

Digital Literacy and Employee Productivity: The Mediating Role of Organizational Support

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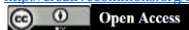
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ABSTRACT

Digital transformation has made digital literacy a core workplace competence, yet the mechanisms through which it raises employee productivity remain unclear. Drawing on conservation of resources theory, organizational support theory and the job demands–resources model, this study proposes that perceived organizational support mediates the relationship between employees' digital literacy and their productivity. It also examines what cross-sectional and longitudinal designs can and cannot reveal about this mechanism. A 17-item instrument and a population model with a priori specified effects were defined. Survey-type data for 400 employees were generated by Monte Carlo simulation and analysed with partial least squares structural equation modelling (PLS-SEM), consistent PLS (PLSc) and 5,000-sample bootstrapping. Three experiments examined parameter recovery across estimators (1,000 replications), the ability of cross-sectional mediation tests to distinguish the hypothesised model from a reversed and a common-cause model (1,500 replications), and the power and false-positive rate of a three-wave half-longitudinal design (8,000 replications). The measurement model met all conventional criteria ($\alpha = .86-.89$, composite reliability = .90–.92, AVE = .64–.65, HTMT $\leq .61$). Digital literacy was positively related to organizational support ($\beta = .392$, $p < .001$), and support to productivity ($\beta = .445$, $p < .001$). The indirect effect ($\beta = .175$, 95 % CI [.131, .223]) accounted for 43 % of the total effect, indicating complementary partial mediation. Standard PLS-SEM under-estimated the indirect effect by 21 %, whereas PLSc was unbiased. Cross-sectional tests 'supported' mediation in at least 99.8 % of samples regardless of whether the true causal order was hypothesised, reversed or driven by a common cause. A three-wave design achieved 92 % power with 200 employees per wave and kept false positives near 5 % with error-free measures. With fallible composite measures, however, false positives rose to 15 % at large samples. The study specifies a resource-based mechanism linking digital literacy to productivity through organizational support and shows that cross-sectional evidence alone cannot establish its direction. It provides a measurement instrument and design guidance for testing the mechanism. The data are simulated, so the estimates illustrate the model and the behaviour of the methods. They are not empirical evidence, and the model must be confirmed with field data.

Introduction

Digital technologies now permeate almost every occupation. Cloud collaboration platforms, enterprise resource planning systems, data dashboards, electronic communication and, increasingly, artificial-intelligence tools shape how work is organised, coordinated and evaluated. Economic research has long shown that information technology raises productivity mainly when it is accompanied by complementary investments in skills and organisational practices (Bresnahan et al., 2002; Brynjolfsson & Hitt, 2000). At the level of the individual employee, the most important of these complementary assets is digital literacy, the capacity to use digital technologies to find, evaluate, create and communicate

information effectively and responsibly (Gilster, 1997; Ng, 2012). European policy frameworks treat digital competence as a key competence for work and citizenship (Vuorikari et al., 2022), and employers increasingly regard it as a baseline requirement.

It seems self-evident that digitally literate employees are more productive. They complete digital tasks faster, make fewer errors, find information more efficiently and adapt more readily to new systems (van Laar et al., 2017). Yet the relationship is neither automatic nor uniform. Digital tools can also create overload, constant connectivity and role ambiguity. These forms of technostress can reduce productivity (Tarafdar et al., 2007), and individual skills are of limited value if the organisational environment does not enable their use. This raises the question of how digital literacy is converted into productive work, and in particular what role the organisation plays in that conversion.

The question matters for practice as well as theory. Organisations spend heavily on digital transformation and on digital-skills training, and they increasingly provide support for employees through digital means such as learning management systems, internal knowledge bases, virtual help desks and collaboration platforms. If digital literacy affects productivity only directly, through faster and more accurate task execution, then skills training alone should yield the expected gains. If, however, a substantial part of its effect depends on employees' ability to mobilise organisational support, then the design and accessibility of support systems become as important as the skills themselves. Employees with weak digital skills may then be doubly disadvantaged: they are less efficient in digital tasks and less able to obtain the support that could help them improve. Understanding the mechanism therefore informs both the targeting of training and the design of support systems.

This study argues that perceived organizational support (POS), employees' general belief that their organisation values their contributions and cares about their well-being (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002), is a central link. Organisational support is increasingly delivered through digital channels such as online learning platforms, self-service HR portals, collaboration tools and digital help desks. Employees with higher digital literacy are better able to find, use and benefit from these resources, and they are more likely to receive developmental opportunities and recognition from organisations that value digital capability. According to organizational support theory, employees who experience such support reciprocate with greater effort and performance (Kurtessis et al., 2017; Rhoades & Eisenberger, 2002). Digital literacy may therefore raise productivity partly by enabling employees to access and mobilise organizational support.

Testing this proposition raises a methodological problem that is often neglected. Mediation models are usually estimated from single-wave surveys, but cross-sectional data cannot establish the temporal and causal ordering that mediation implies (Maxwell & Cole, 2007). The model in which digital literacy leads to support is statistically indistinguishable from a model in which support leads to digital literacy, for example through training, and from a model in which both are caused by a third factor such as the organisation's digital maturity (Fiedler et al., 2011; Thoemmes, 2015). Before a field study is designed, it is therefore important to know whether the hypothesised mechanism can be distinguished from these alternatives at all, and which design would make that possible.

The study has three aims. First, it develops a theoretically grounded model in which organizational support mediates the relationship between digital literacy and employee productivity, and it derives four hypotheses. Second, it operationalises the model with a 17-item instrument and demonstrates the complete PLS-SEM workflow on a simulated sample of 400 employees. Third, it uses Monte Carlo experiments to quantify the bias of conventional estimators, the inability of cross-sectional tests to discriminate between causal orderings, and the capacity of a three-wave design to do so. The data in this paper are simulated from a population model with known parameters. The findings are statements about the model and the methods and are not empirical evidence about real employees.

2. Literature Review and Hypothesis Development

2.1 Digital literacy

The concept of digital literacy was popularised by Gilster (1997) as the ability to understand and use information in multiple formats from a wide range of sources presented via computers. It has since evolved from a narrow focus on operating devices to a multidimensional competence. Eshet-Alkalai (2004) distinguished photo-visual, reproduction, branching, information and socio-emotional literacies. Ng (2012) proposed three overlapping dimensions: technical (operating digital devices and software), cognitive (searching, evaluating and creating digital information critically) and social-emotional (communicating and behaving responsibly online). The European DigComp framework organises digital competence into information and data literacy, communication and collaboration, digital content creation, safety and problem solving (Vuorikari et al., 2022). In a systematic review, van Laar et al. (2017) showed that digital skills overlap substantially with 21st-century skills such as critical thinking, collaboration and problem solving.

In the workplace, digital literacy can be understood as a personal resource, an individual characteristic that helps employees to control their environment and achieve goals (Bakker & Demerouti, 2017; Hobfoll et al., 2018). It is partly general and partly specific to the organisation's systems and practices. Unlike age or 'digital nativeness', it can be developed through training and experience (Ng, 2012). This malleability makes it an attractive target for human-resource interventions.

2.2 Perceived organizational support

Organizational support theory holds that employees develop global beliefs about the extent to which the organisation values their contributions and cares about their well-being (Eisenberger et al., 1986). These beliefs arise from the treatment employees receive, including fair procedures, supervisor support, favourable rewards and job conditions, and developmental opportunities (Rhoades & Eisenberger, 2002). The meta-analysis by Kurtessis et al. (2017), covering several hundred studies, confirmed that POS is related to HR practices, leadership and working conditions as antecedents. It also confirmed relationships with organisational commitment, job satisfaction, well-being and performance as consequences.

Two features of POS are central to this study. First, POS reflects the support that employees actually perceive and use, not merely the support that the organisation formally offers. Two employees in the same organisation can therefore perceive very different levels of support, depending on their ability to recognise and access it. Second, in digitally transformed organisations much support is delivered digitally. Training is offered on e-learning platforms, help is available through online portals and chat tools, recognition is communicated through enterprise social networks, and flexible work arrangements depend on digital infrastructure. Access to organizational support thus increasingly requires digital literacy.

2.3 Employee productivity

Employee productivity refers to the efficiency and effectiveness with which an employee converts time and resources into valued work outputs. It includes the quantity and quality of output, the timeliness of task completion and the efficient use of resources. Productivity overlaps with task performance (Koopmans et al., 2014) but places more emphasis on efficiency, the ratio of outputs to inputs. In survey research it is usually measured through self- or supervisor ratings. Objective indicators, where available, are preferable because they avoid common method variance (Podsakoff et al., 2012). Technology can raise productivity by automating routine tasks and accelerating information processing, but it can also lower productivity through overload and interruptions (Tarafdar et al., 2007). The net effect therefore depends on employees' ability to use technology well and on the support they receive in doing so.

Measuring individual productivity is particularly difficult in knowledge work, where outputs are heterogeneous, quality matters as much as quantity, and contributions are often collective. Objective indicators such as cases closed, tickets resolved or documents processed are available only in some jobs and may encourage a narrow focus on countable outputs. Supervisor ratings capture broader aspects of effectiveness but are subject to halo and leniency effects. Self-ratings are convenient and capture employees' knowledge of their own work, but they are prone to inflation and to shared-method bias with other self-reported predictors (Podsakoff et al., 2012). Combining sources, for example self-rated productivity with supervisor ratings or system-generated activity data, is therefore advisable. The instrument used in this study focuses on dimensions that employees and supervisors can both rate: output volume, quality, timeliness, efficiency and goal attainment.

2.4 Theoretical framework

Three complementary theories inform the model. Conservation of resources (COR) theory proposes that people strive to obtain, retain and protect resources, and that resources tend to generate further resources, forming 'resource caravans' (Hobfoll, 1989; Hobfoll et al., 2018). Digital literacy is a personal resource that enables employees to obtain organisational resources, such as information, training, assistance and recognition, which in turn enable effective work. The JD-R model similarly proposes that personal and job resources reinforce each other and jointly foster engagement and performance (Bakker & Demerouti, 2007, 2017).

Organizational support theory and social exchange theory (Blau, 1964; Eisenberger et al., 1986) explain why support raises productivity. Employees who feel valued and supported experience a felt obligation to reciprocate. They also gain confidence in their capabilities and expect their efforts to be recognised (Kurtessis et al., 2017). Support therefore increases both the motivation and the means to work productively. Social cognitive theory adds that support, for example through encouragement and successful experiences with digital tools, strengthens self-efficacy, which sustains effort and persistence (Bandura, 1997).

Combining these perspectives yields the proposed mechanism. Digitally literate employees are better able to identify, access and use the increasingly digital channels through which support is provided. They are also more likely to be selected for developmental opportunities and to receive recognition for their digital contributions. As a result they perceive more organizational support, which in turn raises their productivity through reciprocity, motivation and resources. Digital literacy may also raise productivity directly by making digital tasks faster and more accurate. The reverse sequence is also theoretically plausible, because organisations that support their employees invest in their digital training. This possibility is examined explicitly in Section 4.

2.5 Hypotheses

Digitally literate employees complete technology-mediated tasks more efficiently, make fewer errors and adapt more quickly to new systems (Ng, 2012; van Laar et al., 2017).

H1. Digital literacy is positively related to employee productivity.

As a personal resource, digital literacy enables employees to access and use digitally delivered organisational resources and to be recognised for their contributions, consistent with the resource-caravan principle of COR theory (Hobfoll et al., 2018).

H2. Digital literacy is positively related to perceived organizational support.

Perceived organizational support increases felt obligation, self-efficacy and access to resources, which in turn raise effort and performance (Kurtessis et al., 2017; Rhoades & Eisenberger, 2002).

H3. Perceived organizational support is positively related to employee productivity.

Combining H2 and H3, organizational support is expected to transmit part of the effect of digital literacy to productivity. Because digital literacy also has direct efficiency benefits, partial mediation is expected (Zhao et al., 2010).

H4. Perceived organizational support mediates the positive relationship between digital literacy and employee productivity.

Figure 1 presents the research model.

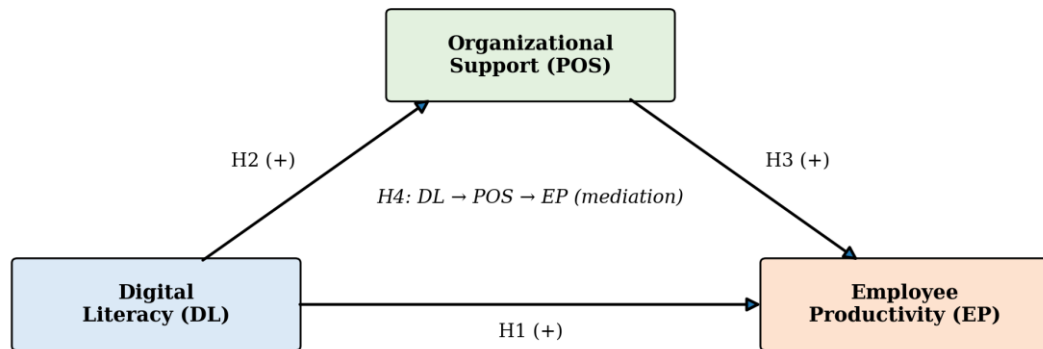


Figure 1. Research model and hypotheses.

2.6 The problem of causal direction

Mediation hypotheses are causal hypotheses. They state that the independent variable changes the mediator, which in turn changes the outcome. The $DL \rightarrow POS \rightarrow EP$ model is one of several causal structures that could produce the same pattern of correlations. Support could build digital literacy: organisations that invest in employees provide digital training, and supported employees feel secure enough to experiment with new tools (Bandura, 1997; Kurtessis et al., 2017). Alternatively, both literacy and perceived support could be products of a common cause, such as a digitally mature organisation that both employs digitally literate people and provides strong digital support. A reciprocal process, in which literacy and support reinforce each other over time, is also plausible and is consistent with the resource-caravan principle of COR theory (Hobfoll et al., 2018).

Methodologists have warned that single-wave mediation analyses cannot discriminate between such structures. Cross-sectional estimates can even be severely biased estimates of longitudinal mediation processes (Cole & Maxwell, 2003; Maxwell & Cole, 2007). Fiedler et al. (2011) showed that a significant indirect effect is compatible with many alternative causal models. Thoemmes (2015) demonstrated that estimating models with reversed arrows and comparing the results cannot identify the correct direction when the models are statistically equivalent. Despite these warnings, reversed-arrow comparisons remain common in applied research. The present study therefore evaluates directly, in the context of the digital literacy–support–productivity model, how cross-sectional tests behave under alternative causal structures, and what a longitudinal design achieves.

3. Methodology

3.1 Research design

The study uses a Monte Carlo simulation design structured according to the ADEMP framework (aims, data-generating mechanisms, estimands, methods and performance measures; Morris et al., 2019). Simulation is used for two purposes. The first is to demonstrate and document the analytical workflow for testing the model, from measurement validation to bootstrapped mediation analysis, before field data are collected. The second is to evaluate, against known population values, three methodological questions that a single empirical dataset cannot answer. How accurately do common estimators recover

the hypothesised effects? Can cross-sectional mediation tests distinguish the hypothesised causal order from plausible alternatives? How large must a longitudinal study be to make that distinction? The simulated data do not represent real employees, and all results in Section 4 are properties of the model and the methods.

3.2 Measurement instrument

Table 1 lists the 17 items, rated on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Digital literacy (DL, six items) covers the technical, cognitive and social-emotional dimensions of Ng (2012) and the competence areas of DigComp 2.2 (Vuorikari et al., 2022): operating digital tools, searching for and evaluating information, creating digital content, communicating and collaborating online, protecting data, and solving technical problems. Perceived organizational support (POS, six items) was adapted from the Survey of Perceived Organizational Support (Eisenberger et al., 1986), with items referring to the organisation's valuation of contributions, care for well-being and provision of help, including digital training and tools. Employee productivity (EP, five items) covers output quantity, quality, timeliness, efficient use of resources and goal attainment, adapted from task-performance measures (Koopmans et al., 2014). All constructs are reflective. In field use, supervisor ratings or objective output data should complement the self-reported productivity items.

Table 1. Measurement instrument (adapted wording)

Construct	Code	Item (5-point Likert scale)	Adapted from
Digital literacy (DL)	DL1	I can use the digital tools and software required in my job confidently.	Ng (2012); Vuorikari et al. (2022)
	DL2	I can find the information I need online quickly and judge whether it is reliable.	
	DL3	I can create digital content (documents, presentations, data files) of good quality.	
	DL4	I can communicate and collaborate effectively with colleagues through digital platforms.	
	DL5	I know how to protect work data and my privacy when using digital tools.	
	DL6	I can solve common technical problems or find help to solve them.	
Perceived organizational support (POS)	POS1	My organisation values my contribution to its success.	Eisenberger et al. (1986)
	POS2	My organisation really cares about my well-being.	
	POS3	Help is available from my organisation when I have a problem.	
	POS4	My organisation provides the training I need to work with digital tools.	
	POS5	My organisation provides the technology and resources I need to do my job well.	
	POS6	My organisation takes pride in my accomplishments at work.	

Employee productivity (EP)	EP1	I complete a high volume of work in the time available.	Koopmans et al. (2014)
	EP2	The quality of my work output is high.	
	EP3	I complete my tasks on time.	
	EP4	I use my working time and resources efficiently.	
	EP5	I achieve the work goals set for me.	

Note. Items are adapted paraphrases for illustration; field studies should use validated original scales and pre-test them in context.

3.3 Data-generating model

The population model (Table 2) specifies standardised latent variables with $DL \rightarrow POS = a = .40$, $POS \rightarrow EP = b = .45$ and $DL \rightarrow EP = c' = .25$. The implied indirect effect is $a \times b = .18$ and the total effect .43. These moderate-to-strong values are consistent with the substantial associations between POS and performance-related outcomes reported in meta-analytic work (Kurtessis et al., 2017). They were fixed before data generation. Items were generated as $\lambda \cdot \eta + e$, with standardised loadings between .71 and .84, and were discretised into five ordered categories. The main sample comprised $n = 400$ employees and was generated with a fixed random seed.

Table 2. Population (data-generating) model and simulation design

Element	Specification
Structural paths	$DL \rightarrow POS: a = .40$; $POS \rightarrow EP: b = .45$; $DL \rightarrow EP: c' = .25$
Implied effects	Indirect $a \times b = .18$; total = .43; population $R^2(POS) = .16$, $R^2(EP) \approx .34$
Indicator loadings	DL: .79, .82, .76, .84, .73, .71; POS: .83, .80, .78, .81, .75, .72; EP: .82, .79, .84, .76, .74
Main sample	$n = 400$ (fixed seed); 5,000 bootstrap resamples
Experiment 1	1,000 replications, $n = 400$; sum-score regression vs. PLS-SEM vs. PLSc
Experiment 2	Structures A (hypothesised), B (reversed), C (common cause) $\times$ 500 replications, $n = 400$
Experiment 3	Three waves; stability .60; cross-lags .20 (direct lag .10); $n = 100\text{--}800 \times$ structures A/B $\times$ error-free vs. composite (reliability .88) $\times$ 400 replications

3.4 Analytical strategy

The model was estimated with PLS-SEM (path-weighting scheme, Mode A; Hair et al., 2019) and with consistent PLS (PLSc), which corrects for measurement error using ρ_A (Dijkstra & Henseler, 2015). The measurement model was evaluated through loadings ($\geq .708$), cross-loadings, Cronbach's α , ρ_A and composite reliability ρ_C (.70–.95), the average variance extracted (AVE $\geq .50$), the Fornell–Larcker criterion and HTMT ($< .85$; Fornell & Larcker, 1981; Henseler et al., 2015). The structural model was evaluated through VIF, path coefficients, R^2 and f^2 (Cohen, 1988). Significance was assessed with 5,000 bootstrap resamples and percentile confidence intervals (Efron & Tibshirani, 1993). Mediation was tested through the confidence interval of the indirect effect and classified following Zhao et al. (2010), Preacher and Hayes (2008) and Hayes (2022). As a robustness check, the alternative model with reversed first-stage ordering ($POS \rightarrow DL \rightarrow EP$) was also estimated on the same data. All analyses were implemented from first principles in Python (NumPy).

3.5 Monte Carlo experiments

Experiment 1 (estimator comparison) generated 1,000 samples of $n = 400$ and compared sum-score regression, PLS-SEM and PLSc in terms of bias, standard deviation and root-mean-square error (RMSE). Experiment 2 (equivalent models) generated 500 samples of $n = 400$ from each of three causal

structures. Structure A is the hypothesised model ($DL \rightarrow POS \rightarrow EP$, with $DL \rightarrow EP$). In structure B the first stage is reversed ($POS \rightarrow DL \rightarrow EP$, with $POS \rightarrow EP$), representing the possibility that support builds digital literacy, for example through training. In structure C a common cause, such as the organisation's digital maturity, raises both DL and POS, while DL and POS each affect EP but DL does not affect POS. In each sample, both the hypothesised and the reversed mediation model were estimated. The proportion of samples in which each yielded a significant indirect effect was recorded, using 95 % Monte Carlo confidence intervals (Preacher & Selig, 2012). Experiment 3 (three-wave design) generated panel data over three waves. Each variable had a stability of .60, and cross-lagged effects of .20 corresponded either to the hypothesised order (A: $DL_1 \rightarrow POS_2$, $POS_2 \rightarrow EP_3$) or to the reversed order (B: $POS \rightarrow DL \rightarrow EP$). Following Cole and Maxwell (2003), the a path was estimated as the effect of DL at wave 1 on POS at wave 2, controlling for POS at wave 1. The b path was estimated as the effect of POS at wave 2 on EP at wave 3, controlling for EP and DL at wave 2. The rate of significant indirect effects was recorded for $n = 100$ to 800 per wave and 400 replications per cell. Under structure A this rate is the power, and under structure B it is the false-positive rate. Both error-free scores and composites with reliability .88 were analysed.

3.6 Reporting standards and transparency

The study follows current reporting recommendations for PLS-SEM (Hair et al., 2019) and for simulation studies (Morris et al., 2019). For the main sample, it reports item-level statistics, all reliability and validity indicators, both estimators, and the results of the alternative (reversed) model. For the experiments, it reports the number of replications, the performance measures (bias, standard deviation, RMSE, power and false-positive rates) and all design factors. Monte Carlo error is small relative to the reported differences. With 500 replications, the standard error of a rejection rate near 1.0 is below .01, and with 400 replications the standard error of a rate near .05 is about .011. Population values, random seeds and design factors are documented in Table 2, so that the results can be reproduced and extended to other parameter values.

4. Results

4.1 Measurement model

Table 3 reports the measurement model. All loadings exceeded .708 (range .745–.864), and every item loaded more highly on its own construct than on any other (the highest cross-loading was .460). Cronbach's α ranged from .859 to .892, ρ_A from .861 to .899 and ρ_C from .899 to .917. The AVE values ($DL = .650$, $POS = .645$, $EP = .641$) supported convergent validity. Table 4 shows that the Fornell–Larcker criterion was met and that all HTMT ratios were well below .85, the highest being .612 for POS–EP. Discriminant validity was therefore established. The first unrotated factor accounted for 40.5 % of the item variance.

Table 3. Measurement model: item statistics, loadings, reliability and convergent validity

Construct	Item	Mean	SD	Loading	α	ρ_A	ρ_C	AVE
Digital literacy	DL1	3.23	1.03	0.814	0.892	0.899	0.917	0.650
	DL2	3.11	1.01	0.805				
	DL3	3.03	1.03	0.803				
	DL4	3.21	1.06	0.864				
	DL5	3.18	1.03	0.759				
	DL6	3.07	1.07	0.788				
Organizational support	POS1	3.27	1.07	0.860	0.889	0.890	0.916	0.645
	POS2	3.16	1.05	0.774				
	POS3	3.08	1.02	0.803				
	POS4	3.30	1.03	0.825				

	POS5	3.17	1.02	0.805				
	POS6	3.02	1.06	0.745				
Employee productivity	EP1	3.24	1.01	0.838	0.859	0.861	0.899	0.641
	EP2	3.15	1.03	0.774				
	EP3	3.01	0.99	0.841				
	EP4	3.25	1.02	0.782				
	EP5	3.16	1.02	0.764				

Note. Simulated data, $n = 400$. α = Cronbach's alpha; ρA = Dijkstra–Henseler reliability; ρC = composite reliability; AVE = average variance extracted.

Table 4. Discriminant validity: Fornell–Larcker criterion (lower triangle) and HTMT (upper triangle)

Construct	DL	POS	EP
Digital literacy (DL)	0.806	0.436	0.455
Organizational support (POS)	0.392	0.803	0.612
Employee productivity (EP)	0.404	0.535	0.800

Note. Bold diagonal values are square roots of AVE .

4.2 Structural model and hypothesis testing

The inner VIF was 1.18. Table 5 and Figure 2 present the structural results. Digital literacy was positively related to perceived organizational support ($\beta = .392$, $t = 9.26$, $p < .001$, 95 % CI [.310, .475]; $f^2 = .182$), supporting H2. Organizational support was positively related to productivity ($\beta = .445$, $t = 11.65$, $p < .001$, CI [.372, .521]; $f^2 = .251$), supporting H3. Digital literacy also had a positive direct effect on productivity ($\beta = .229$, $t = 5.12$, $p < .001$, CI [.143, .317]; $f^2 = .066$), supporting H1. The model explained 15.4 % of the variance in organizational support and 33.1 % in productivity. With PLSc the values were 19.2 % and 41.8 %.

Table 5. Structural model results and hypothesis tests (5,000 bootstrap resamples)

Hypothesis / path	β	SE	t	p	95 % CI	f^2	PLSc β	Decision
H1: DL $\rightarrow$ EP (direct)	0.229	0.045	5.12	< .001	[0.143, 0.317]	0.066	0.236	Supported
H2: DL $\rightarrow$ POS	0.392	0.042	9.26	< .001	[0.310, 0.475]	0.182	0.438	Supported
H3: POS $\rightarrow$ EP	0.445	0.038	11.65	< .001	[0.372, 0.521]	0.251	0.507	Supported
H4: DL $\rightarrow$ POS $\rightarrow$ EP (indirect)	0.175	0.024	7.33	< .001	[0.131, 0.223]	–	0.222	Supported
Total effect DL $\rightarrow$ EP	0.404	0.042	9.52	< .001	[0.322, 0.486]	–	0.459	–

Note. $R^2(POS) = 0.154$; $R^2(EP) = 0.331$ (PLSc: 0.192 and 0.418). $VAF = 43.2$ %. Reversed model ($POS \rightarrow DL \rightarrow EP$) on the same data: indirect = 0.090, 95 % Monte Carlo CI [0.053, 0.134].

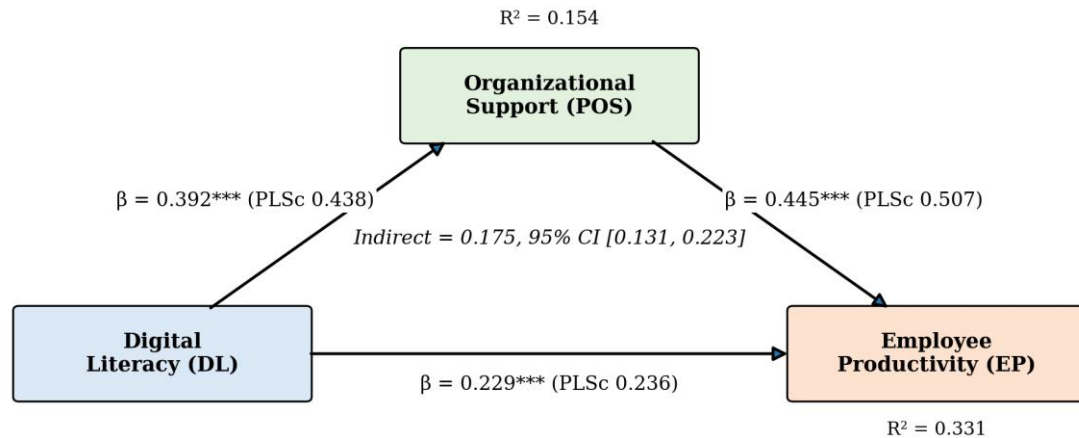


Figure 2. Estimated structural model (PLS-SEM; PLSc estimates in parentheses). * $p < .001$.**

The indirect effect of digital literacy on productivity through organizational support was $\beta = .175$ ($t = 7.33$, 95 % CI [.131, .223]), supporting H4 (Figure 3). Together with the significant direct effect, this indicates complementary partial mediation (Zhao et al., 2010). The total effect was .404 (CI [.322, .486]), of which 43.2 % was transmitted through organizational support (VAF). PLSc yielded larger estimates ($a = .438$, $b = .507$, $c' = .236$, indirect = .222, CI [.167, .286]) and the same substantive conclusions.

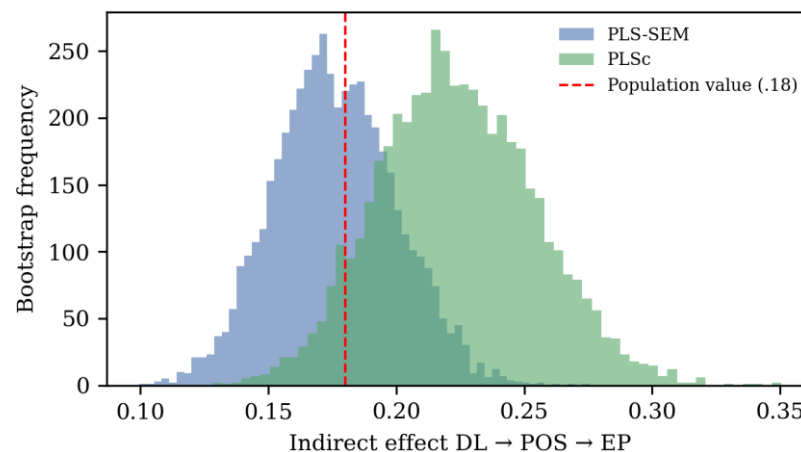


Figure 3. Bootstrap distributions of the indirect effect under PLS-SEM and PLSc (5,000 resamples); dashed line = population value.

The robustness check, however, showed that the reversed model was also supported by the same data. When the first stage was reversed ($POS \rightarrow DL \rightarrow EP$), the indirect effect was .090 with a 95 % Monte Carlo confidence interval of [.053, .134], which also excludes zero. The data are therefore consistent with both causal orderings. Experiment 2 examines whether this ambiguity is a peculiarity of the sample or a general property of cross-sectional mediation tests.

4.3 Estimator comparison (Experiment 1)

Table 6 and Figure 4 summarise 1,000 replications. Sum-score regression and PLS-SEM behaved very similarly. Both under-estimated a by 11–12 % (means .351 and .356 against .40), b by 11–12 % (.398 and .401 against .45), c' by 5–6 % (.235 and .237 against .25) and the indirect effect by 21–22 % (.140 and .143 against .18). PLSc was essentially unbiased for all parameters ($a = .402$, $b = .450$, $c' = .251$, $a \times b = .181$; all within 0.4 % of the true values). Despite its larger sampling variance, PLSc had the lowest RMSE for every parameter except c' (indirect effect: .029 against .044 for PLS-SEM and .046

for sum scores). The main-sample estimates were thus typical of what the conventional estimators produce.

Table 6. Estimator comparison over 1,000 replications: mean (SD), relative bias and RMSE

Parameter	True	Sum-score mean (SD)	Bias %	RMSE	PLS mean (SD)	Bias %	RMSE	PLSc mean (SD)	Bias %	RMSE
a (DL → POS)	0.40	0.351 (0.044)	-12.2	0.065	0.356 (0.043)	-11.0	0.062	0.402 (0.048)	+0.4	0.048
b (POS → EP)	0.45	0.398 (0.041)	-11.5	0.066	0.401 (0.041)	-11.0	0.064	0.450 (0.048)	+0.1	0.048
c' (DL → EP)	0.25	0.235 (0.044)	-6.0	0.047	0.237 (0.044)	-5.3	0.046	0.251 (0.053)	+0.3	0.053
a × b (indirect)	0.18	0.140 (0.022)	-22.3	0.046	0.143 (0.023)	-20.8	0.044	0.181 (0.029)	+0.4	0.029

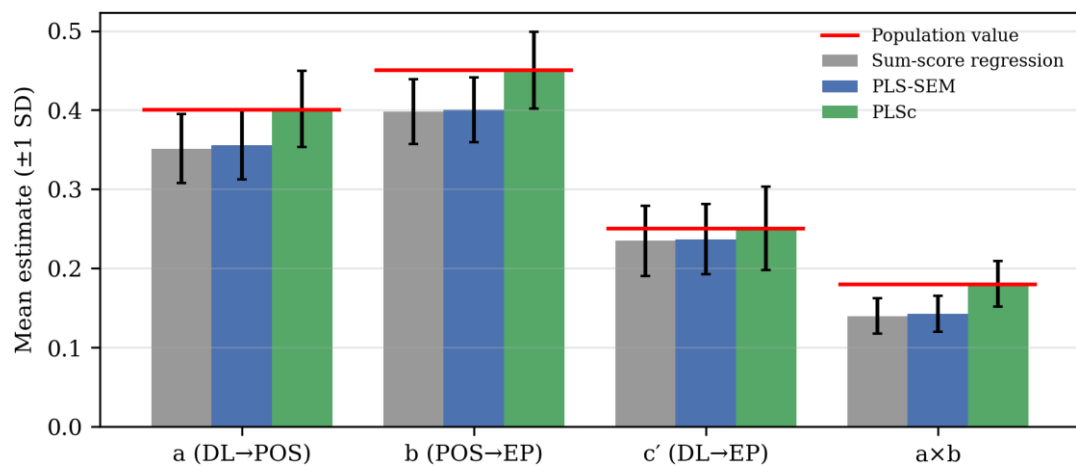


Figure 4. Mean estimates (± 1 SD) of three estimators across 1,000 replications; red lines mark population values.

4.4 Cross-sectional tests and equivalent models (Experiment 2)

Figure 5 and Table 7 present the central result of the study. When the data were generated by the hypothesised model (structure A), the hypothesised mediation model yielded a significant indirect effect in 100 % of samples. The reversed model also did so in 99.8 % of samples, with a smaller mean indirect effect (.084 against .142). When the data were generated by the reversed model (structure B), the pattern was mirrored. The hypothesised model was still 'supported' in 99.8 % of samples (mean indirect effect .085), even though the true effect of DL on POS was zero. When the data were generated by a common cause with no effect of DL on POS (structure C), both models were supported in 100 % of samples. The hypothesised model's mean indirect effect (.143) was indistinguishable from that obtained under the true model A. This is expected, because structures A and C imply identical correlation matrices.

Two conclusions follow. First, a significant indirect effect in cross-sectional data provides no evidence for the hypothesised causal ordering. Every structure produced 'significant mediation' for both orderings, consistent with the equivalence argument of Thoemmes (2015) and the critique of Fiedler et al. (2011). Second, comparing the size of indirect effects across reversed models is also uninformative. Under structure C, the hypothesised model produced a larger indirect effect than the reversed model even though DL had no causal effect on POS. The practice of 'testing' the direction of mediation by reversing arrows and comparing results should therefore be abandoned.

Table 7. Cross-sectional mediation tests under three true causal structures (500 replications each, n = 400)

True structure	Hypothesised model: % significant	Mean indirect	Reversed model: % significant	Mean indirect
A: DL → POS → EP (hypothesised)	100.0	0.142	99.8	0.084
B: POS → DL → EP (reversed)	99.8	0.085	100.0	0.143
C: common cause, no DL → POS	100.0	0.143	100.0	0.085

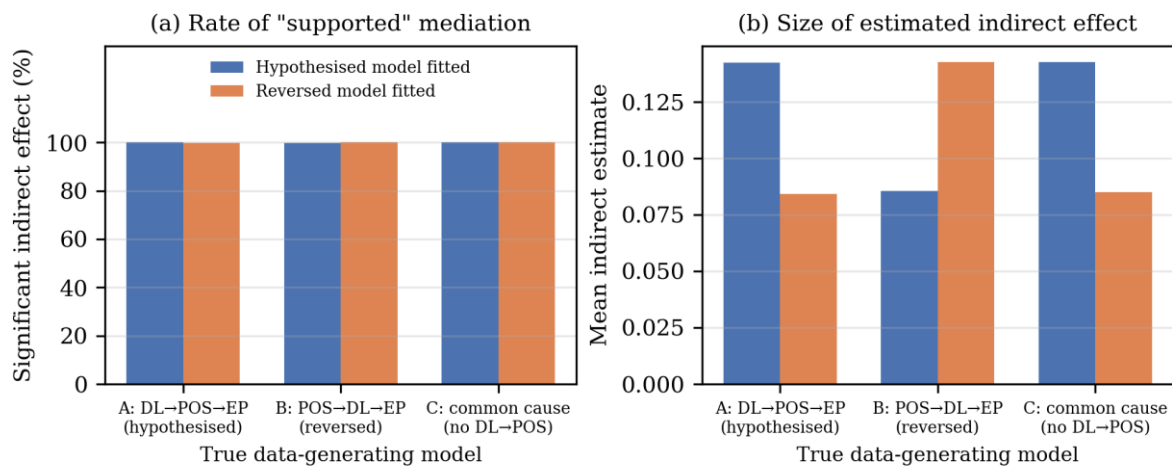


Figure 5. (a) Percentage of samples with a significant indirect effect and (b) mean indirect estimate for the hypothesised and reversed models under three true causal structures.

4.5 The three-wave design (Experiment 3)

Figure 6 and Table 8 show that a three-wave half-longitudinal design can discriminate between the orderings. Under the hypothesised structure, power to detect the lagged indirect effect with error-free measures was .51 at $n = 100$, .92 at $n = 200$ and at least .99 from $n = 300$. With composite measures of reliability .88, power was slightly lower (.44, .87 and .97). Under the reversed structure, where the lagged $DL \rightarrow POS$ effect is zero, the false-positive rate with error-free measures stayed at or below the nominal level (.010 at $n = 100$, .053 at $n = 800$). The design thus correctly rejected the hypothesised ordering when it was false.

With fallible composites, however, the false-positive rate increased with sample size, from .018 at $n = 100$ to .085 at $n = 500$ and .153 at $n = 800$. The reason is that controlling for an imperfectly measured prior level of POS removes only part of its stability, so the correlation between DL at wave 1 and POS at wave 1 leaks into the lagged a path. Longitudinal designs therefore resolve the direction problem only if measurement error is also addressed, for example through latent-variable models with multiple indicators at each wave, or through corrections for unreliability (Cole & Maxwell, 2003).

Table 8. Three-wave design: rate of significant lagged indirect effects (400 replications per cell)

Condition	n = 100	n = 200	n = 300	n = 500	n = 800
Power (A), error-free	0.507	0.920	0.993	1.000	1.000
Power (A), composites	0.440	0.868	0.968	1.000	1.000
False positive (B), error-free	0.010	0.010	0.028	0.040	0.052
False positive (B), composites	0.018	0.030	0.058	0.085	0.152

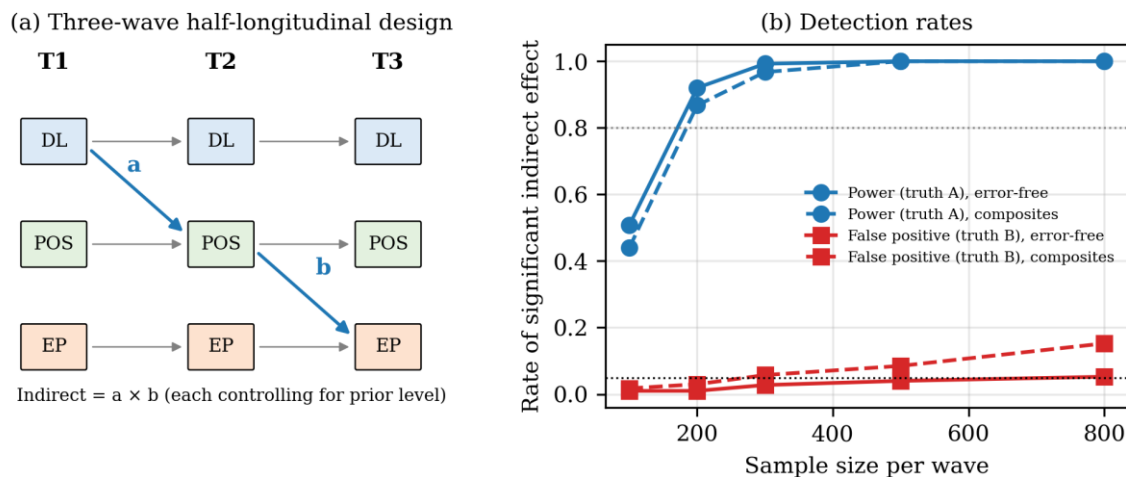


Figure 6. (a) Three-wave half-longitudinal design; (b) power under the hypothesised structure and false-positive rate under the reversed structure as functions of sample size per wave.

5. Discussion

5.1 Theoretical implications

This study proposed that perceived organizational support is a key mechanism through which digital literacy translates into employee productivity. Under the specified model, support transmits more than two-fifths of the total effect. The study also showed what kind of evidence is needed to substantiate this claim. Three theoretical implications follow.

First, the model reframes digital literacy as a resource that operates not only through the individual's direct technical efficiency but also through the individual's relationship with the organisation. This extends COR theory's notion of resource caravans (Hobfoll et al., 2018) to the digital workplace. Personal digital resources enable employees to acquire organisational resources, which then fuel productive work. It also qualifies the common assumption that organizational support is an organisational property applied uniformly to employees. Because support is increasingly delivered through digital channels, the support an employee actually perceives depends partly on that employee's capacity to access it. Organizational support theory has emphasised the organisation's treatment of employees as the source of POS (Rhoades & Eisenberger, 2002). The present model adds the employee's digital capacity to recognise and use that treatment as a complementary source.

Second, the model connects the micro-level literature on digital skills with the macro-level evidence that technology raises productivity only in combination with complementary organisational investments (Bresnahan et al., 2002; Brynjolfsson & Hitt, 2000). Organizational support can be seen as the individual-level counterpart of these complementary investments. The mediation model implies that digital skills and organisational support are not substitutes but links in a single chain. Organisations that invest in one without the other are therefore likely to realise only part of the potential productivity gains.

Third, the findings of Experiment 2 have implications for theory testing itself. The reversed sequence, in which support builds digital literacy through training and encouragement, is theoretically as plausible as the hypothesised one (Bandura, 1997; Kurtessis et al., 2017). The two processes are likely to operate simultaneously as a reciprocal cycle. Cross-sectional mediation analysis cannot separate them, and the common practice of comparing models with reversed arrows does not help (Thoemmes, 2015). Theories of digital literacy and support should therefore be formulated as dynamic, reciprocal processes and tested with designs that can capture reciprocity.

5.2 Methodological implications

Relative to the existing literature, the specified effects are deliberately moderate. Meta-analytic evidence documents substantial associations between perceived organizational support and

performance-related outcomes (Kurtessis et al., 2017), and research on digital skills consistently links them to effective work with technology (van Laar et al., 2017). Because the simulated estimates are not empirical, they cannot be compared quantitatively with these findings. They do show, however, that even a well-specified model with moderate effects, analysed with standard tools, can lead to confident but unjustified conclusions about causal direction. This lesson applies to much of the published survey research on digital skills and workplace outcomes, in which single-wave designs predominate.

Four recommendations follow for empirical research on digital competence and workplace outcomes. (1) Measurement-error-corrected estimators such as PLS or covariance-based SEM should be reported alongside composite-based results, because conventional estimators under-stated the indirect effect by about one-fifth. (2) A significant indirect effect in a cross-sectional study should be interpreted as consistency with, not evidence for, the hypothesised causal order. Authors should state explicitly which alternative orderings and common causes their design cannot exclude (Fiedler et al., 2011; Maxwell & Cole, 2007). (3) Where the direction of effects matters, a design with at least three waves should be used. With moderate cross-lagged effects, around 200 employees per wave provided adequate power. (4) Longitudinal analyses should use latent-variable models with multiple indicators at each wave rather than composites. With composites, measurement error in the controlled prior levels inflated false positives to 15 % in large samples. In addition, the usual procedural remedies for common method variance apply (Podsakoff et al., 2003, 2012). Productivity in particular should be measured from a source other than the employee wherever possible, for example through supervisor ratings, output records or system-usage data.

5.3 Practical implications

For managers and HR professionals, the model suggests that developing employees' digital literacy and providing organizational support are complementary investments. Digital literacy programmes should address not only tool operation but also the cognitive and social-emotional dimensions of digital competence (Ng, 2012; Vuorikari et al., 2022), including information evaluation, online collaboration and data security. Because support is increasingly delivered digitally, organisations should check whether their support channels are accessible to employees with lower digital literacy. Digital-only provision of training, HR services or help risks creating a 'support gap' in which the employees who most need support are least able to obtain it. Hybrid delivery, peer mentoring and simple, well-designed self-service interfaces can reduce this risk.

Organisations should also recognise the reciprocal dynamic between support and literacy. Investment in digital training is itself a visible form of organizational support (Kurtessis et al., 2017). It may therefore raise productivity both by building skills and by strengthening employees' sense of being valued, which can set a virtuous cycle in motion. Monitoring both digital literacy and perceived support over time, for example through brief, repeated pulse surveys linked to objective productivity indicators, would allow organisations to evaluate their digital transformation programmes on evidence rather than assumption. Finally, managers should remain alert to the costs of digital work, such as technostress and information overload (Tarafdar et al., 2007), which can offset the productivity benefits of digital literacy if support is lacking.

5.4 Limitations and future research

The principal limitation is that the data are simulated. The population parameters were set a priori, so the study cannot establish that organizational support actually mediates the effect of digital literacy on productivity in any real organisation, or how large the effects are. Its contribution lies in specifying the model, providing an instrument and analytical template, and quantifying the evidential value of alternative research designs. A multi-wave field study with multiple indicators per construct and non-self-reported productivity measures is the natural next step.

Several further limitations concern the model and the simulation design. The model treats organizational support as a single global perception. Distinguishing generic POS from support specific to digital work, such as training, technical help and resources, could sharpen the mechanism. Plausible moderators include age, job type and the organisation's level of digital maturity. Technostress could be modelled as a competing negative pathway. The simulations assumed linear effects, normal latent variables, equal stabilities and lags, and a single common cause, whereas real organisational data may involve heterogeneous lags, non-normality and nesting in teams or units. Finally, the generalisability of the mechanism across sectors and countries with different levels of digital infrastructure remains to be established.

6. Conclusion

This study examined how digital literacy may raise employee productivity and proposed perceived organizational support as a mediating mechanism grounded in conservation of resources, organizational support and job demands–resources theory. Using a 17-item instrument and simulated data for 400 employees, it demonstrated a complete analytical workflow with PLS-SEM, consistent PLS and bootstrapped mediation tests. Under the specified model, the measurement properties were sound and organizational support transmitted about 43 % of the effect of digital literacy on productivity (indirect effect .175, 95 % CI [.131, .223]). Monte Carlo experiments showed that conventional estimators understate the indirect effect by about a fifth, whereas consistent PLS recovers it accurately. More fundamentally, cross-sectional mediation tests 'confirmed' the hypothesised mechanism in virtually every sample even when the true causal order was reversed or when both variables were driven by a common cause. A three-wave design discriminated between these possibilities with about 200 employees per wave, provided that measurement error was handled with latent-variable methods. The study thus offers a theoretically grounded model, a measurement instrument and evidence-based design guidance. For practice, its central message is that digital skills and organizational support work together: organisations should develop both and ensure that their increasingly digital support channels reach all employees. Confirming the mechanism and its direction with longitudinal field data is the essential next step.

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