


Figure 1. Visualization of the modeled dependencies.

Effects of self-efficacy and perceived autonomy:

H2a. Self-efficacy and perceived autonomy have positive indirect effects on organizational commitment through increased motivation (paths 1 and 2).

H2b. Self-efficacy and perceived autonomy have positive indirect effects on organizational commitment through reduced strain (paths 5 and 4).

Effects of social job resources:

H3a. Collegial support and leadership support have positive indirect effects on organizational commitment through increased motivation (paths 1 and 2).

H3b. Collegial support and leadership support have positive indirect effects on organizational commitment through reduced strain (paths 5 and 4).

Effects of job demands:

H4a. Job demands (dissatisfaction with administrative tasks, size of school class and student behavior) have a negative indirect effect on organizational commitment through increased strain (paths 3 and 4).

H4b. Job demands have a negative indirect effect on organizational commitment through reduced motivation (paths 6 and 2).

3. Data and Methods

3.1. Data Source and Study Design

In the German ‘Deisel’ research project (Nonte et al., 2026), teachers at 16 comprehensive schools (Gesamtschulen) were invited to participate in a standardized online survey in spring 2024. Schools were selected using a purposive sampling strategy. The sampling

strategy was designed to include variation in school-level characteristics rather than to produce a statistically representative sample of all German schools. Selection criteria included regional location, school size, urban–rural context, and the socio-economic composition of the student body. The participating schools were located in two neighboring federal states in Western Germany and represented different local contexts, ranging from more urban to more rural environments. Consequently, the findings should not be interpreted as statistically generalizable to the full population of German teachers or schools. Rather, the sample allows for analytical generalization to comparable comprehensive school contexts undergoing processes of digital transformation. The project, funded by the German Federal Ministry of Research, Technology and Space, employs a multi-method longitudinal cohort design and aims to examine the conditions for successful implementation of the promotion of digital competencies, the stability of its effects, and its long-term sustainability. Within this broader framework, the teacher survey captured teachers’ perspectives on key personal and organizational conditions relevant to implementation processes in the school context. The analyzed sample consisted of 550 teachers (male = 33%, female = 67%, age: $M = 42.2$, $SD = 9.7$). Table 1 reports descriptive statistics for all study variables, including means, standard deviations, ranges, skewness, and kurtosis. Reliability estimates for the multi-item scales were satisfactory to excellent (Cohen, 1988). The present analyses are based on cross-sectional survey data. Therefore, the estimated associations should be interpreted as theoretically informed structural relations rather than as evidence of causal effects.

Table 1. Descriptive statistics for study variables.

Variables	Mean/Percent	SD	Range	N	Skewness	Kurtosis	Cronbach’s α
Motivation (scale)	4.90	0.93	1.6–7	546	0.86	3.40	$\alpha = 0.92$
Strain (scale)	2.68	1.10	1–6.75	546	0.73	3.80	$\alpha = 0.86$
Org. commitment (scale)	4.93	1.08	1.2–7	544	−0.58	3.03	$\alpha = 0.93$
Digital competencies (scale)	3.45	0.64	1–5	402	−0.23	3.45	$\alpha = 0.95$
Self-efficacy (scale)	5.03	0.86	1.3–7	543	−0.52	3.59	$\alpha = 0.90$
Autonomy (scale)	5.23	1.01	1–7	546	−0.74	3.90	$\alpha = 0.85$
Collegial support (scale)	5.66	0.97	2–7	548	−0.74	3.44	$\alpha = 0.88$
School management support (scale)	4.74	1.33	1–7	543	−0.37	2.61	$\alpha = 0.94$
Administrative tasks	4.38	1.47	1–7	550	−0.04	2.45	–
Student behavior issues	4.27	1.57	1–7	550	0.02	2.06	–
Work experience in years	12.34	8.63	1–41	550	0.78	2.86	–
Sex (female)	67.1%	–	–	550	–	–	–

3.2. Measures

To assess the central constructs of this study, we used a set of well-established and psychometrically validated measurement scales. Organizational commitment (15 items, $\alpha = 0.93$) was measured using the Organizational Commitment Questionnaire-G (Maier & Woschée, 2008). Motivation (9 items, $\alpha = 0.92$) was operationalized via work engagement that was assessed via the German version of the Utrecht Work Engagement Scale (UWES-9) developed by Schaufeli and Bakker (2003). Strain (5 items, $\alpha = 0.86$) was operationalized via Meaninglessness of Work, a reversed subscale (higher values indicate greater strain) of the Work Design Questionnaire-D (Stegmann et al., 2010). This operationalization captures a cognitive-affective dimension of strain rather than emotional exhaustion or burnout. Digital competencies (29 items, $\alpha = 0.95$) were assessed with the inventory developed by Quast et al. (2023). Self-efficacy (10 items, $\alpha = 0.90$) was captured using the scale by Schwarzer and Schmitz (2002). Digital competencies were assessed as self-perceived competencies. This approach is appropriate for the present research question because the JD-R framework focuses not only on objectively available resources but also on individuals’ appraisal of their capacity to cope with work demands. At the same time, self-reports

of digital competencies may be affected by overestimation, underestimation, or social desirability. Therefore, the results should be interpreted as reflecting teachers' perceived digital competencies rather than objectively measured performance. Perceived autonomy (5 items, $\alpha = 0.85$) was measured via the psychological Climate questionnaire by [Koys and DeCotiis \(1991\)](#). Collegial support (4 items, $\alpha = 0.88$) and school management support (7 items, $\alpha = 0.94$) were measured using the Work Evaluation Check for Teachers ([Kieschke & Schaarschmidt, 2007](#)). Using simultaneous confirmatory factor analysis (SCFA), all latent constructs showed standardized factor loadings > 0.40 , indicating that the largest amount of variance in the indicators is explained via the latent constructs (see also the measurement part of the SEM in [Table A1](#)). Further exogenous variables used in the analysis are satisfaction with student behavior and satisfaction with administrative tasks (1 = very satisfied and 7 = very dissatisfied), sex (1 = male, 2 = female) and work experience in years. All multi-item scales used in this study were either originally developed in German or were available as validated German-language versions. Therefore, no new translation or back-translation procedure was required for the central constructs. The instruments have been used in prior German-language educational and organizational research and demonstrated satisfactory psychometric properties. Prior to the main survey, the questionnaire was reviewed by members of the research team and tested for comprehensibility, item wording, and technical functionality in the online survey environment.

3.3. Statistical Methods

First, descriptive statistics are presented, followed by testing our theoretical assumptions using structural equation modeling (SEM) with the Software Mplus 8 ([Muthén & Muthén, 2017](#)). SEM was used because it allows the simultaneous estimation of measurement and structural relations while accounting for measurement error ([Bollen, 2014](#)). This is particularly important in the present study, as several central constructs were modeled as latent variables. SEM also allows for the examination of indirect effects and the assessment of their significance ([Hayes, 2013](#)). Given the ordinal nature of many survey items and deviations from multivariate normality, the WLSMV estimator was used, which is well suited for models with categorical and ordinal indicators and provides robust parameter estimates (see [Muthén & Muthén, 2017](#)). When calculating the significance of the indirect effects, we employed the resampling method bootstrapping with bias-corrected confidence intervals ([DiCiccio & Efron, 1996](#)). We requested 2000 resamples to get reliable confidence intervals for our estimates. Therefore, in the multivariate part of the Results section, confidence intervals are reported instead of p -values. To ensure consistency, all confidence intervals are reported at the 95% level.

4. Results

4.1. Descriptive Results

When interpreting the strength of the correlations ([Table 2](#)), we refer to [Cohen \(1988\)](#) (small: $r = 0.10$, medium: $r = 0.30$, large: $r = 0.50$). All correlations are significant ($p < 0.05$). The correlations among job resources and motivation as well as with strain are shown in the proposed directions, whereby the correlations of self-efficacy with motivation ($r = 0.38$) and strain ($r = -0.39$) are the largest. Regarding the correlations with digital competencies, notably while weakly correlated with motivation ($r = 0.18$), the correlation with strain is amongst the largest of the exogenous variables ($r = -0.27$). The correlations of social resources with motivation ($r = 0.24$, $r = 0.27$) and strain ($r = -0.28$, $r = -0.25$) are moderate. The correlations of job demands with motivation and strain are also shown in the expected directions. But, it is noteworthy that administrative tasks are only substantially correlated with motivation ($r = -0.25$), whereby problematic student behavior exhibits

moderate-to-strong correlations with both motivation ($r = -0.36$) and strain ($r = 0.27$). Finally, organizational commitment is strongly correlated with motivation ($r = 0.53$) and moderately to strongly correlated with strain ($r = -0.31$).

Table 2. Pairwise correlation matrix.

	1	2	3	4	5	6	7	8	9
(1) Motivation	1.00								
(2) Strain	−0.36	1.00							
(3) Org. Commitment	0.53	−0.31	1.00						
(4) Dig. Comp.	0.18	−0.27	0.09	1.00					
(5) Self-Efficacy	0.38	−0.39	0.27	0.32	1.00				
(6) Autonomy	0.34	−0.20	0.26	0.10	0.44	1.00			
(7) Colleg. Support	0.24	−0.28	0.42	0.16	0.20	0.18	1.00		
(8) School Management Support	0.27	−0.25	0.61	0.14	0.24	0.31	0.50	1.00	
(9) Adm. Tasks	−0.25	0.09	−0.30	−0.09	−0.17	−0.24	−0.14	−0.38	1.00
(10) Student Behavior	−0.36	0.27	−0.46	−0.13	−0.24	−0.18	−0.20	−0.30	0.27

Note: $n = 550$, mean scores are used for the latent constructs, and all correlations $p < 0.05$.

4.1.1. Multivariate Results

Before examining the structural model of the SEM, we investigated the measurement model: all standardized factor loadings of the latent variables are above 0.40, indicating a substantial part of explained variance in the indicator variables through the latent factors (Brown, 2015).

Next, we examine the structural model, beginning with the explained variance in the endogenous variables. Regarding the interpretation of the explained variance (R^2), we refer to Cohen (1988) (small: $R^2 = 0.02$, medium: $R^2 = 0.13$, and large: $R^2 = 0.26$). Considering this background, it can be noted that for motivation ($R^2 = 0.39$), strain ($R^2 = 0.57$) and organizational commitment ($R^2 = 0.58$), a large share of the variance is explained by the included variables.

Below, the relationships between the variables—and specifically, the standardized path coefficients—are used for interpretation. Following the explanations for interpreting standardized coefficients as effect sizes, effect sizes were categorized as small ($\beta = 0.10$ – 0.29), medium ($\beta = 0.30$ – 0.49), and large ($\beta \geq 0.50$) (Fey et al., 2023; Nieminen, 2022). Taking a look at the structural model, we observe that motivation is moderately positively correlated with organizational commitment ($\beta = 0.40$, 95% CI [0.19, 0.74]), and strain is strongly negatively correlated with organizational commitment ($\beta = -0.50$, 95% CI [−0.64, −0.04]). Regarding the exogenous variables, we can obtain from the results that contrary to Hypotheses *H3a* and *H3b*, collegial support is not significantly correlated with motivation ($\beta = 0.08$, 95% CI [−0.05, 0.21]) but with strain ($\beta = -0.18$, 95% CI [−0.31, −0.05]). Leadership support is significantly linked to motivation ($\beta = 0.16$, 95% CI [0.04, 0.39]) and strain ($\beta = -0.39$, 95% CI [−0.51, −0.07]). Examining the associations of personal job resources with motivation, it becomes apparent that perceived autonomy ($\beta = 0.13$, 95% CI [0.03, 0.30]) and self-efficacy ($\beta = 0.17$, 95% CI [0.08, 0.31]) are significantly correlated with motivation. Perceived autonomy is not significantly related to strain ($\beta = 0.05$, 95% CI [−0.10, 0.13]), but self-efficacy ($\beta = -0.19$, 95% CI [−0.30, −0.08]). Digital competencies are not significantly associated with motivation ($\beta = 0.05$, 95% CI [−0.03, 0.16]) but with strain ($\beta = -0.08$, 95% CI [−0.16, −0.01]). Among the job demands, student behavior issues are significantly negatively correlated with motivation ($\beta = -0.38$, 95% CI [−0.44, −0.32]) and positively with strain ($\beta = 0.42$, 95% CI [0.28, 0.55]). Administrative tasks are significantly correlated with motivation ($\beta = -0.22$, 95% CI [−0.30, −0.12]).

In the following, the indirect effects and the corresponding hypotheses are examined (Table 3). The results indicate that, as hypothesized digital competencies have a significant total indirect positive effect on organizational commitment ($\beta = 0.06$, 95% CI [0.00, 0.13]), although the specific indirect effect via motivation ($H1a$) is not significant ($\beta = 0.02$, 95% CI [−0.03, 0.07]), the specific indirect effect through strain is significant ($H1b$) ($\beta = 0.04$, 95% CI [0.01, 0.10]). Although statistically significant, the indirect effects of digital competencies were comparatively small in magnitude (Cohen, 1988). Digital competencies should therefore be interpreted as one relevant domain-specific personal resource among several determinants of organizational commitment rather than as the dominant explanatory factor in the model.

Regarding the other personal resources, it can be concluded that self-efficacy has a significant positive indirect effect on organizational commitment ($\beta = 0.16$, 95% CI [0.10, 0.22]) via motivation ($H2a$) ($\beta = 0.07$, 95% CI [0.02, 0.15]) and strain ($H2b$) ($\beta = 0.10$, 95% CI [0.01, 0.14]). The total indirect effects and the specific indirect effects of perceived autonomy on organizational commitment are not significant. So, $H2a$ and $H2b$ could only be partially confirmed (for self-efficacy). Examining the indirect effects of the social resources, it can be observed that, like suggested, collegial support has a positive indirect effect on organizational commitment ($\beta = 0.12$, 95% CI [0.03, 0.19]) that is mainly transmitted via strain ($H3b$) ($\beta = 0.09$, 95% CI [0.01, 0.18]) since the specific indirect effect via motivation is not significant ($\beta = 0.03$, 95% CI [−0.04, 0.13]) ($H3b$). School management support has a significant indirect effect on organizational commitment ($\beta = 0.26$, 95% CI [0.16, 0.35]) via motivation ($H3a$) ($\beta = 0.06$, 95% CI [0.01, 0.29]) and strain $H3b$ ($\beta = 0.20$, 95% CI [0.00, 0.30]). The hypotheses on the indirect effects of job demands could be confirmed: student behavior issues significantly decrease organizational commitment ($\beta = -0.36$, 95% CI [−0.42, −0.29]) via motivation ($H4a$) ($\beta = -0.15$, 95% CI [−0.34, −0.07]) and strain ($H4b$) ($\beta = -0.21$, 95% CI [−0.33, −0.03]). Similar significant effects could also be found for administrative tasks ($\beta = -0.15$, 95% CI [−0.21, −0.10]) via motivation ($H4a$) ($\beta = -0.09$, 95% CI [−0.19, −0.04]) and strain ($H4b$) ($\beta = -0.06$, 95% CI [−0.17, −0.00]).

The structural model provides three main findings. First, established resources such as self-efficacy and leadership support showed the most consistent associations with motivation, psychological strain, and organizational commitment. Second, digital competencies were not directly associated with motivation, but their indirect association with organizational commitment operated primarily through psychological strain. Third, job demands were negatively associated with organizational commitment, mainly through increased psychological strain and reduced motivation.

Table 3. Indirect effects on organizational commitment.

Exogenous Variables	Indirect Effects	Mediating Variables	Std. Est.	BC-Bootstrap CI, 95% (LL, UL)
Student behavior	Total indirect		−0.36	[−0.42, −0.29]
	Specific indirect 1	Motivation	−0.15	[−0.34, −0.07]
	Specific indirect 2	Strain	−0.21	[−0.33, −0.03]
Administrative tasks	Total indirect		−0.15	[−0.20, −0.09]
	Specific indirect 1	Motivation	−0.09	[−0.19, −0.04]
	Specific indirect 2	Strain	−0.06	[−0.17, −0.00]
Collegial support	Total indirect		0.12	[0.03, 0.19]
	Specific indirect 1	Motivation	0.03	[−0.04, 0.14]
	Specific indirect 2	Strain	0.09	[0.02, 0.18]

Table 3. Cont.

Exogenous Variables	Indirect Effects	Mediating Variables	Std. Est.	BC-Bootstrap CI, 95% (LL, UL)
School management support	Total indirect Specific indirect 1 Specific indirect 2	Motivation Strain	0.26 0.06 0.20	[0.16, 0.35] [0.01, 0.29] [0.00, 0.30]
Autonomy	Total indirect Specific indirect 1 Specific indirect 2	Motivation Strain	0.03 0.05 −0.03	[−0.05, 0.12] [−0.00, 0.11] [−0.07, 0.01]
Self-efficacy	Total indirect Specific indirect 1 Specific indirect 2	Motivation Strain	0.16 0.07 0.10	[0.10, 0.22] [0.02, 0.15] [0.01, 0.14]
Digital competencies	Total indirect Specific indirect 1 Specific indirect 2	Motivation Strain	0.06 0.02 0.04	[0.00, 0.13] [−0.03, 0.07] [0.01, 0.10]

Note: Results based on SEM presented in Figure 2.

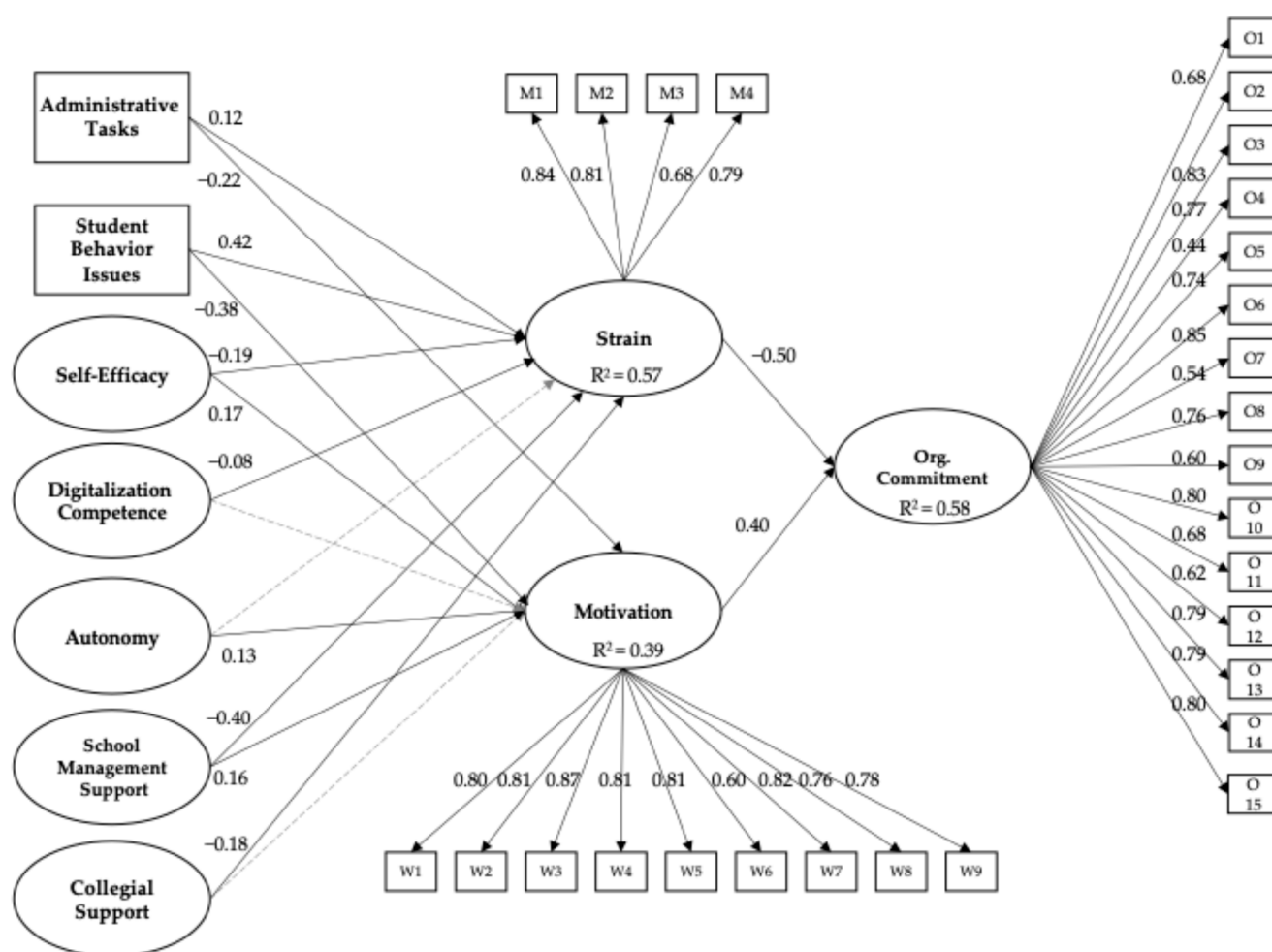


Figure 2. Structural equation model (SEM). Standardized results. Controls: sex, work experience, $N = 550$. Black paths $p < 0.05$, dashed paths = n.s., model fit: $\chi^2(3603) = 8086.087$, $p < 0.001$, RMSEA = 0.05, CFI = 0.91, TLI = 0.91, SRMR = 0.09. Due to the complexity of the model, only standardized factor loadings of endogenous variables could be displayed. See Table A1 for the complete measurement model and Table A2 for the complete structural model.

4.1.2. Robustness Checks

To assess common method bias (CMB), we employed Harman's single-factor test. However, instead of a traditional exploratory factor analysis (EFA), we used a confirmatory factor analysis (CFA), which provides a more sophisticated test of the hypothesis that a single factor can account for all the variance in the data (Podsakoff et al., 2003). Specifically, we compared a one-factor model (where all items load onto a single factor) with the eight-factor structure used in our main analyses. The results indicated a poor fit for the one-factor model ($\chi^2(3320) = 29,872.10$, $p < 0.001$; RMSEA = 0.121; CFI = 0.508; TLI = 0.495; SRMR = 0.171) and a better fit for the eight-factor model ($\chi^2(3292) = 7998.20$, $p < 0.001$; RMSEA = 0.051; CFI = 0.913; TLI = 0.910; SRMR = 0.063). These findings suggest that the variance in the data is not dominated by a single factor. While no single test can entirely rule out CMB, the results of this CFA-based approach provide supportive evidence that common method bias is not a primary concern for the interpretation of our findings.

5. Discussion

The present study contributes to the growing body of JD-R research examining the role of personal resources in shaping occupational well-being under conditions of organizational and technological change. While previous studies in educational settings have primarily emphasized organizational resources such as leadership support, collegial collaboration, and autonomy (e.g., Bakker & Demerouti, 2007; Skaalvik & Skaalvik, 2018), considerably less attention has been devoted to domain-specific resources that are directly linked to the demands created by digital transformation. By conceptualizing teachers' digital competencies as a domain-specific personal resource, the present study extends recent efforts to incorporate context-sensitive personal resources into JD-R models.

A central finding is that digital competencies appear to operate primarily through the health-impairment pathway rather than the motivational pathway. This finding refines rather than challenges the JD-R model by suggesting that the function of personal resources may depend on their degree of domain specificity and their proximity to the demands they are intended to address. This pattern is theoretically consistent with JD-R assumptions suggesting that personal resources become particularly relevant when employees are confronted with demanding or uncertain work environments (Bakker & Demerouti, 2007; Xanthopoulou et al., 2007). In digitally transforming schools, teachers are frequently required to cope with technological complexity, continuous adaptation requirements, and uncertainty regarding the effective use of digital tools. Under such conditions, digital competencies may function less as drivers of motivation and more as resources that help individuals maintain a sense of control and efficacy when facing technology-related challenges.

This interpretation is also consistent with research on technostress and digital work environments. Prior studies have repeatedly highlighted technology-related demands such as overload, complexity, uncertainty, techno-insecurity, and continuous adaptation requirements as central stressors in digitally transformed workplaces (Tarafdar et al., 2019; Molino et al., 2020; La Torre et al., 2019). The present findings extend and refine these technostress-oriented perspectives by suggesting that teachers' digital competencies may constitute an important individual-level resource that mitigates the psychological consequences of such demands. Teachers who possess stronger digital competencies may be better able to understand, evaluate, and utilize digital technologies effectively, thereby reducing the likelihood that digital transformation is experienced as frustrating, overwhelming, or professionally threatening. At the same time, the relatively small magnitude of the observed indirect effects suggests that digital competencies should not be regarded as a dominant determinant of teachers' organizational commitment. Rather, they appear to

represent one component within a broader constellation of personal and organizational resources.

Indeed, the comparatively strong role of leadership support underscores this interpretation. Leadership support exhibited substantially stronger associations with organizational commitment than digital competencies, indicating that digital transformation should not be framed solely as a matter of individual teacher competencies. Rather, digital transformation represents an organizational process that requires supportive leadership practices and enabling working conditions. School leaders can influence whether digitalization becomes an additional source of strain or a resource for professional development by shaping workload conditions, providing clear communication regarding change processes, coordinating professional learning opportunities, and fostering collaborative cultures in which teachers can exchange experiences and jointly develop solutions to technology-related challenges. Consequently, successful digital transformation depends not only on teachers' competencies but also on the organizational contexts within which these competencies are enacted and developed.

Teachers with higher levels of digital competencies appear to perceive digital transformation as more manageable and meaningful, whereas limited competencies may contribute to increased strain. In this regard, our findings extend existing JD-R research on technostress and ICT-related job demands in educational and public sector contexts, which has primarily conceptualized digitalization as a source of additional job demands, such as technological complexity, overload, uncertainty, and continuous adaptation requirements (e.g., [Z. Cheng et al., 2026](#); [Tarafdar et al., 2007](#); [Zhang et al., 2026](#)).

The results further highlight the importance of considering both personal and organizational resources when analyzing teacher well-being—the replication of previous findings regarding school management support, collegial support and self-efficacy underscores the continued relevance of established resource dimensions ([Dicke et al., 2018](#)). In line with the JD-R framework, these findings suggest that teacher well-being is best understood as the outcome of an interaction between individual capacities and contextual conditions. Interestingly, leadership support is particularly relevant in explaining differences in motivation, strain and organizational commitment and has a relevant indirect effect on organizational commitment. These findings are consistent with earlier research that has demonstrated the importance of school management support for teachers' well-being and commitment ([Hein & Urban, 2025](#), [Ismail et al., 2021](#), [Reintjes et al., 2025b](#); [Saifullah et al., 2025](#)).

The findings contribute to a more differentiated understanding of digital transformation in schools by showing that digital competencies primarily function as strain-reducing resources rather than as direct motivational drivers. Rather than being inherently beneficial or detrimental, digital technologies appear to function as context-dependent elements within the JD-R model. On the one hand, digital transformation introduces new job demands, such as increased complexity, continuous adaptation, and the need to acquire new competencies ([Scheiter, 2021](#)). On the other hand, it provides opportunities for professional learning ([OECD, 2025a](#)), instructional innovation ([Najmudin et al., 2025](#)), and enhanced student outcomes ([Eickelmann & Gerick, 2020](#)). The present study suggests that the balance between these demands and resources is crucial. Digital competencies, in particular, appear to play a role by shaping how technological demands are perceived and managed. In this sense, digital competencies can be understood as a mechanism through which digital transformation is translated into either strain or motivation.

Although the present study focuses on teachers, the findings have broader implications for understanding digital learning environments. Previous research has shown that students' well-being in digital contexts is associated with the development of digital competencies rather than with the mere frequency of digital media use ([Berger et al., 2025](#)).

This suggests that the effects of digitalization on educational processes depend on how technologies are pedagogically integrated. Teachers play a central role in this process, as their competencies, attitudes, and well-being influence how digital tools are used in the classroom (Li et al., 2022; Rubach & Lazarides, 2021; Wu et al., 2021). Accordingly, teacher well-being can be understood as an important condition for the successful implementation of digital learning environments.

The findings also carry important implications for educational leadership and school development. While digital competencies constitute a relevant personal resource, the strongest indirect effects observed in the present study were associated with leadership support. This finding highlights that successful digital transformation should not be conceptualized solely as a matter of individual teacher competencies but as an organizational process requiring supportive leadership structures (Dexter & Richardson, 2020). School leaders can contribute to reducing technology-related strain by providing protected time for digital professional development, coordinating structured peer-support systems, reducing unnecessary administrative burdens during technology implementation phases, and establishing collaborative cultures that encourage experimentation and mutual learning. In addition, leadership teams should ensure that digital innovations are introduced with clear pedagogical goals, realistic workload expectations, and opportunities for teachers to exchange experiences and jointly solve implementation problems (e.g., Reis-Anderson, 2023).

5.1. Limitations and Future Directions

Several limitations of the present study should be acknowledged. First, because the data are cross-sectional, we cannot draw causal conclusions. Although the model specification was theoretically derived from the JD-R framework, alternative causal directions are possible. For example, teachers who experience lower psychological strain or stronger organizational commitment may evaluate their digital competencies more positively. Longitudinal designs are therefore needed to examine the temporal ordering of digital competencies, strain, motivation, and organizational commitment.

Second, all central constructs were assessed using self-report measures. Although the CFA-based comparison of the hypothesized measurement model with a single-factor model suggests that common method variance is unlikely to fully account for the observed relationships (Podsakoff et al., 2003), common method bias cannot be completely ruled out. Future studies should combine self-reports with additional data sources. In this context, while self-reports are a common measure of perceived competencies, we acknowledge that they may be subject to overestimation; indeed, empirical research has shown that individuals frequently overestimate their own skills in digital domains (Aesaert et al., 2017).

Third, the operationalization of psychological strain should be considered carefully. In contrast to many JD-R studies that conceptualize health impairment primarily through emotional exhaustion or burnout-related indicators (e.g., Adil & Kamal, 2020; McCarthy & Dragouni, 2021), the present study operationalized strain as perceived meaninglessness of work. Consequently, the findings refer to a specific cognitive-affective dimension of psychological strain rather than to health impairment more broadly. Future studies should examine whether the observed relationships can be replicated using indicators such as emotional exhaustion, burnout symptoms, psychosomatic complaints, or psychological distress.

Fourth, some job demands were measured using single-item indicators. Although these indicators captured clearly defined aspects of teachers' work demands, they do not allow for reliability estimation and may not fully capture the multidimensional nature of job demands in schools. Future studies should therefore use multi-item scales to assess job demands in school.

Finally, the sample was drawn from comprehensive schools in two federal states in Germany and was based on purposive rather than probability sampling. Although the sampling strategy ensured variation in school contexts, the findings cannot be generalized statistically to all German schools. Future research should replicate the model in different school types, federal states, and national education systems.

The findings have several implications for future research and educational practice. First, like [Scholze and Hecker \(2023, 2024\)](#) who included digital job demands and digital resources into a JD-R model for organizations in general, we recommend that research on digital transformation and well-being should adopt an integrative perspective that considers the interplay between personal and organizational resources. Second, further studies are needed to examine how digital competencies develop over time and how they interact with other resource dimensions such as resilience and self-efficacy ([Ismail et al., 2021](#)).

Furthermore, the growing diffusion of generative artificial intelligence further increases the relevance of the present findings. While earlier forms of digitalization primarily required operational and informational competencies, contemporary educational environments increasingly require teachers to engage with AI-supported systems whose outputs are probabilistic, dynamic, and often difficult to evaluate ([UNESCO, 2023](#); [Vuorikari et al., 2022](#)). As a result, teachers face new demands related to uncertainty management, accountability, information verification, and pedagogical decision-making ([Galindo-Domínguez et al., 2024](#); [Ng et al., 2023](#)). These developments suggest that the relationship between digital competencies and occupational well-being may become even more important in the future, as digital competencies increasingly determine teachers' capacity to navigate rapidly evolving technological environments. In this context, digital competence frameworks may need to be expanded to include AI-related competencies (e.g., [Hu et al., 2025](#)). Such competencies include the ability to formulate effective prompts, critically evaluate AI-generated outputs, verify information accuracy, identify biases and hallucinations, and make responsible decisions regarding the educational use of AI systems. From a JD-R perspective, these competencies can be interpreted as emerging personal resources that may mitigate novel forms of technology-related strain while simultaneously enabling teachers to benefit from the opportunities associated with AI-supported educational innovation.

From a practical perspective, the results suggest that promoting teacher well-being in the digital era requires more than providing technological infrastructure. Because this study builds on earlier findings that underscored the impact of school leadership actions on teachers' well-being ([Hein & Urban, 2025](#); [Ismail et al., 2021](#); [Reintjes et al., 2025b](#); [Saifullah et al., 2025](#)), it points to a potentially decisive lever: providing school leaders with training in digitalization so that they can effectively support teachers in the digital transition. As [Ismail et al. \(2021\)](#) demonstrated, such support can also raise teachers' self-efficacy. Beyond technical expertise, such leadership support should manifest in concrete practices, such as providing protected time for digital professional development and establishing organizational structures like peer-coaching networks (as [Huong et al., 2025](#), can show for teacher educators) that help institutionalize digital competencies as a collective resource. At the organizational level, schools may benefit from monitoring indicators such as perceived digital workload, participation in digital professional development, availability of peer coaching, perceived usefulness of digital tools, and teachers' perceptions of leadership support during digital transformation. Such indicators can help identify whether digitalization is experienced as a resource-enhancing process or as an additional source of strain. In addition, recent research indicates that interventions aimed at improving teacher well-being are most effective when they combine the development of personal resources with organizational support systems ([Lillelien & Jensen, 2025](#)). This highlights the importance of systemic approaches to school development.

5.2. Conclusions

This study examined teachers' digital competencies as domain-specific personal resources within the JD-R framework. The findings suggest that digital competencies are associated with organizational commitment primarily through reductions in psychological strain rather than through increases in motivation. This pattern indicates that, in digitally transforming schools, digital competencies may be particularly important for helping teachers cope with technology-related demands.

At the same time, the comparatively stronger role of leadership support and self-efficacy demonstrates that digital competencies should not be viewed in isolation. Teacher well-being in digital transformation depends on the interplay between individual capacities and supportive organizational conditions. Strengthening teachers' digital competencies is therefore important, but it should be embedded in broader school development strategies that provide leadership support, collegial collaboration, protected time for professional learning, and realistic workload conditions.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: The dataset is available from the authors on request, and information on the data is provided in the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Measurement model.

Measurement Model Latent Variables	Items	Estimate	S.E.	p-Value
Motivation	Motivation_1	0.80	0.02	$p < 0.001$
	Motivation_2	0.81	0.02	$p < 0.001$
	Motivation_3	0.87	0.02	$p < 0.001$
	Motivation_4	0.81	0.02	$p < 0.001$
	Motivation_5	0.81	0.02	$p < 0.001$
	Motivation_6	0.60	0.03	$p < 0.001$
	Motivation_7	0.82	0.02	$p < 0.001$
	Motivation_8	0.76	0.02	$p < 0.001$
	Motivation_9	0.78	0.02	$p < 0.001$

Table A1. Cont.

Measurement Model Latent Variables	Items	Estimate	S.E.	p-Value
Org. Commitment	OrgCommitment_1	0.68	0.03	$p < 0.001$
	OrgCommitment_2	0.83	0.02	$p < 0.001$
	OrgCommitment_3	0.77	0.03	$p < 0.001$
	OrgCommitment_4	0.44	0.04	$p < 0.001$
	OrgCommitment_5	0.74	0.02	$p < 0.001$
	OrgCommitment_6	0.85	0.02	$p < 0.001$
	OrgCommitment_7	0.54	0.03	$p < 0.001$
	OrgCommitment_8	0.76	0.02	$p < 0.001$
	OrgCommitment_9	0.60	0.03	$p < 0.001$
	OrgCommitment_10	0.80	0.02	$p < 0.001$
	OrgCommitment_11	0.68	0.03	$p < 0.001$
	OrgCommitment_12	0.62	0.04	$p < 0.001$
	OrgCommitment_13	0.79	0.02	$p < 0.001$
	OrgCommitment_14	0.79	0.02	$p < 0.001$
	OrgCommitment_15	0.80	0.03	$p < 0.001$
Collegial Support	CollegialSupport_1	0.89	0.01	$p < 0.001$
	CollegialSupport_2	0.92	0.02	$p < 0.001$
	CollegialSupport_3	0.85	0.02	$p < 0.001$
	CollegialSupport_4	0.78	0.03	$p < 0.001$
School Management Support	SchoolMgmtSupport_1	0.90	0.01	$p < 0.001$
	SchoolMgmtSupport_2	0.87	0.01	$p < 0.001$
	SchoolMgmtSupport_3	0.88	0.01	$p < 0.001$
	SchoolMgmtSupport_4	0.75	0.02	$p < 0.001$
	SchoolMgmtSupport_5	0.76	0.02	$p < 0.001$
	SchoolMgmtSupport_6	0.88	0.01	$p < 0.001$
	SchoolMgmtSupport_7	0.81	0.02	$p < 0.001$
Autonomy	Autonomy_1	0.82	0.02	$p < 0.001$
	Autonomy_2	0.83	0.02	$p < 0.001$
	Autonomy_3	0.87	0.02	$p < 0.001$
	Autonomy_4	0.60	0.03	$p < 0.001$
	Autonomy_5	0.76	0.03	$p < 0.001$
Self-Efficacy	SelfEfficacy_1	0.58	0.04	$p < 0.001$
	SelfEfficacy_2	0.68	0.03	$p < 0.001$
	SelfEfficacy_3	0.64	0.03	$p < 0.001$
	SelfEfficacy_4	0.62	0.03	$p < 0.001$
	SelfEfficacy_5	0.77	0.02	$p < 0.001$
	SelfEfficacy_6	0.81	0.02	$p < 0.001$
	SelfEfficacy_7	0.78	0.02	$p < 0.001$
	SelfEfficacy_8	0.76	0.02	$p < 0.001$
	SelfEfficacy_9	0.79	0.02	$p < 0.001$
	SelfEfficacy_10	0.79	0.02	$p < 0.001$
Strain	Strain_1	0.84	0.02	$p < 0.001$
	Strain_2	0.81	0.02	$p < 0.001$
	Strain_3	0.68	0.03	$p < 0.001$
	Strain_4	0.79	0.02	$p < 0.001$
Digital Competencies	DigitalCompetencies_1	0.70	0.02	$p < 0.001$
	DigitalCompetencies_2	0.73	0.02	$p < 0.001$
	DigitalCompetencies_3	0.75	0.02	$p < 0.001$
	DigitalCompetencies_4	0.69	0.02	$p < 0.001$
	DigitalCompetencies_5	0.72	0.02	$p < 0.001$
	DigitalCompetencies_6	0.65	0.03	$p < 0.001$
	DigitalCompetencies_7	0.73	0.02	$p < 0.001$
	DigitalCompetencies_8	0.70	0.02	$p < 0.001$
	DigitalCompetencies_9	0.71	0.02	$p < 0.001$
	DigitalCompetencies_10	0.71	0.02	$p < 0.001$

Table A1. Cont.

Measurement Model		Estimate	S.E.	p-Value
Latent Variables	Items			
	DigitalCompetencies_11	0.78	0.02	$p < 0.001$
	DigitalCompetencies_12	0.73	0.02	$p < 0.001$
	DigitalCompetencies_13	0.73	0.02	$p < 0.001$
	DigitalCompetencies_14	0.75	0.02	$p < 0.001$
	DigitalCompetencies_15	0.75	0.02	$p < 0.001$
	DigitalCompetencies_16	0.58	0.03	$p < 0.001$
	DigitalCompetencies_17	0.57	0.03	$p < 0.001$
	DigitalCompetencies_18	0.62	0.03	$p < 0.001$
	DigitalCompetencies_19	0.61	0.03	$p < 0.001$
	DigitalCompetencies_20	0.67	0.03	$p < 0.001$
	DigitalCompetencies_21	0.71	0.03	$p < 0.001$
	DigitalCompetencies_22	0.74	0.02	$p < 0.001$
	DigitalCompetencies_23	0.69	0.02	$p < 0.001$
	DigitalCompetencies_24	0.64	0.03	$p < 0.001$
	DigitalCompetencies_25	0.57	0.03	$p < 0.001$
	DigitalCompetencies_26	0.64	0.03	$p < 0.001$
	DigitalCompetencies_27	0.63	0.03	$p < 0.001$
	DigitalCompetencies_28	0.50	0.03	$p < 0.001$
	DigitalCompetencies_29	0.53	0.03	$p < 0.001$
Residual Correlations		Estimate	S.E.	p-Value
Variable 1	Variable 2			
Motivation_2	Motivation_1	0.84	0.02	$p < 0.001$
Motivation_4	Motivation_3	0.57	0.04	$p < 0.001$
Motivation_9	Motivation_8	0.60	0.03	$p < 0.001$
DigitalCompetencies_2	DigitalCompetencies_1	0.58	0.04	$p < 0.001$
DigitalCompetencies_10	DigitalCompetencies_9	0.64	0.03	$p < 0.001$
DigitalCompetencies_10	DigitalCompetencies_11	0.60	0.03	$p < 0.001$
DigitalCompetencies_11	DigitalCompetencies_9	0.41	0.04	$p < 0.001$
DigitalCompetencies_15	DigitalCompetencies_14	0.34	0.04	$p < 0.001$
DigitalCompetencies_17	DigitalCompetencies_16	0.65	0.02	$p < 0.001$
DigitalCompetencies_17	DigitalCompetencies_18	0.62	0.03	$p < 0.001$
DigitalCompetencies_18	DigitalCompetencies_16	0.49	0.03	$p < 0.001$
DigitalCompetencies_27	DigitalCompetencies_26	0.65	0.03	$p < 0.001$
DigitalCompetencies_29	DigitalCompetencies_28	0.81	0.02	$p < 0.001$
SelfEfficacy_2	SelfEfficacy_1	0.34	0.04	$p < 0.001$
SelfEfficacy_2	SelfEfficacy_3	0.33	0.04	$p < 0.001$
SelfEfficacy_5	SelfEfficacy_4	0.36	0.04	$p < 0.001$
DigitalCompetencies_7	DigitalCompetencies_6	0.50	0.04	$p < 0.001$

Table A2. Structural model.

Dependent Variables	Independent Variables	Estimate	BC-Bootstrap CI, 95% (LL, UL)
Strain	Collegial Support	−0.18	[−0.31, −0.05]
	School Management Support	−0.40	[−0.52, −0.07]
	Autonomy	0.05	[−0.10, −0.13]
	Digital Competencies	−0.08	[−0.17, −0.01]
	Self-Efficacy	−0.19	[−0.30, −0.08]
	Student Behavior	0.42	[0.29, 0.55]
	Administrative Tasks	0.12	[0.02, 0.27]
	Work Experience	0.01	[−0.08, 0.10]
	Sex	0.06	[−0.03, 0.15]

Table A2. Cont.

Dependent Variables	Independent Variables	Estimate	BC-Bootstrap CI, 95% (LL, UL)
Motivation	Collegial Support	0.08	[−0.05, 0.02]
	School Management Support	0.16	[0.04, 0.40]
	Autonomy	0.13	[0.03, 0.25]
	Self-Efficacy	0.17	[0.09, 0.31]
	Digital Competencies	0.05	[−0.03, 0.16]
	Student Behavior	−0.38	[−0.44, −0.32]
	Administrative Tasks	−0.22	[−0.30, −0.13]
	Work Experience	0.01	[−0.06, 0.08]
	Sex	0.11	[0.03, 0.18]
	Motivation	0.40	[0.20, 0.72]
Org. Commitment	Strain	−0.50	[−0.64, −0.04]
	Work Experience in Years	0.04	[−0.04, 0.12]
	Sex	0.04	[−0.03, 0.12]
R ²			
Motivation		0.39	
Org. Commitment		0.58	
Strain		0.57	

Note

- ¹ Consistent with standard terminology in structural equation modeling (SEM) research (Bollen, 2014), the terms ‘(direct) effects’ and ‘indirect effects’ are used throughout this study to describe the associations within the theoretical model. It should be noted that these terms refer to statistical associations and do not imply causal relationships, which would be beyond the scope of the present cross-sectional design. Accordingly, all interpretations are made with caution to avoid causal claims.

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