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ARTICLE

Strategic Competitive Intelligence and Digital Leadership: Cognitive Appraisal Pathways from Digital Work Demands to Service Innovation

Inteligência Competitiva Estratégica e Liderança Digital: Percursos de Avaliação Cognitiva das Demandas do Trabalho Digital à Inovação em Serviços

Zhongmin Pi
International College, National Institute of Development Administration (NIDA), Bangkok, Thailand.
E-mail: 815307306@qq.com

Xuemei Sun
International College, National Institute of Development Administration (NIDA), Khlong Chan, Bang Kapi, Bangkok 10240, Thailand.
E-mail: xuemei.sun@nida.ac.th

RESUMO | Objetivo: Este estudo explica por que as exigências do trabalho digital podem tanto promover quanto restringir o desempenho inovador em serviços e examina se a liderança digital percebida modifica a maneira como os funcionários da linha de frente interpretam essas exigências. O estudo posiciona esses processos em nível do empregado como uma microfundamentação humana da Inteligência Competitiva Estratégica em hotéis digitalizados. **Metodologia/Abordagem:** Foram obtidos dados de uma pesquisa em duas ondas, com respostas pareadas de 453 funcionários da linha de frente de hotéis cinco estrelas na China. O modelo de mediação paralela e moderação de primeiro estágio foi estimado por meio de Modelagem de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM), com 5.000 reamostragens *bootstrap*. **Originalidade/Relevância:** A pesquisa em Inteligência Competitiva enfatiza as rotinas organizacionais de informação. Este estudo complementa essa perspectiva ao examinar como os funcionários interpretam as exigências decorrentes da implementação e utilização de sistemas de inteligência digital, sem tratar a Inteligência Competitiva como um construto empiricamente mensurado. **Principais Resultados:** As exigências do trabalho digital apresentaram relação positiva com os três tipos de avaliação cognitiva. A avaliação como desafio (*challenge appraisal*) predisse maior desempenho inovador em serviços, enquanto as avaliações como obstáculo (*hindrance appraisal*) e ameaça (*threat appraisal*) predisseram menor desempenho. A relação direta entre as exigências e o desempenho tornou-se não significativa após a inclusão das vias de avaliação cognitiva, embora o efeito total tenha permanecido positivo. A liderança digital percebida fortaleceu a relação entre as exigências digitais e a avaliação como desafio e enfraqueceu sua relação com a avaliação como ameaça, mas não alterou significativamente a avaliação como obstáculo. A mediação moderada foi confirmada por meio da avaliação como desafio, não foi confirmada por meio da avaliação como obstáculo e mostrou-se sensível ao critério adotado por meio da avaliação como ameaça. **Contribuições Teóricas/Metodológicas:** Os resultados identificam a avaliação

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Corresponding Author: Xuemei Sun – xuemei.sun@nida.ac.th
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cognitiva como uma microfundamentação do trabalho em serviços habilitado por inteligência. Os líderes digitais podem fortalecer a percepção das exigências como oportunidades de desenvolvimento e reduzir a percepção de perdas potenciais, enquanto os obstáculos operacionais exigem o redesenho da tecnologia e dos fluxos de trabalho.

Palavras-chave | Inteligência competitive. Demandas digitais de trabalho. Liderança digital percebida. Avaliação cognitive. Inovação em serviços. Hotelaria.

ABSTRACT | Purpose: This study explains why demanding digital work can both promote and constrain service innovative performance and examines whether perceived digital leadership changes how frontline employees interpret those demands. It positions these employee-level processes as a human microfoundation of strategic competitive intelligence in digitalized hotels. **Methodology/approach:** Two-wave matched survey data were obtained from 453 frontline employees of five-star hotels in China. The parallel mediation and first-stage moderation model was estimated with partial least squares structural equation modeling and 5,000 bootstrap resamples. **Originality/Relevance:** Competitive intelligence research emphasizes organizational information routines. This study complements that perspective by examining how employees interpret the demands of enacting digital intelligence systems without treating competitive intelligence as an empirically measured construct. **Key findings:** Digital work demands were positively related to all three appraisals. Challenge appraisal predicted higher service innovative performance, whereas hindrance and threat appraisals predicted lower performance. The direct demand–performance path was nonsignificant after the appraisal routes were included, although the total effect remained positive. Perceived digital leadership strengthened the digital-demand relationship with challenge appraisal and weakened its relationship with threat appraisal, but did not significantly alter hindrance appraisal. Moderated mediation was supported through challenge, unsupported through hindrance, and criterion-sensitive through threat. **Theoretical/methodological contributions:** The findings identify cognitive appraisal as a microfoundation of intelligence-enabled service work. Digital leaders can strengthen developmental meaning and reduce anticipated loss, whereas operational obstacles require technology and workflow redesign.

Keywords | Competitive intelligence. Digital work demands. Perceived digital leadership. Cognitive appraisal. Service innovation. Hospitality.

1. INTRODUCTION

Hotels increasingly rely on property-management systems, customer databases, mobile platforms, artificial intelligence, and other data-enabled tools to coordinate service delivery (Dwivedi et al., 2021; Verhoef et al., 2021). These technologies do not improve service by themselves. Frontline employees must combine system outputs with situational judgment, customer interaction, and service recovery, and their willingness to generate, promote, and implement new ideas is central to service innovative performance (Baradarani & Kilic, 2018; Hu et al., 2009; Wu et al., 2023). At the same time, digitalized work expands what employees must learn, monitor, coordinate, and repair. System switching, persistent connectivity, data interpretation, and technical failure can consume the same resources that employees need for adaptive and innovative service (Scholze & Hecker, 2024; Ye & Chen, 2024).

These technologies also support competitive intelligence (CI), the ethical and systematic process through which organizations plan information needs, collect and analyze internal and external signals, disseminate intelligence, use it in decisions, and learn through feedback (Calof & Wright, 2008; Pellissier & Nenzhelele, 2013a, 2013b). Frontline employees contribute by reading guest and system signals, applying insight in service recovery and personalization, and returning implementation feedback. CI remains an organizational capability rather than an individual outcome.

This tension makes digital work demands (DWD) neither inherently enabling nor inherently debilitating. Much of the digital-work literature nevertheless assigns technologies or stressors a positive or negative character before examining how employees understand the encounter (Mazzola & Disselhorst, 2019; Shi et al., 2024). Cognitive appraisal theory offers a different starting point: a demanding condition acquires motivational significance through employees' judgments of prospective gain, blocked goal attainment, and possible harm (Lazarus, 1991; Lazarus & Folkman, 1984). Accordingly, the same requirement can be seen as a challenge that invites mastery, a hindrance that obstructs progress, or a threat that signals loss of competence, status, or security. In intelligence-enabled work, these appraisals help determine whether digital information reaches service action.

At the intersection of CI and digital work, less is known about the employee-level conditions under which digitally distributed information becomes service action. Appraisals should not be redefined as CI, but they can enable or constrain an intelligence system (Li & Minghat, 2026). Two issues remain insufficiently resolved. First, hindrance and threat are often collapsed into a single adverse response, even though blocked progress is not equivalent to anticipated personal loss (Searle & Auton, 2015; Tuckey et al., 2015). Their separation is especially important in hotel service, where poorly integrated systems may be inconvenient without being personally threatening, while monitoring, automation, or rapidly changing competence standards may evoke threat even when a system is operationally efficient. Second, research on digital leadership has emphasized direct associations with creativity and innovation but has said less about whether employees' perceptions of a supervisor's digital competence, direction, and support change the meaning assigned to demanding digital work (Gao & Gao, 2024; Zhu et al., 2022). A leader may make digital demands appear more developmental or less threatening, yet may be unable to remove workflow barriers embedded in the technology itself.

To address these issues, this study develops a parallel appraisal model in which challenge, hindrance, and threat transmit the relationship between DWD and service innovative performance (SIP). Perceived digital leadership (PDL) is modeled as a first-stage moderator of each DWD–appraisal relationship. A diagnostic direct path from DWD to SIP is retained to determine whether appraisal accounts for the association beyond any residual direct influence. The model is tested with two-wave matched survey data from 453 frontline employees working in Chinese five-star hotels and estimated with PLS-SEM. The study makes three contributions. It first explains the bright and dark sides of digitalized work through employees' interpretations rather than through predetermined categories of technology. It then distinguishes hindrance from threat and shows why the two adverse appraisals need not respond to the same contextual resource. Finally, it specifies perceived digital leadership as a selective appraisal resource rather than a uniformly beneficial condition. This account keeps the explanatory focus on digital work, employee appraisal, and service innovation while clarifying the managerial boundary between leadership intervention and technology or workflow redesign. In addition, it identifies an employee-level process through which intelligence-bearing digital infrastructure may support innovative service action, without claiming that competitive intelligence itself was measured.

2. THEORETICAL BACKGROUND AND HYPOTHESES

Competitive intelligence provides the organizational context, while the job demands–resources perspective and cognitive appraisal theory provide employee-level explanatory mechanisms. CI literature explains how organizations direct information needs, collect and analyze signals, disseminate intelligence, act on it, and learn through feedback. The job demands–resources perspective clarifies why digital enactment requires effort and why leadership can operate as a resource; appraisal theory explains how employees assign distinct meanings to comparable digital demands. Integrating these levels permits analysis of how organizational intelligence routines encounter frontline cognition without treating CI as a measured individual construct.

2.1 Competitive Intelligence And Digital Service Work

Competitive intelligence is a coordinated capability, not a database or an occasional competitor search. It reduces decision uncertainty by converting legally and ethically obtained internal and external information into actionable intelligence (Calof & Wright, 2008; Pellissier & Nenzhelele, 2013b). The cycle begins with decision-makers' intelligence needs and key intelligence topics (Herring, 1999). It proceeds through collection, analysis, dissemination, utilization in decisions and action, and feedback that redirects later work (Dishman & Calof, 2008; Pellissier & Nenzhelele, 2013a; Prescott, 1999). Analysis is decisive because information must be evaluated, integrated, and translated into implications for action (Fleisher & Bensoussan, 2007). Environmental scanning supplies external signals, while strategic intelligence links their interpretation to positioning and renewal decisions (Cavallo et al., 2021).

In hotels, this cycle is distributed across systems and frontline practice. Planning may focus on guest preferences, service failures, competitor offerings, demand patterns, or emerging technologies. Property-management and customer systems, booking channels, review platforms, and employee–guest encounters supply data. Analytics and judgment interpret those signals; dashboards, alerts, and shared records disseminate them; service recovery, personalization, workflow changes, and new service ideas constitute utilization; their outcomes provide feedback. Frontline employees are thus collectors, interpreters, recipients, and generators of information within the wider cycle.

The cycle can fail at its human interface even when technical infrastructure is present. Switching can disrupt collection, poor integration can delay dissemination, and monitoring fears can suppress reports of errors or weak signals. Manageable learning demands, by contrast, may expand pattern recognition and informed action. CI scholarship distinguishes organizational capability from the individual attributes that enable its execution (Li & Minghat, 2026). Accordingly, CI is the organizational context, while DWD, appraisal, and PDL are employee-level conditions where intelligence routines are enacted. The model addresses a microfoundation of CI-enabled service innovation without inserting an unmeasured CI construct.

2.2 Digital Work Demands and Cognitive Appraisal

The job demands–resources perspective describes demands as aspects of work requiring sustained effort, whereas resources facilitate learning, coping, and goal attainment (Bakker & Demerouti, 2017; Bakker et al., 2023). Within intelligence-enabled service work, DWD refers not to a particular technology but to the effort required to learn, use, coordinate through, interpret, and solve problems with digital systems. This perspective explains resource consumption, but appraisal theory explains why comparable demands can produce different responses. During primary appraisal, employees judge whether an encounter offers gain, obstructs progress, or carries potential harm; during secondary appraisal, they evaluate coping capacity (Lazarus & Folkman, 1984). DWD is therefore modeled as a contextual input and the three appraisals as distinct interpretive mechanisms.

Digital demands can be challenging because mastering new tools may improve service effectiveness, strengthen employability, and create transferable expertise. For example, integrated customer information and mobile coordination can broaden the solutions available during a guest encounter. Employees are likely to construe the necessary effort as an investment when learning appears manageable and promises valued outcomes, consistent with evidence that organizational AI adoption can prompt constructive job crafting when it is interpreted favorably (Cheng et al., 2023). A challenge appraisal thus indicates expected growth, not an absence of difficulty (Lazarus & Folkman, 1984; LePine et al., 2005).

H1: *Digital work demands are positively associated with challenge appraisal.*

The same requirements can impede goal pursuit. Re-entering information, moving repeatedly across platforms, responding to digital interruptions, and repairing unstable systems may fragment attention without adding visible service value. Hindrance appraisal concerns this experience of blocked progress and avoidable effort, rather than anticipated damage to the self (Tuckey et al., 2015; Webster et al., 2011). It should become more likely as DWD rises, particularly when systems are poorly integrated or employees have little control over their use (Scholze & Hecker, 2024; Ye & Chen, 2024).

H2: *Digital work demands are positively associated with hindrance appraisal.*

Threat involves a different judgment: that the demand could produce future loss or failure. Digital systems can expose errors, intensify monitoring, alter standards of competence, and diminish the perceived value of existing expertise. Employees may consequently fear damage to customer evaluations, professional standing, or continued employment. These concerns become salient when DWD seems difficult to control and coping resources appear inadequate (Bai et al., 2025; Lazarus & Folkman, 1984; Tuckey et al., 2015).

H3: *Digital work demands are positively associated with threat appraisal.*

2.3 Appraisals, Intelligence Use, and Service Innovation

Service innovative performance can be understood as one downstream expression of using customer and operational intelligence in action. Employees must notice emerging needs, combine

technical and experiential knowledge, advocate unfamiliar ideas, and persist during implementation (Hu et al., 2009; Wu et al., 2023). Challenge appraisal should encourage this investment by directing attention toward attainable gain and learning. Hindrance appraisal channels attention toward procedures and blocked tasks, while threat appraisal encourages vigilance, risk avoidance, and resource conservation. Both negative orientations can interrupt the movement from intelligence to experimentation, although threat should be especially restrictive when competence or security is at stake (Lazarus, 1991; LePine et al., 2005; Tuckey et al., 2015).

H4: *Challenge appraisal is positively associated with service innovative performance.*

H5: *Hindrance appraisal is negatively associated with service innovative performance.*

H6: *Threat appraisal is negatively associated with service innovative performance.*

If appraisal carries the effect of a demand, DWD should have one positive indirect association with SIP through challenge and two negative indirect associations through hindrance and threat. Estimating the routes in parallel permits each mechanism to be evaluated while the others are present. A nonhypothesized DWD→SIP path remains in the model as a diagnostic because additional mechanisms—such as efficiency, overload, or control—could leave residual effects in either direction.

H7: *Challenge appraisal mediates a positive relationship between digital work demands and service innovative performance.*

H8: *Hindrance appraisal mediates a negative relationship between digital work demands and service innovative performance.*

H9: *Threat appraisal mediates a negative relationship between digital work demands and service innovative performance.*

2.4 Digital Leadership as an Intelligence-Enabling Resource

PDL captures employees' belief that their immediate supervisor has current digital expertise, advances transformation proactively, communicates a coherent direction, and motivates participation (Zeike et al., 2019; Zhu et al., 2022). In an intelligence-enabled work system, these qualities can clarify why information is collected, how system outputs should inform service decisions, and what support is available when employees act on them. From a job demands–resources perspective, PDL supplies informational, developmental, and social resources; from an appraisal perspective, it provides credible cues about the value of digital change and employees' capacity to cope.

When PDL is high, a supervisor can translate a technology initiative into workable service goals, model learning, and link digital mastery to future capability. These cues increase the perceived value and attainability of growth, so the positive relationship between DWD and challenge appraisal should become stronger (Gao & Gao, 2024; Zhu et al., 2022).

H10: *Perceived digital leadership positively moderates the relationship between digital work demands and challenge appraisal, such that the relationship is stronger when perceived digital leadership is high.*

PDL may also weaken the two negative appraisals, but by different routes. Digitally capable supervisors can clarify procedures, organize training, and obtain support, making system

requirements less likely to be seen as wasted effort. They can also strengthen coping expectations and signal that transformation is intended to develop employees rather than displace them, reducing anticipated harm to competence, status, or security. Thus, PDL should attenuate the DWD–hindrance and DWD–threat relationships. Any conditional indirect association with SIP should then follow from the combination of these first-stage interactions and the respective appraisal–performance paths.

H11: *Perceived digital leadership negatively moderates the relationship between digital work demands and hindrance appraisal, such that the relationship is weaker when perceived digital leadership is high.*

H12: *Perceived digital leadership negatively moderates the relationship between digital work demands and threat appraisal, such that the relationship is weaker when perceived digital leadership is high.*

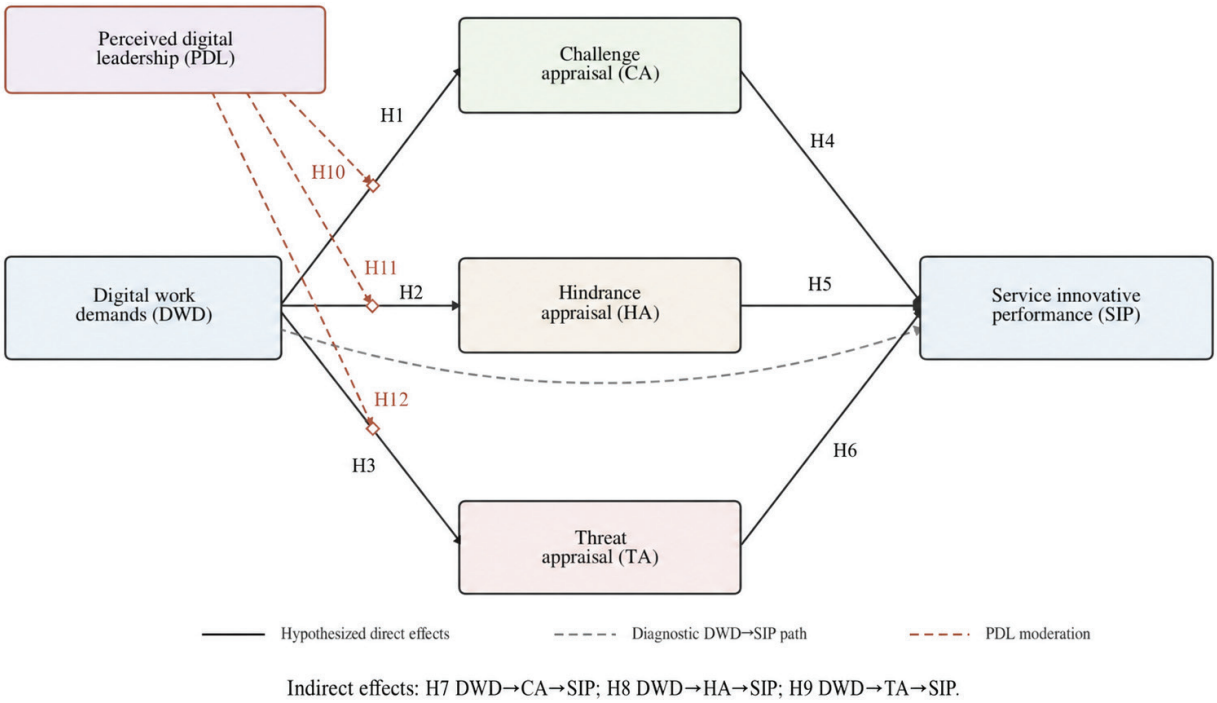

Figure 1. Conceptual model

Note: DWD = digital work demands; PDL = perceived digital leadership; SIP = service innovative performance. The DWD→SIP path is estimated as a diagnostic direct path. Control variables predict SIP only in the robustness model. Competitive intelligence is the organizational context and is not modeled as a latent construct.

3. METHOD

The time-lagged design separated the focal predictors and appraisals from the later measurement of service innovative performance. The following subsections describe the sample, measures, and analytical procedures.

3.1 Research Design, Sampling, and Participants

A quantitative, time-lagged two-wave survey was conducted at the individual level. Eligibility required at least six months of continuous employment in a Chinese five-star hotel, regular customer contact, and routine use of digital systems or technology-enabled service tools. Participants worked in front office, food and beverage, housekeeping, concierge, guest relations, and comparable functions. Before accessing the questionnaire, participants received the approved participant information sheet and provided electronic informed consent. Participation was voluntary, respondents could withdraw before submission, and no direct identifiers were requested. The design was observational rather than experimental and therefore supports temporal separation, not causal identification.

Recruitment followed a two-stage cluster-based procedure. From a frame of 772 five-star hotels, 251 primary and 100 reserve properties were selected by simple random sampling without replacement. Within participating hotels, human resources, training, or operations departments distributed the questionnaire and were asked to rotate or randomly invite eligible employees from departmental lists or duty rosters. Because local distribution and voluntary response determined final participation, the design is described as cluster-based rather than as a strictly self-weighting probability sample.

Online data collection occurred from May 25 to July 25, 2026, in two waves approximately three to four weeks apart. Of 738 Time 1 questionnaires, 676 passed initial screening; Time 2 yielded 528 responses. Anonymous codes linked 487 cases after unsuccessful matches were removed. A further 34 cases failed predefined eligibility or quality criteria, including implausibly short completion, invariant patterns, failed attention checks, excessive missingness, or logical inconsistency. The final sample comprised 453 matched respondents. DWD, PDL, appraisals, and controls were measured at Time 1 and SIP at Time 2. This separation reduces same-occasion consistency motives but does not eliminate common-method or causal-inference concerns (Podsakoff et al., 2012).

Women represented 56.3% of the sample. The largest age group was 26–35 years. Regarding education, 44.8% held a bachelor's degree and 30.7% held a college diploma. Employees with one to three years of cumulative work experience accounted for 34.0%, followed by four to six years at 25.6%. More than half reported regular or frequent use of digital systems. The profile is consistent with a relatively young, digitally exposed frontline hotel workforce.

3.2 Measures

Established multi-item scales used seven response categories ranging from 1 (strongly disagree) to 7 (strongly agree) (Hinkin, 1998; Preston & Colman, 2000). The items were translated and back-translated, contextualized for hotel work, reviewed by subject-matter experts, and piloted before formal data collection. Examples of hotel systems were added only to clarify context; the underlying construct meanings were retained. Table 1 reports the scale sources and administration waves.

Table 1. Measurement constructs and sources

Construct	Code	Items	Wave	Main sources
Digital work demands	DWD	4	T1	Ye and Chen (2024); Hai et al. (2025)
Perceived digital leadership	PDL	5	T1	Adapted from Zeike et al. (2019) and Gao and Gao (2024)
Challenge appraisal	CA	4	T1	He et al. (2024)
Hindrance appraisal	HA	3	T1	He et al. (2024)
Threat appraisal	TA	3	T1	Bai et al. (2025)
Service innovative performance	SIP	6	T2	Hu et al. (2009); Wu et al. (2023)
Control variables	—	5	T1	Gender, age, education, work experience, system-use frequency

Note: T1 = Time 1; T2 = Time 2.

DWD was measured with four items adapted from digital work-requirement and digital competence-at-work measures used in hospitality research (Hai et al., 2025; Ye & Chen, 2024). The items assess requirements to use hotel information systems to complete tasks, communicate through digital platforms, connect with internal and external stakeholders through digital networks, and use digital tools to solve customer problems.

PDL was assessed from employees' perspective with five items adapted from the digital leadership measure developed by Zeike et al. (2019) and used in Chinese employee research (Gao & Gao, 2024; Zhu et al., 2022). The items capture supervisors' digital expertise, up-to-date knowledge, proactive advancement of transformation, ability to inspire employees, and clarity about the structures and processes required for transformation. One representative item is: "My immediate supervisor proactively advances digital transformation in our work unit."

Challenge appraisal was measured with four items adapted from He et al. (2024), focusing on learning digital skills, gaining development opportunities, trying new approaches, and concentrating on task accomplishment. Hindrance appraisal used three items from the same source to assess whether digital demands obstruct expected accomplishment, restrict the use of capabilities, or impede mastery of complex tasks. Threat appraisal was measured with three items adapted from Bai et al. (2025), capturing anticipated negative effects, accumulating difficulties, and concerns about inability to adapt.

SIP was assessed with six items used by Wu et al. (2023) and based on Hu et al. (2009). The measure covers idea generation, the search for new service methods, idea promotion, resource acquisition, implementation planning, and overall innovative contribution. Gender, age, educational attainment, cumulative work experience, and digital-system use frequency were included as control variables because they may influence capability accumulation and innovation-related behavior. Following recommendations to avoid overcontrolling, the controls were directed only to SIP and evaluated in a separate robustness model (Becker, 2005).

3.3 Analytical Strategy

SmartPLS 4.1 estimated the model with the path-weighting scheme and standardized coefficients. PLS-SEM was appropriate for the model's prediction-oriented emphasis, parallel indirect effects, first-stage moderation, and control-variable robustness test (Hair et al., 2022). The algorithm used a maximum of 3,000 iterations and a 10^{-7} stop criterion. Moderation was assessed with the two-stage method: scores from the first-stage latent variables formed the PDL×DWD product used in the structural model.

The measurement model was evaluated with loadings, Cronbach's alpha, rho_A, composite reliability (rho_C), average variance extracted (AVE), HTMT, and outer VIF values. Structural diagnostics included inner VIF, R^2, adjusted R^2, f^2, path estimates, indirect and conditional effects, SRMR, and NFI. Inference relied on 5,000 bootstrap resamples, two-tailed tests, $\alpha = .05$, and percentile 95% confidence intervals. Because an indirect effect is a product with a potentially asymmetric sampling distribution, exclusion of zero from the percentile interval was the prespecified decision criterion (Nitzl et al., 2016); corresponding t-based p values are retained to show criterion-sensitive results. Conditional estimates were calculated at the PDL mean and one standard deviation below and above it.

4. RESULTS AND DISCUSSION

Measurement quality is assessed first, followed by structural, indirect, conditional, and robustness results; the findings are then interpreted theoretically.

4.1 Measurement Model

Loadings ranged from .748 to .894; alpha ranged from .829 to .911, composite reliability from .896 to .931, and AVE from .688 to .776. PDL produced a rho_A estimate of 1.021, a finite-sample boundary anomaly reported rather than suppressed. Its alpha (.899), rho_C (.917), loadings (.748–.894), and AVE (.688) nevertheless support reliability and convergence. The maximum outer VIF was 2.596 (Table 2).

Table 2. Reliability and convergent validity

Construct	Loading range	α	rho_A	rho_C	AVE
CA	.833–.870	.873	.876	.913	.724
DWD	.854–.883	.889	.890	.923	.750
HA	.841–.881	.829	.853	.896	.742
PDL	.748–.894	.899	1.021[a]	.917	.688
SIP	.808–.852	.911	.916	.931	.691
TA	.872–.892	.856	.858	.912	.776

Note: α = Cronbach's alpha; rho_C = composite reliability; AVE = average variance extracted. [a]The boundary-exceeding rho_A estimate for PDL is interpreted together with the other reliability evidence.

Discriminant validity was supported: the largest HTMT value was .590 between DWD and CA, and all remaining ratios were below .85 (Henseler et al., 2015). Fornell–Larcker results and cross-loadings were consistent with this conclusion, indicating that the three appraisals are empirically distinct (Table 3).

Table 3. Heterotrait–monotrait ratios

Construct	CA	DWD	HA	PDL	SIP	TA
CA	—					
DWD	.590	—				
HA	.075	.251	—			
PDL	.040	.038	.064	—		
SIP	.214	.133	.082	.145	—	
TA	.184	.358	.096	.054	.083	—

4.2 Structural Model and Hypothesis Tests

The maximum inner VIF was 1.553. The model explained 29.8% of CA, 5.8% of HA, 10.9% of TA, and 5.9% of SIP; adjusted R^2 values were .293, .052, .103, and .050. The estimated-model SRMR was .049 and NFI was .882. These statistics are descriptive rather than absolute pass–fail criteria, and the modest SIP variance is consistent with a discretionary outcome shaped by multiple individual and organizational conditions.

Table 4. Structural path results

Hypothesis/path	β	t	p	95% percentile CI	f^2	Decision
H1: DWD→CA	.537	15.620	<.001	[.469, .605]	.407	Supported
H2: DWD→HA	.211	4.831	<.001	[.129, .300]	.047	Supported
H3: DWD→TA	.303	6.647	<.001	[.212, .391]	.102	Supported
H4: CA→SIP	.171	3.053	.002	[.062, .281]	.023	Supported
H5: HA→SIP	−.093	1.962	.050	[−.187, −.001]	.009	Supported[a]
H6: TA→SIP	−.120	2.441	.015	[−.217, −.023]	.014	Supported
Diagnostic: DWD→SIP	.089	1.429	.153	[−.032, .213]	.005	Nonsignificant
PDL→CA	−.032	.624	.532	[−.126, .072]	.001	Nonsignificant
PDL→HA	.057	1.025	.305	[−.078, .144]	.003	Nonsignificant
PDL→TA	.016	.251	.802	[−.122, .115]	.000	Nonsignificant
H10: PDL×DWD→CA	.151	3.466	.001	[.059, .228]	.034	Supported
H11: PDL×DWD→HA	−.079	1.769	.077	[−.154, .021]	.007	Not supported
H12: PDL×DWD→TA	−.103	2.183	.029	[−.196, −.010]	.012	Supported

Note: Two-tailed tests. [a]The unrounded p value for H5 was .04984; the percentile confidence interval excluded zero.

DWD increased CA, HA, and TA, supporting H1–H3. CA enhanced SIP, whereas HA and TA reduced it, supporting H4–H6; the HA result was marginal at the third decimal place. The diagnostic DWD→SIP path was nonsignificant. PDL had no significant main effects, but PDL×DWD strengthened CA and weakened TA, supporting H10 and H12. The interaction predicting HA was nonsignificant, so H11 was not supported (Table 4).

4.3 Indirect and Conditional Effects

Table 5. Specific indirect, direct, and total effects of digital work demands

Effect	β	t	p	95% percentile CI	Inference
H7: DWD→CA→SIP	.092	2.935	.003	[.032, .156]	Supported
H8: DWD→HA→SIP	−.020	1.723	.085	[−.0448, −.0003]	Supported by CI[a]
H9: DWD→TA→SIP	−.036	2.275	.023	[−.070, −.007]	Supported
Total indirect effect	.036	.926	.355	[−.039, .113]	Nonsignificant
Direct effect	.089	1.429	.153	[−.032, .213]	Nonsignificant
Total effect	.125	2.553	.011	[.026, .221]	Significant

Note: [a]The percentile bootstrap interval for H8 excluded zero, whereas the symmetric t-based p value was .085. The interval was the prespecified decision criterion for indirect effects; H8 is therefore interpreted cautiously.

The indirect effects moved in opposite directions: DWD increased SIP through CA and reduced it through HA and TA. The CA and TA routes were clearly significant. The small HA route had a percentile interval excluding zero but a nonsignificant symmetric p value and is therefore interpreted cautiously. Offsetting positive and negative components produced a nonsignificant aggregate indirect effect, although the total DWD effect remained positive (Table 5).

Table 6. Conditional direct effects of digital work demands on appraisals

PDL level	DWD→CA β (p)	DWD→HA β (p)	DWD→TA β (p)
Low (−1 SD)	.386 (<.001)	.290 (<.001)	.406 (<.001)
Mean	.537 (<.001)	.211 (<.001)	.303 (<.001)
High (+1 SD)	.688 (<.001)	.132 (.039)	.199 (.005)

At high PDL, the DWD→CA slope was nearly twice its low-PDL value (.688 versus .386), whereas the DWD→TA slope was approximately halved (.199 versus .406). The HA slope also declined, but its interaction was not statistically reliable (Table 6 and Figure 2).

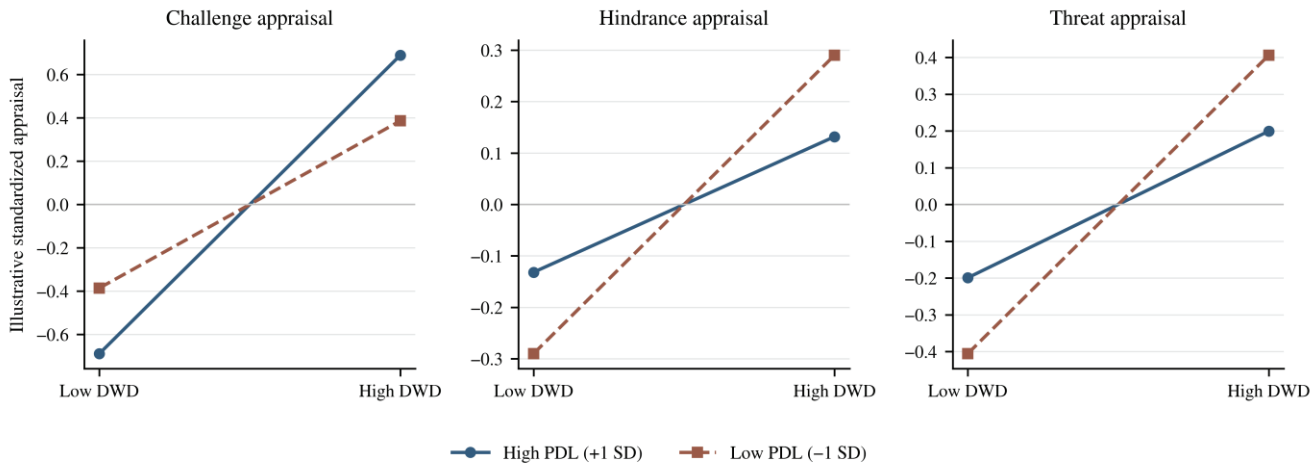

Figure 2. Simple slopes for the moderating role of perceived digital leadership

Note: Lines are based on standardized conditional slopes at PDL ±1 SD and are centered at the construct means. The plot is illustrative; inferential conclusions are based on the bootstrapped interaction coefficients.

Table 7. Conditional indirect effects and indices of moderated mediation

Path / PDL level	β	p	95% percentile CI	Inference
DWD→CA→SIP: low	.066	.007	[.023, .119]	Significant
DWD→CA→SIP: mean	.092	.003	[.032, .156]	Significant
DWD→CA→SIP: high	.118	.003	[.042, .199]	Significant
Index via CA	.026	.024	[.006, .051]	Significant
DWD→HA→SIP: low	−.027	.078	[−.0604, −.0004]	CI excludes zero[a]
DWD→HA→SIP: mean	−.020	.085	[−.0448, −.0003]	CI excludes zero[a]
DWD→HA→SIP: high	−.012	.207	[−.036, .001]	Nonsignificant
Index via HA	.007	.212	[−.002, .020]	Nonsignificant
DWD→TA→SIP: low	−.049	.025	[−.095, −.009]	Significant
DWD→TA→SIP: mean	−.036	.023	[−.070, −.007]	Significant
DWD→TA→SIP: high	−.024	.070	[−.0536, −.0029]	CI excludes zero[a]
Index via TA	.012	.129	[.0001, .0309]	Criterion-sensitive[b]

Note: [a]The percentile interval and symmetric p value yield different decisions; interpret cautiously. [b]The percentile interval narrowly excludes zero, whereas p = .129. The clearly supported moderated-mediation result is the challenge pathway.

The conditional indirect effect through CA increased with PDL, and its moderated-mediation index was significant. The HA index was nonsignificant. Conditional negative effects through TA weakened as PDL increased, but the moderated-mediation index was criterion-sensitive: its percentile interval narrowly excluded zero while the symmetric p value did not. Accordingly, attenuation of TA is supported, but variation in the complete indirect threat route is interpreted cautiously (Table 7).

4.4 Robustness Analysis with Control Variables

A robustness model added gender, age, education, work experience, and digital-system use frequency as predictors of SIP. The maximum inner VIF was 1.572, SRMR was .044, and NFI was .868. SIP R^2 increased from .059 to .120 (adjusted R^2 from .050 to .102); appraisal R^2 values were unchanged because controls did not predict the mediators (Table 8).

Table 8. Robustness model with control variables

Path/effect	Primary β	Primary p	Controlled β	Controlled p	Controlled 95% CI
DWD→CA	.537	<.001	.537	<.001	[.470, .605]
DWD→HA	.211	<.001	.211	<.001	[.129, .300]
DWD→TA	.303	<.001	.303	<.001	[.212, .391]
CA→SIP	.171	.002	.154	.004	[.050, .258]
HA→SIP	−.093	.050	−.100	.031	[−.191, −.010]
TA→SIP	−.120	.015	−.132	.005	[−.226, −.040]
DWD→SIP	.089	.153	.103	.086	[−.014, .222]
PDL×DWD→CA	.151	.001	.151	.001	[.060, .228]
PDL×DWD→HA	−.079	.077	−.079	.077	[−.154, .021]
PDL×DWD→TA	−.103	.029	−.103	.029	[−.196, −.011]
Indirect via CA	.092	.003	.083	.005	[.026, .143]
Indirect via HA	−.020	.085	−.021	.062	[−.046, −.002]
Indirect via TA	−.036	.023	−.040	.009	[−.073, −.012]
Gender→SIP	—	—	.011	.908	[−.169, .196]
Age→SIP	—	—	.065	.123	[−.015, .147]
Education→SIP	—	—	.126	.005	[.034, .213]
Work experience→SIP	—	—	.114	.008	[.031, .199]
System-use frequency→SIP	—	—	.165	<.001	[.077, .253]

Note: Control coding follows the original dataset; higher education, experience, and system-use categories indicate higher levels. Percentile confidence intervals are rounded from the SmartPLS bootstrap output.

Focal conclusions were stable. Education, work experience, and system-use frequency positively predicted SIP, whereas gender and age did not. CA and TA remained significant mediators, the HA result remained criterion-sensitive, and interaction estimates were essentially unchanged.

4.5 Competitive Intelligence at the Human Interface

DWD activated challenge, hindrance, and threat rather than producing a single favorable or unfavorable response. The result is consistent with appraisal theory: the experienced meaning of a demand cannot be inferred directly from the work condition itself. From a CI perspective, the same intelligence-bearing digital system can expand learning, obstruct task accomplishment, and signal

possible loss. Organizational access to data is therefore insufficient unless employees can translate it into service action.

The appraisals had distinct implications for SIP. Challenge supported innovative performance, whereas hindrance and threat constrained it. The hindrance coefficient was small and sensitive to the inferential criterion, while threat showed a clearer negative association. Thus, workflow obstruction may reduce employees' willingness to invest discretionary effort in experimentation, but anticipated damage to competence or security provides a more dependable reason for caution and resource protection. Within the CI cycle, challenge supports learning, pattern recognition, and experimentation; hindrance reflects friction in collection, dissemination, or use; and threat may suppress voice, error reporting, and experimentation.

Once the appraisal routes were entered, DWD had no significant direct relationship with SIP. The positive total effect nonetheless contained a favorable challenge component and unfavorable hindrance and threat components. A single total or bivariate coefficient would therefore conceal processes operating in opposite directions. For CI, this indicates that information may be available and technically distributable while its conversion into innovative action remains contingent on how employees interpret the associated work (Dishman & Calof, 2008).

PDL also showed a selective rather than uniform role. It strengthened the DWD–challenge relationship and weakened the DWD–threat relationship, but it did not significantly change hindrance appraisal. Supervisory digital competence and direction therefore mattered when employees judged growth potential and anticipated loss. The unsupported hindrance interaction marks a substantive boundary: leaders can influence how change is understood, but cannot necessarily eliminate duplicate procedures, fragmented platforms, interruptions, or poor interface design. In intelligence-enabled work, supervisors can clarify priorities, model evidence-based decisions, and create safety around adaptation, but technical and process failures still require work-system redesign. Taken together, this pattern suggests that digital strategic capability depends on combining technological infrastructure with employee sensemaking and intelligence-driven decision-making; that organizational capability was not directly measured here.

4.6 Contributions to Competitive Intelligence

First, the study contributes an employee-level microfoundation to CI research without redefining CI as an individual psychological construct. Competitive intelligence remains an organizational capability for directing, analyzing, disseminating, and using information (Calof & Wright, 2008; Pellissier & Nenzhelele, 2013a). The present model explains why its digital enactment can generate different service outcomes when employees encounter the work requirements embedded in those routines. It therefore connects organizational intelligence architecture with frontline cognition at the point of execution.

Second, the findings locate the bright and dark consequences of digital work in employees' appraisals rather than in fixed categories of technology. Observing challenge, hindrance, and threat simultaneously demonstrates that a single demanding condition can carry meanings of gain,

obstruction, and loss. This formulation extends job demands–resources reasoning by showing that resource consumption does not, by itself, determine the direction of employees' responses.

Third, the study gives threat a distinct explanatory role. Hindrance and threat were only weakly associated, differed in their relationships with SIP, and responded differently to PDL. The evidence therefore extends the argument that hindrances are not threats (Tuckey et al., 2015) to digitally mediated hotel service and cautions against using a single negative-appraisal category. In CI terms, this separates operational blockage in an intelligence process from anticipated personal loss generated by that process.

Finally, the model specifies perceived digital leadership as an appraisal resource. Its contribution was conditional: PDL made the developmental meaning of DWD more salient and its threatening meaning less salient, without producing a universal improvement across appraisal forms. This asymmetric pattern identifies the boundary of digital leadership within intelligence-enabled work.

4.7 Managerial Implications for Intelligence-Enabled Service

Hotels should manage the CI cycle as both an information process and a work system. Planning should identify a small set of service-related intelligence priorities and involve frontline employees who encounter guest and operational signals. Environmental scanning should combine competitor and market information with weak signals from guest reviews, system logs, and frontline observations. Collection and analysis require integrated access to customer, review, and operational data, together with training in how to interpret system outputs. Dissemination and utilization require concise alerts, clear decision rights, and safe opportunities to test service improvements. Closing the feedback loop means recording customer reactions and implementation outcomes and using them to update systems, strategic-intelligence priorities, and operating routines.

Hotel managers should address the interpretation of digital change alongside its technical implementation. Supervisors can strengthen challenge appraisal by linking each system to observable service gains and allowing employees to test improved routines safely. Reducing threat requires credible signals about coping and future value. Hotels should explain how monitoring data will be used and provide accessible reskilling and technical support. These practices protect the collection of weak signals and encourage employees to contribute information rather than withhold it for self-protection.

Leadership development is not a substitute for system design. Duplicate entry, fragmented platforms, unreliable interfaces, and continual interruption require process integration, usable technology, adequate staffing, and communication rules. Repeated cycles in which relevant signals are interpreted, acted on, and fed back can support service renewal and may contribute to sustainable competitive advantage. The present study informs this possibility but does not claim to have measured sustained advantage directly.

4.8 Limitations and Future Research

Several boundary conditions qualify the findings. The sample was limited to frontline employees in Chinese five-star hotels, so the model should be reassessed across hotel segments, service occupations, and institutional settings. The study used a two-wave, time-lagged observational design rather than a single-occasion cross-sectional survey; nevertheless, temporal separation does not establish causality. The design relied on self-reports. Supervisor assessments, behavioral innovation indicators, experience sampling, and intervention studies would provide stronger temporal and causal evidence.

Second, the connection to CI is theoretically grounded but not directly operationalized. The study did not measure hotel-level CI maturity, the quality of specific cycle stages, intelligence use, or strategic decision outcomes. Future multilevel research should combine employee appraisal data with organizational measures of planning, collection, analysis, dissemination, utilization, and feedback. Interviews with intelligence users, process mapping, system logs, and longitudinal case evidence would permit methodological triangulation and reveal where the cycle succeeds or fails.

Third, PDL and the appraisals were measured in the same wave. A three-wave design or experiment could establish temporal order more clearly by introducing leadership cues before appraisal and subsequent innovation. The PDL rho_A estimate also exceeded one, despite acceptable loadings, alpha, rho_C, and AVE. Replication should validate the adapted employee-perception scale and use multilevel designs to distinguish individual perceptions from shared leadership at hotel or unit level.

Finally, the overall DWD construct may conceal meaningful demand types. Learning requirements, system switching, information overload, algorithmic monitoring, connectivity, and substitution concerns could produce different appraisal profiles. SIP explained variance was modest. Larger preregistered studies should examine demand-specific mechanisms and the criterion-sensitive indirect effects.

5. FINAL CONSIDERATIONS

Digital work demands reach service innovative performance through competing interpretations. Innovation benefits when employees view demanding technology as an attainable route to learning, but it suffers when they experience blocked progress or anticipate personal loss. Perceived digital leadership reinforces the challenge route and limits threat; it does not reliably remove hindrance. Effective digital transformation therefore requires supervisors who give change credible developmental meaning and work systems that remove avoidable friction.

For competitive intelligence, the central implication is that digital infrastructure becomes decision-relevant intelligence only through human interpretation and action. Appraisal is one microfoundation of this conversion: it affects whether frontline employees learn from signals, use them in service experimentation, report problems, and return feedback to the organization. The study does not claim that CI was empirically measured or that sustainable competitive advantage was demonstrated. It shows instead how leadership and work-system design can improve the

employee-level conditions under which intelligence-enabled service innovation occurs. At the organizational level, these conditions can strengthen strategic intelligence and digital strategic capability by supporting intelligence-driven decision-making, although those capabilities were not directly measured.

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Data Availability: The individual-level survey data are not publicly available because the participant information and informed consent process did not authorize unrestricted public deposition, and combinations of demographic and occupational characteristics may present a risk of participant re-identification. Suitably de-identified data supporting the findings may be made available by the corresponding author upon reasonable request, subject to applicable ethical and institutional requirements.

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