Tec Empresarial
P-ISSN: 1659-2395; E-ISSN: 1659-3359

Digital Fatigue, Cognitive Overload, and Interface Complexity in Electronic Health Record Systems: The Mediating Role of Technostress and the Moderating Role of Digital Health Literacy on Clinical Decision Agility

Ayinqa Syahira Sudradjat[A], Richelle Kartawinata[B], Oscar Jayanagara[C]

Abstract

Hospital adoption of Electronic Health Record (EHR) systems improves documentation, but it also exposes healthcare professionals to digital fatigue, information overload, and complex interfaces that may strain clinical work. Drawing on Cognitive Load Theory and the Job Demands–Resources model, this study examines whether digital fatigue, cognitive overload, and interface complexity are associated with healthcare professionals' self-perceived clinical decision agility through technostress, and whether digital health literacy buffers these associations. A cross-sectional survey was conducted in hospitals that have implemented EHR systems. Using purposive sampling, data were obtained from 201 healthcare professionals (nurses, physicians, and other clinical staff) who actively use EHRs, and were analysed using PLS-SEM with bootstrapping and Importance-Performance Map Analysis (IPMA). Digital fatigue was strongly and positively associated with technostress, and technostress was negatively associated with clinical decision agility. Digital fatigue showed a significant negative indirect association with clinical decision agility through technostress (β = −0.824) but a significant positive direct association (β = 0.801), yielding a near-zero total effect (−0.023), a pattern consistent with inconsistent (competitive) mediation. Because technostress was almost entirely explained by the predictors (R^2 = 0.953), these opposing coefficients should be interpreted with caution. Cognitive overload and interface complexity were not significantly associated with technostress, and digital health literacy weakened only the digital fatigue–technostress association. The model explained very little variance in clinical decision agility (R^2 = 0.062; Q^2predict = −0.050), indicating that most of its variation arises from factors outside the model. The findings identify technostress as a relevant correlate of perceived decision agility in EHR-intensive work and call for multi-site, longitudinal studies using objective decision outcomes.

Keywords: *Clinical Decision Agility, Digital Fatigue, Digital Health Literacy, Electronic Health Record, Technostress, PLS-SEM.*

[A] *Department of Hospital Administration, Faculty of Economics and Business, Universitas Pelita Harapan, Tangerang, Indonesia, Email: 01615250046@student.uph.edu*
[B] *Department of Hospital Administration, Faculty of Economics and Business, Universitas Pelita Harapan, Tangerang, Indonesia, Email: 01615250025@student.uph.edu*
[C] *Faculty of Economics and Business, Universitas Pelita Harapan, Tangerang, Indonesia, Email: oscar.fe@uph.edu*

INTRODUCTION

The digital transformation of hospitals has accelerated rapidly in recent years through the implementation of electronic health record (EHR) systems, aimed at enhancing service efficiency, patient documentation accuracy, and health information integration. EHR usage enables healthcare professionals to access patient data in real-time, expedites care coordination, and supports data-driven clinical decision-making. However, the intensive use of digital systems in healthcare delivery also imposes significant mental and cognitive strain on healthcare professionals. Continuous EHR use requires them to manage vast amounts of patient information, excessive system notifications, complex digital documentation demands, and system interfaces that are not always intuitive. These conditions give rise to phenomena such as digital fatigue, cognitive overload, and technostress within digitally enabled hospital work environments. Research by Alenazi et al. (2024) indicates that intensive EHR use is associated with increased digital fatigue and a decline in the quality of clinical decision-making among healthcare professionals. Furthermore, Gander et al. (2019) show that demanding work patterns are associated with greater fatigue and reduced alertness among nurses during patient care.

A primary issue arising from hospital digital transformation is the increased cognitive and mental pressure placed on healthcare professionals due to the use of complex digital systems. In clinical practice, healthcare professionals are required to process large volumes of patient information quickly and accurately amidst high time pressures. Krieglstein et al. (2023) explain that high cognitive load can impair information-processing effectiveness and reduce performance on complex tasks. Laker et al. (2018) also emphasise that information overload during clinical decision-making can compromise the quality and efficiency of the resulting decisions. Additionally, the complexity of EHR interfaces may exacerbate the mental strain experienced by users. Azadi and García-Peñalvo (2025) explain that human–computer interaction elements within clinical decision support systems are critical determinants of the effectiveness of digital health systems, and Wang and Hsu (2020) and Faudzi et al. (2024) indicate that complex interface designs increase extraneous cognitive load and impair the user experience. Such conditions may hinder healthcare professionals' ability to make clinical decisions rapidly, accurately, and adaptively a capacity referred to in this study as clinical decision agility.

Beyond cognitive strain and system complexity, the use of digital technology in hospitals also gives rise to technostress among healthcare professionals. Technostress refers to psychological strain resulting from the demands of technology use, system complexity, and the pressure to adapt to a digital work environment (Ragu-Nathan et al., 2008; Tarafdar et al., 2007). Muhamad et al. (2025) found that technostress among hospital healthcare professionals is closely linked to burnout and fatigue stemming from the use of digital technology in healthcare delivery. Conversely, the ability of healthcare professionals to understand and

utilise digital health technologies is a crucial factor in navigating digital transformation. Chung et al. (2025) show that digital literacy and nursing informatics competence act as job resources that are associated with lower burnout and higher work engagement, highlighting digital health literacy as a potentially important resource for professionals working with EHRs.

Prior studies have examined these phenomena largely in separate streams. Studies of fatigue and decision fatigue (Alenazi et al., 2024; Maier et al., 2025; Perry et al., 2025) link exhaustion to poorer clinical decisions; studies of cognitive and information overload (Krieglstein et al., 2023; Laker et al., 2018) show that excessive information hampers information processing; and studies of interface design (Azadi & García-Peñalvo, 2025; Faudzi et al., 2024; Wang & Hsu, 2020) show that design complexity raises users' mental load. Research on technostress in healthcare (Muhamad et al., 2025) and on digital literacy as a job resource (Chung et al., 2025) has developed in parallel.

Despite this growing body of evidence, an important theoretical problem remains unresolved. Existing studies typically treat EHR-related burden as a single, undifferentiated workload and test its direct association with outcomes such as burnout or decision quality. They do not distinguish between burden that depletes the user's cognitive resources over time (digital fatigue), burden that arises from the volume of information to be processed (cognitive overload), and burden imposed by the design of the system itself (interface complexity). From the perspective of Cognitive Load Theory, these sources of load are not equivalent: they act on different parts of the limited working-memory budget and may therefore relate to strain and performance through different routes. In addition, the Job Demands–Resources (JD-R) literature proposes that personal resources can buffer either the link between demands and strain or the link between strain and outcomes (Bakker & Demerouti, 2007), yet it remains unclear at which stage digital health literacy operates in EHR-intensive clinical work. The field therefore lacks evidence on (a) which type of EHR-related load is most closely tied to technostress, (b) whether technostress is the pathway through which these loads relate to clinicians' decision agility, and (c) where in this process digital health literacy exerts a buffering role.

The outcome of interest, clinical decision agility, also requires clarification. In this study, clinical decision agility is defined as a healthcare professional's self-perceived capacity to recognise changes in a patient's clinical situation, retrieve and integrate the relevant information from the EHR, and adjust clinical decisions promptly and appropriately during routine care. The construct differs from several related concepts. *Decision quality* refers to the correctness of a decision judged against an external standard or patient outcome, whereas clinical decision agility concerns the clinician's perceived capacity to respond and adapt. *Decision speed* captures only the temporal dimension, whereas agility combines timeliness with flexibility and appropriateness. *Clinical reasoning* denotes the cognitive process through which clinicians collect

cues, interpret information, and reach a judgement (Levett-Jones et al., 2010); clinical decision agility concerns how readily that process can be adapted when conditions change in a digitally mediated workflow. *Adaptive performance* is a broad job-performance dimension covering adaptation to new tasks, technologies, and situations across work roles (Pulakos et al., 2000); clinical decision agility is narrower, being limited to clinical decisions made with EHR information. Because it is measured through self-report, the construct reflects perceived capability and is not equivalent to objectively verified decision quality or patient-safety outcomes.

Accordingly, this study models digital fatigue, cognitive overload, and interface complexity as distinct EHR-related demands, technostress as the strain mechanism linking these demands to clinical decision agility, and digital health literacy as a personal resource whose buffering role is tested at both the demand–strain and the strain–outcome stages. The study contributes by (1) differentiating three sources of EHR-related load within a single model grounded in Cognitive Load Theory, (2) testing whether these loads relate to perceived clinical decision agility through technostress, and (3) locating the stage at which digital health literacy buffers this process. Understanding these mechanisms is relevant for hospital managers seeking to design EHR workflows and training programmes that support clinicians' decision-making in digitally intensive settings.

LITERATURE REVIEW

Cognitive Load Theory (CLT) holds that working memory has a limited capacity and that performance deteriorates when the total load imposed by a task exceeds this capacity (Sweller, 1988; Sweller et al., 1998). CLT distinguishes intrinsic load, which stems from the inherent complexity of the information to be processed, from extraneous load, which is imposed by the way the information is presented. Applied to EHR use, cognitive overload represents the volume and complexity of clinical information, alerts, and documentation demands that must be processed, while interface complexity represents design-induced extraneous load (Faudzi et al., 2024). Digital fatigue fits CLT from a different angle: rather than adding load to a single task, prolonged and repetitive EHR use depletes the cognitive resources available to handle that load, effectively narrowing the working-memory capacity a clinician can deploy.

CLT explains why these conditions make information processing harder, but it does not by itself explain how sustained load becomes psychological strain or how individual resources protect against it. The study therefore complements CLT with the Job Demands–Resources (JD-R) model (Bakker & Demerouti, 2007; Demerouti et al., 2001) and the technostress creator–inhibitor framework (Ragu-Nathan et al., 2008; Tarafdar et al., 2007). In JD-R terms, digital fatigue, cognitive overload, and interface complexity are job demands or, in technostress terms, technostress creators that require sustained cognitive effort. When such

demands persistently exceed capacity, they set off a health-impairment process in which strain (technostress) develops and is in turn associated with poorer performance (lower clinical decision agility). Digital health literacy is conceptualised as a personal resource and a technostress inhibitor (Chung et al., 2025; Norman & Skinner, 2006). In CLT terms, familiarity with digital health tools allows users to process system information with more automated schemas, lowering the effective extraneous load of a given task; in JD-R terms, such a resource can buffer both the demand–strain and the strain–performance relationships.

Taken together, the three perspectives describe one mechanism: EHR-related demands consume limited cognitive capacity (CLT); persistent overload of this capacity is experienced as technostress (JD-R health-impairment process; technostress creators); technostress is associated with a lower perceived capacity to make agile clinical decisions; and digital health literacy, as a personal resource and technostress inhibitor, is expected to weaken the demand–strain and strain–outcome links. This integrated logic underpins each hypothesis below.

Hypothesis Development

Digital Fatigue and Technostress

Digital fatigue describes a state of mental and physical exhaustion resulting from continuous, intensive use of digital technology, including EHR systems in clinical practice. In CLT terms, fatigue reduces the cognitive capacity available for coping with system demands; in JD-R terms, it is a demand that depletes the energy needed to manage technology use, making strain more likely. In the healthcare context, professionals experiencing digital fatigue tend to perceive higher pressure when using EHRs (Gander et al., 2019; Muhamad et al., 2025). Therefore:
H1: Digital fatigue is positively associated with technostress.

Cognitive Overload and Technostress

Cognitive overload occurs when the volume and complexity of information exceed an individual's processing capacity. Within EHR systems, excessive clinical information, alerts, and the need for rapid processing raise intrinsic and extraneous load. When users repeatedly struggle to comprehend and respond to these demands, overload is expected to be experienced as technostress (Krieglstein et al., 2023; Laker et al., 2018; Tarafdar et al., 2007). Therefore:
H2: Cognitive overload is positively associated with technostress.

Interface Complexity and Technostress

Interface complexity refers to the intricacy of the visual layout, navigation, and information organisation within a digital system. Non-intuitive navigation and poorly organised information impose extraneous load, diverting attention from clinical content to system operation and acting as a technostress creator. Previous research indicates that interface design complexity increases extraneous cognitive load and

diminishes the user experience (Faudzi et al., 2024; Wang & Hsu, 2020). Therefore:
H3: Interface complexity is positively associated with technostress.

Digital Fatigue and Clinical Decision Agility

Because fatigue narrows the cognitive capacity available for evaluating clinical information, it is expected to reduce clinicians' perceived ability to respond quickly and flexibly to changing patient situations. Digital fatigue and decision fatigue have been associated with reduced quality of clinical decision-making among healthcare professionals (Alenazi et al., 2024; Maier et al., 2025). Therefore:
H4: Digital fatigue is negatively associated with clinical decision agility.

Interface Complexity and Clinical Decision Agility

A simple and intuitive interface helps healthcare professionals obtain clinical information quickly, whereas a complex EHR interface adds extraneous load that can slow access to critical information and reduce decision effectiveness. Clinical decision support systems that incorporate human–computer interaction principles have been linked to better usability and decision support (Azadi & García-Peñalvo, 2025; Wang & Hsu, 2020). Therefore:
H5: Interface complexity is negatively associated with clinical decision agility.

Technostress and Clinical Decision Agility

Under the JD-R health-impairment process, strain undermines performance. Technology-related stress can reduce focus, work efficiency, and information-processing capacity, making it harder for professionals to evaluate and respond to clinical information promptly. Technology-induced stress has been linked to burnout and poorer clinical work (Abu Arra et al., 2023; Muhamad et al., 2025). Therefore:
H6: Technostress is negatively associated with clinical decision agility.

The Mediating Role of Technostress

The integrated framework implies that EHR-related demands relate to clinical decision agility partly through the strain they generate. Digital fatigue is expected to increase technostress, which in turn is associated with lower decision agility (Gander et al., 2019; Muhamad et al., 2025). The same logic applies to cognitive overload, whose information demands may be experienced as strain that hampers the evaluation of clinical information (Krieglstein et al., 2023; Laker et al., 2018), and to interface complexity, whose design-induced load may generate strain that disrupts attention to clinical content (Azadi & García-Peñalvo, 2025; Faudzi et al., 2024). Therefore:
H7: Technostress mediates the negative association between digital fatigue and clinical decision agility.
H8: Technostress mediates the negative association between cognitive overload and clinical decision agility.

H9: Technostress mediates the negative association between interface complexity and clinical decision agility.

For consistency with the mediation analysis, the direct path from cognitive overload to clinical decision agility was also estimated, but it was not formally hypothesised.

The Moderating Role of Digital Health Literacy at the Demand–Strain Stage

Digital health literacy enables healthcare professionals to locate, understand, evaluate, and use digital health information effectively (Norman & Skinner, 2006). As a personal resource, it is expected to reduce the extent to which EHR demands translate into strain: literate users can filter relevant information, operate system functions with more automated routines, and adapt more quickly to system changes, thereby lowering the effective load of fatigue, information volume, and interface complexity (Chung et al., 2025; Faudzi et al., 2024). Therefore:

H10: Digital health literacy weakens the positive association between digital fatigue and technostress.

H11: Digital health literacy weakens the positive association between cognitive overload and technostress.

H12: Digital health literacy weakens the positive association between interface complexity and technostress.

The Moderating Role of Digital Health Literacy at the Demand/Strain–Outcome Stage

JD-R also allows resources to buffer the link between demands or strain and performance. Professionals with higher digital health literacy may maintain their perceived decision agility despite fatigue, technostress, or a complex interface because they can still retrieve and use the information needed for clinical decisions (Alenazi et al., 2024; Azadi & García-Peñalvo, 2025; Chung et al., 2025; Muhamad et al., 2025). Therefore:

H13: Digital health literacy weakens the negative association between digital fatigue and clinical decision agility.

H14: Digital health literacy weakens the negative association between technostress and clinical decision agility.

H15: Digital health literacy weakens the negative association between interface complexity and clinical decision agility.

Conceptual Framework

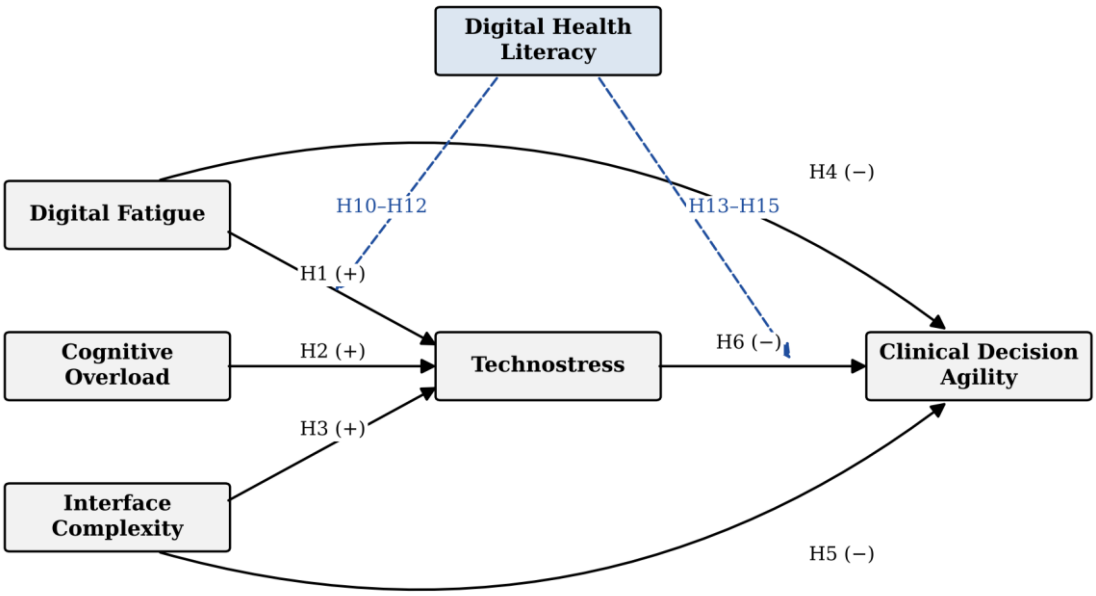


Figure 1. Research Framework

Figure 1 summarises the model. Digital fatigue, cognitive overload, and interface complexity are modelled as EHR-related demands (technostress creators) that are expected to be positively associated with technostress (H1–H3) and negatively associated with clinical decision agility directly (H4–H5) and indirectly through technostress (H7–H9). Technostress is expected to be negatively associated with clinical decision agility (H6). Digital health literacy is modelled as a personal resource (technostress inhibitor) that is expected to weaken the demand–strain links (H10–H12) and the demand/strain–outcome links (H13–H15). Its main effects on technostress and clinical decision agility were included in the estimated model so that each interaction term was tested together with its constituent main effects.

METHOD

Research Design and Setting

This study used a quantitative, cross-sectional, explanatory survey design. The study was conducted in hospitals and healthcare facilities that have implemented EHR systems in their daily clinical services, so that all respondents worked with an operational EHR when the data were collected. Data were collected over a period of approximately one to two weeks using a structured questionnaire.

Population, Sampling, and Participants

The target population comprised healthcare professionals physicians, nurses, and other clinical staff who use the EHR in their daily clinical work. Participants were selected through purposive (non-probability) sampling. The inclusion criteria were: (a) working as a clinical healthcare professional and (b) actively using the EHR system in daily

clinical documentation and patient care and patient care. The questionnaire was distributed to healthcare professionals meeting these criteria, and a total of 201 responses were analysed. An a priori power analysis (G*Power; $f^2 = 0.15$, $\alpha = 0.05$, power = 0.80, eight predictors of clinical decision agility) indicated a minimum of approximately 109 respondents, so the final sample was adequate for the structural model. Because purposive sampling was used, the findings are not intended to be statistically generalised to all healthcare professionals, but inferential tests are used to assess whether the observed relationships are distinguishable from sampling variability.

Ethical Considerations

Participation in the study was voluntary. Before completing the questionnaire, respondents were informed of the purpose of the study, that their participation was voluntary, and that they could stop at any time without consequence; completing and submitting the questionnaire was treated as informed consent. The questionnaire did not ask for names, employee numbers, or other direct identifiers, and the names of the participating hospitals are not reported. The data were used solely for research purposes, accessed only by the research team, and are reported in aggregate form.

Measures

All constructs were measured with items adapted from prior studies and contextualised to EHR use by healthcare professionals (Table 1). Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores on digital fatigue, cognitive overload, interface complexity, and technostress indicate greater burden, whereas higher scores on digital health literacy and clinical decision agility indicate more favourable levels.

Clinical decision agility was operationalised as the clinician's self-perceived capacity to recognise changing clinical situations, retrieve and integrate EHR information, and adjust decisions promptly and appropriately. The items therefore capture the perceived speed, flexibility, and appropriateness of clinical decisions made with EHR information. Because the measure is self-reported, it reflects perceived capability rather than objectively verified decision quality.

During measurement-model assessment, five items (CDA2, CO1, DHL5, IC5, and IC6) were removed because they did not meet the outer-loading criterion of 0.70. Each construct retained at least three items (cognitive overload) and up to seven items (technostress), all with loadings above 0.70, so each construct continues to be represented by multiple indicators of the same content domain.

Table 1. Measurement Instruments: Conceptual Basis and Item Status

Construct	Operational definition	Conceptual basis	Initial items	Retained items	Removed
Digital fatigue (DF)	Mental and physical exhaustion from continuous EHR use	Alenazi et al. (2024); Gander et al. (2019)	6	DF1–DF6 (6)	–
Cognitive overload (CO)	Information volume and processing demands exceeding capacity	Krieglstein et al. (2023); Laker et al. (2018)	4	CO2–CO4 (3)	CO1
Interface complexity (IC)	Complexity of EHR layout, navigation, and information structure	Faudzi et al. (2024); Wang & Hsu (2020)	7	IC1–IC4, IC7 (5)	IC5, IC6
Technostress (TS)	Psychological strain associated with EHR-related technology demands	Muhamad et al. (2025); Tarafdar et al. (2007)	7	TS1–TS7 (7)	–
Digital health literacy (DHL)	Ability to access, understand, evaluate, and use digital health information and systems	Chung et al. (2025); Norman & Skinner (2006)	7	DHL1–DHL4, DHL6–DHL7 (6)	DHL5
Clinical decision agility (CDA)	Self-perceived capacity to make prompt, flexible, and appropriate clinical decisions using EHR information	Abu Arra et al. (2023); Laker et al. (2018)	7	CDA1, CDA3–CDA7 (6)	CDA2

Note: All items used a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Removed items had outer loadings below 0.70.

Data Analysis

Data were analysed with partial least squares structural equation modelling (PLS-SEM) in SmartPLS. PLS-SEM was chosen because the model contains several latent constructs, mediation and moderation paths, and a prediction-oriented objective (Hair et al., 2019, 2021). The measurement model was assessed through outer loadings (≥ 0.70), Cronbach's alpha and composite reliability (≥ 0.70), average variance extracted (AVE ≥ 0.50), and indicator-level collinearity (VIF < 5). Because several constructs describe closely related forms of digital and psychological burden, their empirical distinctiveness was also examined through the structural results, in particular the shared variance between digital fatigue and technostress and the resulting construct-level collinearity (Henseler et al., 2015).

The structural model was assessed through construct-level collinearity, R^2, f^2, and out-of-sample predictive power using PLSpredict (Q^2predict, RMSE, and MAE; Shmueli et al., 2019). Inference was based on the bootstrapping procedure in SmartPLS using two-tailed tests at α

= 0.05; standard errors and 95% confidence intervals are reported for all hypothesised effects. Mediation was assessed through the significance of indirect effects and classified following Zhao et al. (2010). Interaction terms were created with the two-stage approach (Becker et al., 2018), with all constituent main effects (including the main effects of digital health literacy on technostress and clinical decision agility) included in the model, and the significant interaction was probed with simple-slope analysis at ±1 SD of digital health literacy. Finally, an Importance-Performance Map Analysis (IPMA) was performed for clinical decision agility (Ringle & Sarstedt, 2016).

RESULT AND DISCUSSION

Respondent Profile

The final sample consisted of 201 healthcare professionals nurses, physicians, and other clinical staff who actively used the EHR in their daily clinical work and met the inclusion criteria described above. All respondents used the EHR in their clinical work, which is the context to which the measurement items refer.

Measurement Model

Table 2. Outer Loadings

Indicator	Construct	Outer loading
CDA1	Clinical Decision Agility	0.745
CDA3	Clinical Decision Agility	0.769
CDA4	Clinical Decision Agility	0.704
CDA5	Clinical Decision Agility	0.741
CDA6	Clinical Decision Agility	0.826
CDA7	Clinical Decision Agility	0.752
CO2	Cognitive Overload	0.926
CO3	Cognitive Overload	0.814
CO4	Cognitive Overload	0.863
DF1	Digital Fatigue	0.807
DF2	Digital Fatigue	0.865
DF3	Digital Fatigue	0.864
DF4	Digital Fatigue	0.892
DF5	Digital Fatigue	0.860
DF6	Digital Fatigue	0.840
DHL1	Digital Health Literacy	0.841
DHL2	Digital Health Literacy	0.875
DHL3	Digital Health Literacy	0.903
DHL4	Digital Health Literacy	0.837
DHL6	Digital Health Literacy	0.844
DHL7	Digital Health Literacy	0.813
IC1	Interface Complexity	0.828
IC2	Interface Complexity	0.851

Indicator	Construct	Outer loading
IC3	Interface Complexity	0.747
IC4	Interface Complexity	0.826
IC7	Interface Complexity	0.749
TS1	Technostress	0.779
TS2	Technostress	0.890
TS3	Technostress	0.857
TS4	Technostress	0.892
TS5	Technostress	0.824
TS6	Technostress	0.844
TS7	Technostress	0.839
DHL × CO	Interaction term	1.000
DHL × DF	Interaction term	1.000
DHL × IC	Interaction term	1.000

All retained indicators have outer loadings above 0.70, ranging from 0.704 to 0.926, supporting indicator reliability. The interaction terms have loadings of 1.000 because they are single-indicator constructs created in the two-stage procedure.

Table 3. Reliability and Convergent Validity

Construct	Cronbach's alpha	rho_a	rho_c	AVE
Clinical Decision Agility	0.859	0.875	0.889	0.573
Cognitive Overload	0.846	0.972	0.902	0.755
Digital Fatigue	0.926	0.928	0.942	0.731
Digital Health Literacy	0.929	0.987	0.941	0.727
Interface Complexity	0.863	0.893	0.900	0.642
Technostress	0.934	0.936	0.947	0.718

Cronbach's alpha ranges from 0.846 to 0.934, composite reliability (rho_c) from 0.889 to 0.947, and AVE from 0.573 to 0.755, all above the recommended thresholds. The rho_a values for cognitive overload (0.972) and digital health literacy (0.987) exceed 0.95, which may indicate partly redundant item wording within these scales; this is noted as a measurement limitation.

Table 4. Indicator-Level Collinearity (Outer VIF)

Indicator	VIF	Indicator	VIF
CDA1	1.574	DHL4	3.771
CDA3	2.112	DHL6	4.035
CDA4	1.907	DHL7	2.549
CDA5	1.964	IC1	1.968
CDA6	2.084	IC2	2.216
CDA7	1.516	IC3	1.793
CO2	2.072	IC4	1.966
CO3	1.924	IC7	1.821
CO4	2.121	TS1	2.069

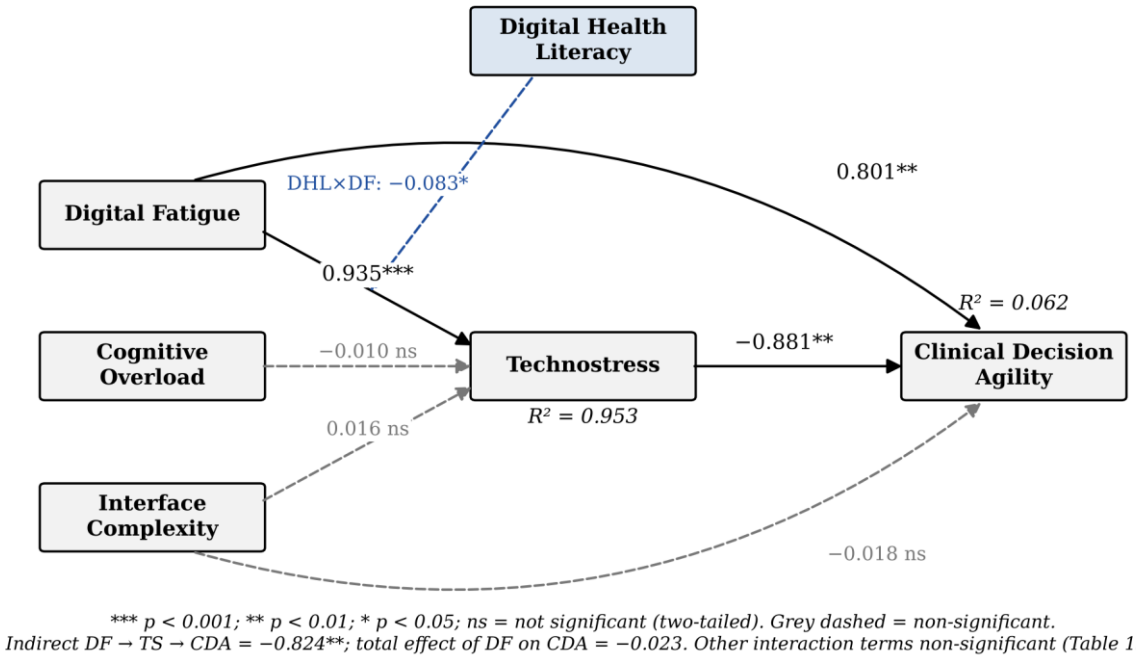
Indicator	VIF	Indicator	VIF
DF1	2.131	TS2	3.662
DF2	2.915	TS3	2.783
DF3	2.779	TS4	3.591
DF4	3.459	TS5	2.373
DF5	2.701	TS6	2.821
DF6	2.490	TS7	2.834
DHL1	2.229	DHL × CO	1.000
DHL2	2.404	DHL × DF	1.000
DHL3	3.701	DHL × IC	1.000

Indicator-level VIF values range from 1.516 to 4.035, below the threshold of 5, so collinearity among indicators of the same construct is not a concern. Collinearity between constructs is assessed separately in the structural model below.

Empirical Distinctiveness of the Constructs

Outer loadings, reliability, and AVE show that each construct is measured reliably, but they do not by themselves show that the constructs are empirically distinct. The structural results indicate that this is a concern for one pair of constructs. Digital fatigue and technostress share most of their variance: the predictors explain 95.3% of the variance in technostress, the f^2 of digital fatigue on technostress is 13.506, and the implied construct-level VIF of technostress in the clinical decision agility equation is about 21.3 (see below). These values suggest that, in this sample, the digital fatigue and technostress scales capture a largely common experience of EHR-related exhaustion and strain. The other constructs cognitive overload, interface complexity, digital health literacy, and clinical decision agility show only weak structural associations with each other ($f^2 \leq 0.039$ except for the DHL × DF interaction), which does not suggest redundancy among them. Findings involving the separate roles of digital fatigue and technostress are therefore interpreted as tentative throughout the remainder of the paper.

Structural Model



*** p < 0.001; ** p < 0.01; * p < 0.05; ns = not significant (two-tailed). Grey dashed = non-significant.
Indirect DF → TS → CDA = −0.824**; total effect of DF on CDA = −0.023. Other interaction terms non-significant (Table 15).

Figure 2. Structural Model Results

Figure 2 summarises the estimated structural model, including the path coefficients and the variance explained in the endogenous constructs.

Collinearity

Because technostress and clinical decision agility are explained by the same set of remaining predictors, the R^2 of technostress (0.953) implies a construct-level VIF of approximately $1/(1 - 0.953) \approx 21.3$ for technostress in the clinical decision agility equation, far above the threshold of 5. Digital fatigue is likewise expected to show a high VIF in that equation. This severe collinearity means that the separate direct coefficients of digital fatigue and technostress on clinical decision agility are estimated with low precision and must be interpreted with caution.

Table 5. Coefficient of Determination (R^2)

Construct	R^2	R^2 adjusted
Clinical Decision Agility	0.062	0.023
Technostress	0.953	0.951

The predictors explain 95.3% of the variance in technostress. This value is unusually high for behavioural research and, together with the very large f^2 of digital fatigue (13.506), suggests that digital fatigue and technostress share most of their variance; based on the f^2 formula, the remaining predictors jointly account for about 31.8% of the variance in technostress when digital fatigue is omitted. The result may reflect conceptual overlap between the two scales, common method variance, or both, and is examined further in the Discussion. In contrast, the model

explains only 6.2% of the variance in clinical decision agility (adjusted R^2 = 0.023), indicating weak explanatory power: almost all variation in perceived decision agility is attributable to factors not included in the model.

Table 6. Effect Size (f^2)

Path	f^2
Cognitive Overload → Clinical Decision Agility	0.017
Cognitive Overload → Technostress	0.002
Digital Fatigue → Clinical Decision Agility	0.034
Digital Fatigue → Technostress	13.506
Digital Health Literacy → Clinical Decision Agility	0.000
Digital Health Literacy → Technostress	0.000
DHL × Cognitive Overload → Clinical Decision Agility	0.007
DHL × Cognitive Overload → Technostress	0.000
DHL × Digital Fatigue → Clinical Decision Agility	0.007
DHL × Digital Fatigue → Technostress	0.107
DHL × Interface Complexity → Clinical Decision Agility	0.001
DHL × Interface Complexity → Technostress	0.000
Interface Complexity → Clinical Decision Agility	0.000
Interface Complexity → Technostress	0.005
Technostress → Clinical Decision Agility	0.039

The f^2 of digital fatigue on technostress (13.506) is exceptionally large and far exceeds conventional benchmarks (0.02, 0.15, 0.35). The interaction DHL × DF → technostress has a small-to-medium effect (0.107). All other effects are negligible to small (0.000–0.039), including all predictors of clinical decision agility.

Table 7. Out-of-Sample Predictive Power (PLSpredict)

Construct	Q^2predict	RMSE	MAE
Technostress	0.947	0.236	0.159
Clinical Decision Agility	−0.050	1.035	0.808

Technostress shows high predictive relevance (Q^2predict = 0.947), consistent with its high R^2. For clinical decision agility, Q^2predict is negative (−0.050), meaning that the model predicts new cases less accurately than a naive benchmark based on the training-sample mean. The model therefore has no out-of-sample predictive power for clinical decision agility, and statements about explaining or improving clinical decision agility are made with corresponding caution.

Hypothesis Testing

Tables 8–11 report the direct, indirect, total, and interaction effects separately. All p-values are two-tailed. Standard errors were derived from

the bootstrapping results as |β|/t, and 95% confidence intervals were computed as β ± 1.96 × SE.

Table 8. Direct Effects

Hypothesis	Path	β	SE	t	p	95% CI	Decision
H1 (+)	DF → TS	0.935	0.026	36.070	< 0.001	[0.884; 0.986]	Supported
H2 (+)	CO → TS	−0.010	0.017	0.597	0.550	[−0.043; 0.023]	Not supported
H3 (+)	IC → TS	0.016	0.017	0.921	0.357	[−0.018; 0.050]	Not supported
H4 (−)	DF → CDA	0.801	0.278	2.886	0.004	[0.257; 1.345]	Not supported (significant, opposite sign)
H5 (−)	IC → CDA	−0.018	0.108	0.167	0.868	[−0.229; 0.193]	Not supported
H6 (−)	TS → CDA	−0.881	0.289	3.051	0.002	[−1.447; −0.315]	Supported

Note: (+)/(−) = hypothesised direction. SE = |β|/t; 95% CI = β ± 1.96 × SE. Standardised coefficients above 1 in the confidence interval of H4 reflect the strong collinearity between DF and TS. CDA = clinical decision agility; CO = cognitive overload; DF = digital fatigue; DHL = digital health literacy; IC = interface complexity; TS = technostress.

Table 9. Indirect (Mediation) Effects

Hypothesis	Path	β	SE	t	p	95% CI	Decision
H7	DF → TS → CDA	−0.824	0.273	3.021	0.003	[−1.359; −0.289]	Supported (competitive mediation)
H8	CO → TS → CDA	0.009	0.017	0.539	0.590	[−0.024; 0.042]	Not supported
H9	IC → TS → CDA	−0.014	0.017	0.832	0.406	[−0.047; 0.019]	Not supported

Note: SE = |β|/t; 95% CI = β ± 1.96 × SE.

Table 10. Total Effects on Clinical Decision Agility

Predictor	Direct effect	Indirect effect via TS	Total effect	Pattern
Digital Fatigue	0.801	−0.824	−0.023	Opposing direct and indirect effects (competitive mediation)
Interface Complexity	−0.018	−0.014	−0.032	No mediation; negligible total effect
Cognitive Overload	0.133	0.009	0.142	No mediation; small total effect
Technostress	−0.881	–	−0.881	Direct effect only

Note: Total effects equal direct plus indirect effects and correspond to the importance values in the IPMA. The direct effect of cognitive overload (a non-hypothesised path) is obtained as the IPMA total effect minus its indirect effect.

Table 11. Interaction (Moderation) Effects

Hypothesis	Interaction path	β	SE	t	p	95% CI	Decision
H10	DHL × DF → TS	−0.083	0.037	2.245	0.025	[−0.155; −0.011]	Supported
H11	DHL × CO → TS	0.003	0.017	0.180	0.857	[−0.030; 0.036]	Not supported
H12	DHL × IC → TS	−0.003	0.017	0.174	0.861	[−0.037; 0.031]	Not supported
H13	DHL × DF → CDA	−0.102	0.084	1.218	0.223	[−0.266; 0.062]	Not supported
H14	DHL × TS → CDA	–	–	–	–	–	Not tested (term not in estimated model)
H15	DHL × IC → CDA	−0.037	0.077	0.480	0.631	[−0.188; 0.114]	Not supported

Note: SE = |β|/t; 95% CI = β ± 1.96 × SE. All interaction terms were estimated together with their constituent main effects.

Interpretation of Direct Effects

Digital fatigue is strongly and positively associated with technostress (H1: β = 0.935, p < 0.001), supporting H1. Cognitive overload (H2: β = −0.010, p = 0.550) and interface complexity (H3: β = 0.016, p = 0.357) are not significantly associated with technostress, so H2 and H3 are not supported. Technostress is negatively associated with clinical decision agility (H6: β = −0.881, p = 0.002), supporting H6. Interface complexity is not significantly associated with clinical decision agility (H5: β = −0.018, p = 0.868). Digital fatigue has a significant direct association with clinical decision agility (β = 0.801, p = 0.004), but in the positive direction, opposite to the negative association hypothesised; H4 is therefore not supported.

Interpretation of Indirect and Total Effects

The indirect association of digital fatigue with clinical decision agility through technostress is negative and significant (H7: β = −0.824, p = 0.003), supporting H7. Because the direct association is positive and significant while the indirect association is negative and significant, the pattern corresponds to competitive (inconsistent) mediation (Zhao et al., 2010), also described as a suppression effect (MacKinnon et al., 2000). The two components nearly cancel each other, producing a total effect of only −0.023. In substantive terms, there is no evidence that digital fatigue, considered as a whole, is associated with clinical decision agility; the positive direct coefficient appears only when technostress is held constant. Given the severe collinearity between digital fatigue and technostress in the clinical decision agility equation (implied VIF ≈ 21.3) and the large standard errors of both coefficients (≈ 0.28–0.29), the opposing direct and indirect coefficients may be partly a statistical artefact rather than two distinct substantive processes. Technostress does not mediate the associations of cognitive overload (H8: β = 0.009, p

= 0.590) or interface complexity (H9: β = −0.014, p = 0.406) with clinical decision agility.

Interpretation of Moderation Effects

Digital health literacy significantly weakens the positive association between digital fatigue and technostress (H10: β = −0.083, p = 0.025; f^2 = 0.107), supporting H10. Simple-slope analysis (Figure 3) shows that the standardised slope of digital fatigue on technostress is 1.018 at low digital health literacy (−1 SD), 0.935 at the mean, and 0.852 at high digital health literacy (+1 SD). The association therefore remains very strong at all levels of literacy but is somewhat weaker among professionals with higher literacy. A standardised slope above 1 at low literacy is a further sign of the near-redundancy between digital fatigue and technostress. Digital health literacy does not moderate the associations of cognitive overload (H11: β = 0.003, p = 0.857) or interface complexity (H12: β = −0.003, p = 0.861) with technostress, nor the associations of digital fatigue (H13: β = −0.102, p = 0.223) or interface complexity (H15: β = −0.037, p = 0.631) with clinical decision agility.

Regarding H14, the originally estimated model did not contain a DHL × technostress interaction term: the three interaction terms specified were DHL × DF, DHL × CO, and DHL × IC, each linked to both technostress and clinical decision agility (Table 6). The coefficient previously reported under H14 therefore did not correspond to the hypothesised interaction and has been withdrawn. Because the DHL × TS term was not part of the estimated model, H14 could not be evaluated in this study; it is retained as a proposition for future research.

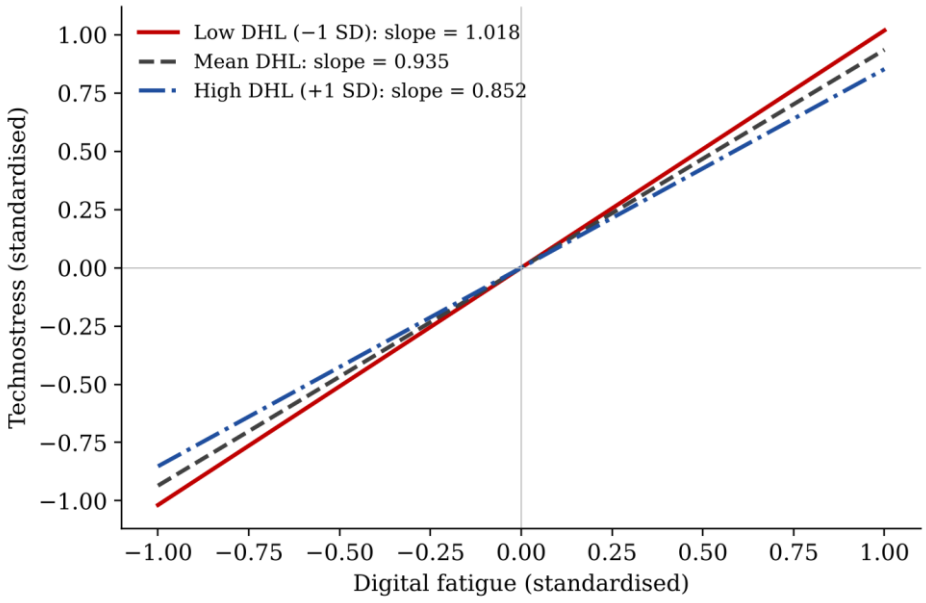


Figure 3. Simple-Slope Plot: Moderating Effect of Digital Health Literacy on the Digital Fatigue–Technostress Association

Importance-Performance Map Analysis

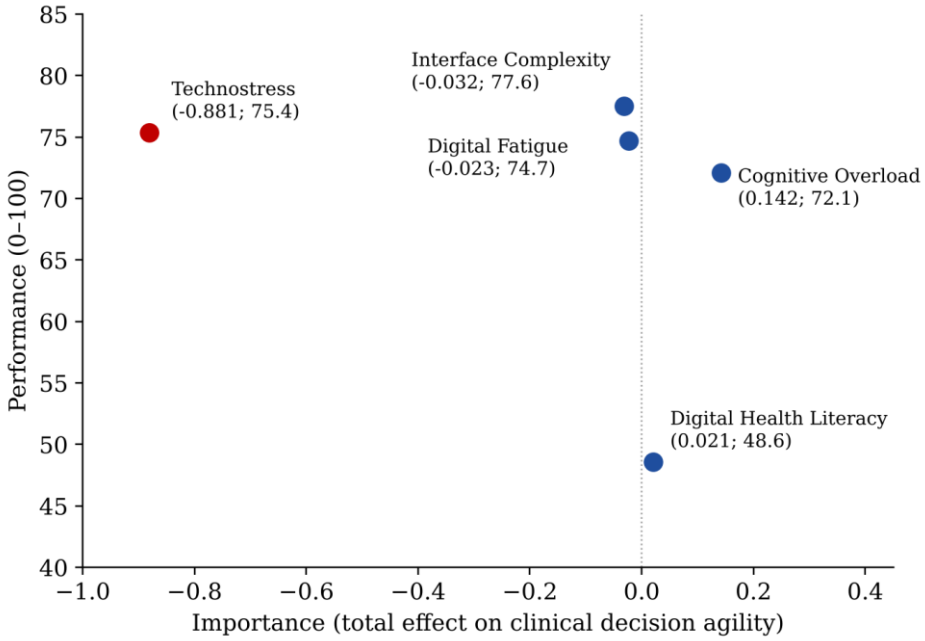


Figure 4. IPMA Map for Clinical Decision Agility

In the IPMA, importance is the unstandardised total effect of each construct on clinical decision agility, and performance is the construct's mean latent score rescaled to 0–100 using the formula (score − scale minimum) / (scale maximum − scale minimum) × 100 (Ringle & Sarstedt, 2016). Because the IPMA rescales scores in the original scale direction, a high performance value means a high level of the construct. For desirable constructs (digital health literacy) a high value is favourable, but for undesirable constructs (technostress, digital fatigue, cognitive overload, and interface complexity) a high value indicates a high level of burden and is unfavourable (Table 12).

Table 12. IPMA Results for Clinical Decision Agility

Construct	Importance (total effect)	Performance (0–100)	Approx. mean (1–5)	Meaning of a high performance value
Technostress	−0.881	75.379	≈ 4.0	High technostress (unfavourable)
Cognitive Overload	0.142	72.108	≈ 3.9	High overload (unfavourable)
Digital Health Literacy	0.021	48.588	≈ 2.9	High literacy (favourable)
Digital Fatigue	−0.023	74.732	≈ 4.0	High fatigue (unfavourable)
Interface Complexity	−0.032	77.553	≈ 4.1	High complexity (unfavourable)

Note: Approximate means were back-calculated from the performance values as 1 + 4 × (performance / 100) and are shown for interpretation only.

Technostress has the largest absolute importance (−0.881): within the model, a one-point reduction in technostress is associated with the largest increase in perceived clinical decision agility. Its performance of 75.379 does not indicate good performance; it shows that respondents reported a relatively high level of technostress. Technostress is therefore both strongly related to the outcome and present at a high level, which places it as the most relevant construct to monitor within this model. Digital fatigue and interface complexity have high performance values, meaning respondents reported high fatigue and high perceived complexity, but their total effects on clinical decision agility are close to zero (−0.023 and −0.032), reflecting offsetting direct and indirect effects. Digital health literacy shows the lowest performance (48.588), indicating only moderate literacy, and a very small importance (0.021). These priorities must be read cautiously, because the model explains only 6.2% of the variance in clinical decision agility and the importance of technostress is affected by its collinearity with digital fatigue.

Discussion

The strongest finding is the very close association between digital fatigue and technostress ($\beta = 0.935$; $R^2 = 0.953$). This is consistent with the view that resource depletion from intensive EHR use is closely tied to technology-related strain (Muhamad et al., 2025) and with evidence that sustained work demands accumulate as fatigue (Gander et al., 2019). However, the magnitude is far above what is usually observed between distinct behavioural constructs. Three explanations are possible and cannot be separated with the present data: the two scales may capture largely the same experience of EHR-related exhaustion and strain; common method variance from single-source, single-time self-report may have inflated the association; or both. The implied construct-level VIF of about 21.3 between the two constructs supports the interpretation that they overlap empirically. The finding is therefore best interpreted as showing that, in this sample, digital fatigue and technostress form a closely intertwined strain experience, rather than as a precise estimate of a causal effect.

Cognitive overload and interface complexity were not significantly associated with technostress or, through technostress, with clinical decision agility. Several explanations are possible, none of which was measured directly. First, respondents may have adapted to the complexity and information load of their EHR, so that these demands are no longer experienced as stressful. Second, because digital fatigue shares almost all of its variance with technostress, cognitive overload and interface complexity may relate to technostress mainly through variance they share with digital fatigue, leaving little unique effect. Third, the scales may not have been sufficiently contextualised to the specific EHR in use, or the variation in perceived complexity may have been limited because respondents worked with the same or similar EHR systems. Fourth, the relationships may differ across EHR platforms and professional groups, which could not be examined here. These

explanations are offered as possibilities for future research, not as findings of this study.

Technostress was negatively associated with perceived clinical decision agility, in line with the JD-R health-impairment process and with studies linking fatigue and strain to poorer clinical decision-making (Maier et al., 2025; Perry et al., 2025; Abu Arra et al., 2023). The positive direct coefficient of digital fatigue requires careful interpretation. Statistically, it represents the association between clinical decision agility and the small part of digital fatigue that is not shared with technostress. One possible substantive reading is that, once strain is held constant, reported digital fatigue partly reflects the intensity of a clinician's involvement with the EHR, which may coincide with greater exposure to clinical decisions. Equally plausible, however, is a suppression artefact produced by the severe collinearity between digital fatigue and technostress. The near-zero total effect (−0.023) indicates that, overall, digital fatigue is not associated with clinical decision agility in this sample. The present design does not allow a choice between these interpretations, and the opposing coefficients should not be read as evidence that fatigue improves decision-making.

Digital health literacy weakened the digital fatigue–technostress association but did not moderate any other path. This pattern is consistent with the JD-R proposition that personal resources buffer the demand–strain link (Bakker & Demerouti, 2007) and with Chung et al. (2025), who describe digital literacy as a job resource. Theoretically, it suggests that literacy operates at the demand–strain stage rather than at the strain–outcome stage. The buffering effect was modest ($f^2 = 0.107$), and the slope of fatigue on technostress remained very strong even at high literacy (0.852). Literacy did not buffer the associations of cognitive overload or interface complexity, suggesting that literacy alone is unlikely to offset information- or design-related demands.

The weak explanatory and predictive performance for clinical decision agility ($R^2 = 0.062$; $Q^2predict = −0.050$) is an important result in itself. It indicates that EHR-related demands and technostress account for very little of the variation in clinicians' perceived decision agility. Clinically relevant factors outside the model are likely to be more important, including professional experience, workload and staffing levels, task urgency, the availability of decision support, EHR usability, organisational support, and decision authority. In addition, self-rated decision agility may be subject to ceiling effects and self-enhancement, which restrict variance and weaken observed associations. Consequently, the findings do not support claims that managing the modelled variables would substantially improve clinical decision agility.

Theoretical Implications

The study contributes to the literature in three ways. First, by separating three sources of EHR-related load, it shows that resource depletion (digital fatigue) is far more closely tied to technostress than information volume (cognitive overload) or design-induced load (interface

complexity), refining the application of Cognitive Load Theory to EHR work. Second, it locates the buffering role of digital health literacy at the demand–strain stage of the JD-R process, specifically for fatigue. Third, it shows that the direct and strain-mediated associations of digital fatigue with decision agility can run in opposite directions, highlighting the need to report total effects and test for suppression when demand and strain constructs are highly correlated.

Practical Implications

Because the data are cross-sectional and the model explains little variance in clinical decision agility, practical implications are tentative. Hospital managers may consider monitoring EHR-related fatigue and technostress, for example through periodic staff surveys, and reviewing documentation burden and workflow design where fatigue is high. Training that strengthens digital health literacy may help to reduce the extent to which fatigue is experienced as technostress, although the effect observed was modest. Interventions aimed at clinical decision agility should also address factors outside this model, such as staffing, experience, and decision support. The effectiveness of any such intervention needs to be tested in intervention or longitudinal studies.

Limitations

Several limitations should be noted. First, the cross-sectional design does not allow causal inference; reverse causality is possible (for example, lower perceived decision agility may increase technostress). Second, all variables were self-reported by the same respondents at one time point, so common method variance, self-perception bias, and social-desirability bias may have influenced the results, particularly the very strong DF–TS association. Third, clinical decision agility was measured as perceived capability; actual decision quality, speed, and patient-safety outcomes were not verified. Fourth, the sample was obtained through purposive sampling of professionals using EHR systems in a limited number of settings, which limits generalisability to other hospitals and EHR platforms. Fifth, digital fatigue and technostress overlapped strongly, and the high rho_a values for cognitive overload and digital health literacy suggest some item redundancy. Sixth, professional groups may experience EHR demands differently; a detailed demographic breakdown and subgroup analysis by profession were not part of the present analysis and should be addressed in future studies. Finally, common method bias was addressed only through the design and the interpretation of results rather than through a statistical test, so its influence cannot be ruled out.

CONCLUSION

This study examined how three EHR-related demands relate to healthcare professionals' perceived clinical decision agility through technostress and how digital health literacy conditions these relationships. Digital fatigue was very strongly associated with

technostress, and technostress was negatively associated with perceived clinical decision agility. Digital fatigue showed opposing direct (positive) and indirect (negative) associations with clinical decision agility that almost cancelled out, a competitive-mediation pattern that should be interpreted cautiously because of the strong overlap between digital fatigue and technostress. Cognitive overload and interface complexity were not significantly associated with technostress, and digital health literacy weakened only the association between digital fatigue and technostress. Because the model explained very little of the variance in clinical decision agility and had no out-of-sample predictive power for it, technostress should be regarded as one relevant correlate of perceived decision agility rather than its main determinant.

For hospital management, the results suggest monitoring EHR-related fatigue and technostress and strengthening digital health literacy as supportive measures, while recognising that clinical decision agility depends largely on factors beyond those modelled here. Future research should use multi-site samples covering different EHR platforms and professional groups, refine the measurement of digital fatigue and technostress to improve discriminant validity, include variables such as workload, staffing, experience, decision support, EHR usability, organisational support, and decision authority, combine self-reports with objective or observer-rated decision outcomes, and adopt longitudinal or intervention designs to examine causal ordering.

DECLARATIONS

Ethics and consent: Participation was voluntary and anonymous, and all respondents were informed of the purpose of the study before completing the questionnaire.

Data availability: The anonymised dataset is available from the corresponding author on reasonable request.

Conflict of interest: The authors declare no conflict of interest.

REFERENCES

Abu Arra, A. Y., Ayed, A., Toqan, D., Albashtawy, M., Salameh, B., Sarhan, A. L., & Batran, A. (2023). The factors influencing nurses' clinical decision-making in emergency department. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 60*. https://doi.org/10.1177/00469580231152080

Alenazi, A. M., Al-Anzi, R. L., Alotaibi, H. L., Al-Rashidi, H. S. A., Al-Rashidi, A. S. A., Al-Anazi, A. F. D., … Al Khammash, M. M. A. (2024). Digital fatigue and clinical decision-making among nurses using EHR systems. *The Review of Diabetic Studies*, 211–222.

Azadi, A., & García-Peñalvo, F. J. (2025). Optimizing clinical decision support system functionality by leveraging specific human-computer interaction elements: Insights from a systematic review. *JMIR Human Factors, 12*(1), e69333.

Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology, 22*(3), 309–328.

Becker, J.-M., Ringle, C. M., & Sarstedt, M. (2018). Estimating moderating effects in PLS-SEM and PLSc-SEM: Interaction term generation∗data treatment. *Journal of Applied Structural Equation Modeling, 2*(2), 1–21.

Chung, J., Jung, H., Park, S. M., & Lee, K. (2025). Effects of digital literacy and nursing informatics competency as job resources on nurses' burnout and work engagement: A cross-sectional study. *BMC Nursing, 24*(1), 1486.

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499–512.

Faudzi, M. A., Cob, Z. C., Ghazali, M., Omar, R., & Sharudin, S. A. (2024). User interface design in mobile learning applications: Developing and evaluating a questionnaire for measuring learners' extraneous cognitive load. *Heliyon, 10*(18).

Gander, P., O'Keeffe, K., Santos-Fernandez, E., Huntington, A., Walker, L., & Willis, J. (2019). Fatigue and nurses' work patterns: An online questionnaire survey. *International Journal of Nursing Studies, 98*, 67–74. https://doi.org/10.1016/j.ijnurstu.2019.06.011

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10.

Krieglstein, F., Beege, M., Rey, G. D., Sanchez-Stockhammer, C., & Schneider, S. (2023). Development and validation of a theory-based questionnaire to measure different types of cognitive load. *Educational Psychology Review, 35*(1), 9.

Laker, L. F., Froehle, C. M., Windeler, J. B., & Lindsell, C. J. (2018). Quality and efficiency of the clinical decision-making process: Information overload and emphasis framing. *Production and Operations Management, 27*(12), 2213–2225.

Levett-Jones, T., Hoffman, K., Dempsey, J., Jeong, S. Y.-S., Noble, D., Norton, C. A., Roche, J., & Hickey, N. (2010). The 'five rights' of clinical reasoning: An educational model to enhance nursing students' ability to identify and manage clinically 'at risk' patients. *Nurse Education Today, 30*(6), 515–520.

MacKinnon, D. P., Krull, J. L., & Lockwood, C. M. (2000). Equivalence of the mediation, confounding and suppression effect. *Prevention Science, 1*(4), 173–181.

Maier, M., Powell, D., Murchie, P., & Allan, J. L. (2025). Systematic review of the effects of decision fatigue in healthcare professionals on medical decision-making. *Health Psychology Review, 19*(4), 717–762.

Muhamad, N. A., Ma'amor, N. H., Jamalluddin, N. H., Rosli, I. A., Leman, F. N., Tengku Baharudin Shah, T. P. N., … Member of Technostress Study. (2025). Technostress and its associated factors: Burnout and fatigue among Malaysian healthcare workers (HCWs) in state hospitals. *PLoS One, 20*(3), e0319506.

Norman, C. D., & Skinner, H. A. (2006). eHealth literacy: Essential skills for consumer health in a networked world. *Journal of Medical Internet Research, 8*(2), e9.

Perry, K., Jones, S., Stumpff, J. C., Kruer, R., Czosnowski, L., Kashiwagi, D., & Kara, A. (2025). Decision fatigue in hospital settings: A scoping review. *Journal of Hospital Medicine, 20*(4), 385–395.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Pulakos, E. D., Arad, S., Donovan, M. A., & Plamondon, K. E. (2000). Adaptability in the workplace: Development of a taxonomy of adaptive performance. *Journal of Applied Psychology, 85*(4), 612–624.

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research, 19*(4), 417–433.

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems, 116*(9), 1865–1886.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285.

Sweller, J., van Merriënboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review, 10*(3), 251–296.

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems, 24*(1), 301–328.

Wang, J., & Hsu, Y. (2020). The relationship of symmetry, complexity, and shape in mobile interface aesthetics, from an emotional

perspective A case study of the smartwatch. *Symmetry*, *12*(9), 1403.

Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206.