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Article

From tools to boundary conditions: AI maturity as an accelerator of digital-nomad-oriented management practices

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Abstract: Artificial intelligence (AI) is widely discussed as a productivity tool, yet empirical research rarely theorizes AI as a boundary condition that alters whether, and how strongly, digital-era management practices translate into employee and organizational outcomes. Drawing on socio-technical systems theory and emerging views of algorithmic agency, we argue that AI maturity - distinct from digital integration because it reflects the extent to which predictive and generative AI are embedded in workflows, coordination routines, decision support, and planning - amplifies the effectiveness of digital-nomad-oriented management practices. We test this AI accelerator effect using a cross-regional survey dataset (N = 372) of employees and managers recruited through digital-nomad communities and collaborating organizations across China, the United States, and Europe. Hierarchical regression models with heteroskedasticity-robust standard errors show that AI maturity strengthens the positive association between DRISA practices and employee engagement. AI maturity also conditions the performance consequences of spatial flexibility: simple slopes indicate that spatial flexibility is performance-reducing when AI maturity is low but performance-enhancing when AI maturity is high. These results reposition AI maturity as a coordination capability that changes the marginal returns to autonomy- and flexibility-oriented work designs, while clarifying its conceptual distinctiveness from broader digital integration and underscoring that sustainable digitally flexible work depends on adequate coordination capacity.

Keywords: algorithmic agency; socio-technical systems; distributed work; employee engagement; organizational performance

1. Introduction

Remote and location-independent work has shifted from a peripheral arrangement to a central feature of contemporary organizing. Evidence from field experiments and meta-analyses indicates that telework can improve satisfaction and, under enabling conditions, performance [1,2]. Post-pandemic studies further show that work-from-anywhere, hybrid work, and durable work-from-home arrangements can improve retention and support productivity when implemented with appropriate managerial and technical support [3–5]. At the same time, large-scale remote-work evidence also shows that collaboration can become more siloed and less spontaneous, especially when dispersed work is weakly coordinated [6,7]. Work-design studies similarly emphasize that the benefits of remote work depend on role clarity, support, and the quality of local routines [8,9]. These tensions are particularly visible in nomad-oriented work systems, where employees operate across locations, time zones, and varying rhythms of coordination.

Digital nomadism has emerged as one visible expression of this broader shift. Digital nomads are commonly described as knowledge workers who rely on digital technologies to work remotely while engaging in sustained mobility [10,11]. Recent syntheses also treat digital nomadism as a broader ecosystem of location-independent work practices and identities rather than a narrow lifestyle label [12,13]. This work highlights how remote work, leisure, and mobility increasingly blend in hybrid ways [14], and how salaried or corporate nomads extend the phenomenon beyond freelancers and entrepreneurs [15]. Place-based and mobility-oriented reviews further show that this form of work depends on infrastructures, routines, and destination characteristics that make sustained mobility workable [16].

Distributed collaboration research suggests that dispersion amplifies the mutual knowledge problem: team members find it harder to develop shared context and to diagnose misunderstandings, increasing conflict and rework [17,18]. Telework research likewise highlights risks of professional isolation and weaker performance when communication and coordination mechanisms are insufficient [19]. Recent work on reconfigured virtual teams and flexwork similarly shows that dispersion requires renewed e-leadership, spacing, and identity routines rather than simply more digital tools [20,21]. In practice, organizations therefore rely on bundles of managerial and technological practices to make distributed work sustainable.

Beyond firm-level efficiency, understanding when AI-enabled distributed work becomes viable also matters for sustainable social development because it shapes decent work, employee well-being, inclusive access to geographically flexible employment, and the governance quality of digitally mediated work systems.

At the same time, organizations are rapidly adopting artificial intelligence (AI) to augment work. The management literature has advanced important insights on algorithmic control and the contested use of algorithms in work systems [22]. Another stream emphasizes automation-augmentation tensions and human-AI symbiosis in organizational decision making [23,24]. More recent integrative work reframes AI as an organizational capability that depends on governance, routines, and collective design choices rather than isolated tools [25–28]. Yet much empirical research still treats AI primarily as a direct productivity input instead of a boundary condition that changes whether management practices translate into engagement and performance [29,30].

We develop this argument by introducing AI maturity, defined as the extent to which an organization embeds AI into workflows, coordination routines, decision making, and planning. In the current organizational wave, this includes both predictive or analytical AI and generative AI applications such as meeting summarization, knowledge retrieval, drafting support, workflow augmentation, and scenario exploration. AI maturity is related to, yet distinct from, general digital maturity because it captures whether AI participates in coordination, judgment support, and workflow execution rather than remaining an isolated productivity tool [31,32]. This distinction is consistent with socio-technical systems theorizing, which treats technology as enacted through organizational routines and structures rather than as a neutral standalone device [33]. A mature AI environment therefore reflects not only adoption, but also integration, governance, and repeated use in everyday organizing.

The focus of our empirical environment is the DRISA management capability system, which includes Digital Integration, Remote Adaptability, Individual Autonomy, Spatial Flexibility, and Agile Management. DRISA refers to a set of practices intended to govern distributed and nomad-oriented labor. It combines management routines that enhance autonomy and flexibility with digital integration that facilitates information movement. Nonetheless, even thoughtful practices may fail to produce engagement and performance when coordination capacity is limited. Research on mobile technologies and flexible knowledge work captures this autonomy paradox: the same arrangements that increase freedom can also intensify strain, coordination burdens, and boundary pressure [34].

We suggest an AI accelerator effect: the more mature AI becomes, the more effectively distributed-work management practices translate into outcomes because coordination frictions are reduced, information-processing burdens are lower, and alignment across dispersed actors is faster. First, we argue that DRISA practices are positively related to employee engagement and that this relationship becomes stronger when AI maturity is high, because AI-assisted workflows can increase psychological availability and make autonomous work easier to enact [35,36]. Second, we propose that spatial flexibility - the ability to work effectively across locations - has a more positive relationship with organizational performance when AI maturity is high. Under low AI maturity, spatial flexibility can undermine performance by magnifying delays, misalignment, and rework; under high AI maturity, AI-enabled coordination can convert spatial flexibility into a performance advantage.

We test these arguments using a cross-regional survey dataset (N = 372) collected from China, the United States, and Europe. Our results support both moderation predictions. AI maturity strengthens the DRISA–engagement relationship and, more strongly, conditions the spatial flexibility–performance relationship such that spatial flexibility is beneficial only when AI maturity is high. These findings contribute to AI-in-management and remote work research by theorizing AI maturity as a contingent coordination capability and by demonstrating that AI changes the marginal effectiveness of autonomy- and flexibility-oriented practices rather than simply increasing efficiency.

This paper makes three contributions. First, it extends AI management research by reframing AI maturity as a boundary condition that changes the effectiveness of management practices, complementing work on learning algorithms and AI theorizing in organizations [37,38]. Second, it advances socio-technical theorizing by conceptualizing AI maturity as algorithmic agency-an organizational layer that participates in coordination and thereby shapes distributed-work outcomes [33]. Third, it contributes to digital nomad and nomad-oriented work research by providing cross-regional quantitative evidence on how management practices and AI maturity jointly influence engagement and performance in dispersed work systems.

2. Theory and hypotheses

2.1. Digital-nomad-oriented management practices: DRISA as a capability system

Digital nomadism and location-independent work are often described as individual mobility regimes, but at the organizational level they require a distinctive management capability system. When work is coordinated across distance, organizations must create mechanisms that substitute for face-to-face monitoring and informal information sharing. Prior research on teleworks and virtual teams suggests that effective distributed coordination depends on reliable communication infrastructure, shared norms, clarity of interdependencies, and timely feedback; absent these conditions, distance can produce misunderstandings, delays, and coordination neglect. Recent studies of reconfigured virtual teams and flex work reinforce this point by showing that effective distributed coordination depends not only on infrastructure and interdependence clarity, but also on leadership routines and social arrangements [20,21]. Accordingly, we conceptualize DRISA as a bundle of complementary practices that jointly support nomad-oriented organizing rather than as a set of independent tools.

The DRISA framework conceptualizes digital-nomad-oriented management practices as five complementary dimensions that together represent an integrated capability system (**Figure 1**):

(a) Digital Integration captures interoperability and standardization of digital tools, enabling shared visibility and cross-location access to information.

(b) Remote Adaptability describes the ability of an organization to adjust work patterns and resources to remote conditions, such as asynchronous rhythms or rapid changes in routines.

(c) Individual Autonomy represents the freedom to choose how tasks are performed and paced, which is especially significant when direct supervision is costly and employees must self-regulate.

(d) Spatial Flexibility refers to policies and resources that allow employees to work effectively across locations without disrupting continuity.

(e) Agile Management describes the iterative planning, fast feedback, and cross-functional coordination patterns that enable teams to manage uncertainty in dynamic situations.

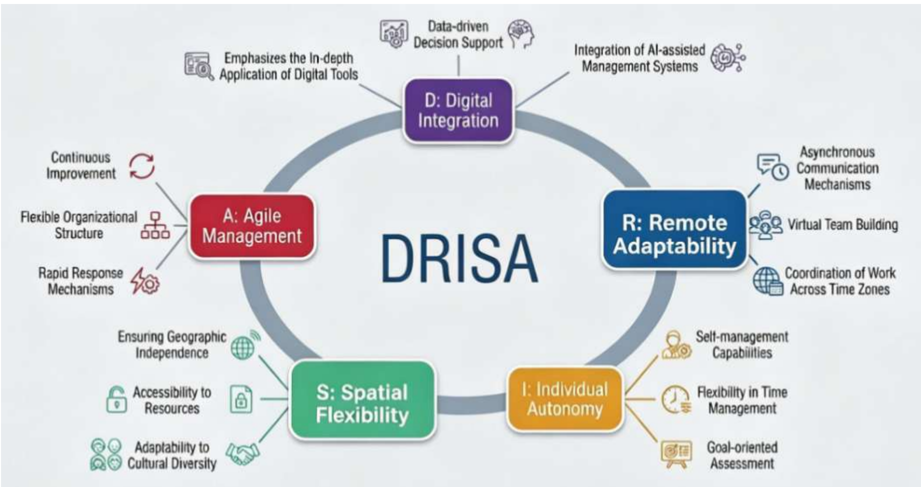

Figure 1. Five-Dimensional DRISA Model and its Sub-elements

Every dimension has theoretical meaning by itself, yet the value of DRISA is reflected in the interaction between them: digital integration and remote adaptability offer infrastructure and rules of the game; autonomy and spatial flexibility offer discretion and mobility; and agile management offers a coordination discipline that helps prevent autonomy from degenerating into misalignment.

2.1.1. DRISA practices and employee engagement

Employee engagement is an enduring and positive condition of work characterized by vigor, dedication, and absorption [39]. Engagement is strongly associated with performance and retention, and it is especially pertinent in distributed settings where physical distance can weaken meaning, identity, and spirit [1,19]. Recent remote-work research further shows that sustaining engagement outside shared offices requires deliberate work design, social support, and boundary-management routines that reduce loneliness, overload, and uncertainty [8,9,20,21].

Kahn [35] argues that involvement depends on psychological meaningfulness, psychological safety, and psychological availability. Distributed and nomad-oriented work may undermine these conditions because workers receive fewer cues about priorities, less social reinforcement, and more costly interruptions. DRISA practices are intended to offset those losses by supplying resources that help employees remain connected to, and invested in, their work.

The JD-R model provides a complementary perspective: engagement increases when job resources such as autonomy, feedback, support, and tools outweigh demands and facilitate goal attainment [36,40]. Informational resources are strengthened through digital integration; social resources and coordination routines are enabled by remote adaptability; meaning is supported through autonomy and ownership; spatial flexibility expands choice and removes unnecessary locational constraints; and agile management provides clarity and feedback. Taken together, these resources should enhance employees' capacity to sustain energetic participation in their work. Therefore, we expect a positive relationship between DRISA practices and employee engagement.

Hypothesis 1 (H1): DRISA management practices are positively related to employee engagement.

2.1.2. DRISA as a socio-technical capability configuration

Building on the JD-R logic outlined in Section 2.1.1, the configuration view sheds light on why flexibility-focused practices may be counterproductive. Autonomy may become a source of ambiguity and duplication of labor when digital tools are poorly integrated, coordination routines are weak, and spatial flexibility produces misalignment. This dynamic echoes the autonomy paradox: mobile and flexible technologies can simultaneously expand discretion and intensify demands through constant connectivity and coordination [34]. Recent studies of flex work likewise show that flexibility can generate identity strain and require organizations to re-regulate expectations, working relationships, and everyday routines [21]. Hence, the success of DRISA practices may depend on additional coordination mechanisms that shape how those practices are enacted.

2.2. AI maturity as algorithmic agency

The technologies of AI may affect organizing in multiple ways. An increased body of literature describes how algorithms can be used to track, assess, and prod workers into action, creating a contested terrain of control [22,41]. Another stream highlights AI augmentation and human-AI symbiosis, emphasizing that AI not only automates but may also add work or reshape responsibility [23,24]. Integrative scholarship therefore frames AI less as a single tool and more as a socio-technical capability whose value depends on governance, routines, and organizational design [25,26].

To link AI to the effectiveness of distributed work, we treat AI maturity as an organizational capability. Capability-based perspectives conceptualize AI as a bundle of data, analytics, skills, routines, and governance structures that can create value when embedded in work systems [27,29]. Expanding on this view, we define AI maturity as the degree to which AI becomes part of regular workflows, coordination processes, decision support, and planning, and is aligned with organizational strategy. The definition emphasizes integration rather than mere adoption: two organizations may use the same AI tools, but in the more mature organization, AI outputs are incorporated into everyday coordination and decision making.

We conceptualize AI maturity as algorithmic agency: an algorithmic layer within a socio-technical fabric that can participate in coordination through information processing, recommendation, and visibility across dispersed practices [31,33]. Algorithmic agency does not imply that AI replaces managerial judgment; rather, it means AI-enabled artefacts can expand coordination capacity by reducing information-processing bottlenecks and supporting faster alignment across distributed actors. This interpretation is also consistent with recent work that treats managing with AI as a question of interaction, collective agency, and context rather than simple automation [28,32].

2.2.1. AI maturity as an accelerator of the DRISA → engagement relationship

DRISA practices provide resources for engagement, but their effectiveness depends on how easily employees can enact them in day-to-day work. Autonomy, for example, strengthens engagement when employees have adequate informational support and coordination mechanisms; otherwise, it can generate uncertainty, rework, and frustration [17,34]. Similarly, remote-adaptability routines are less effective when information is dispersed across channels and difficult to synthesize.

AI maturity enhances the implementation of DRISA practices through three main channels. First, AI applications can reduce administrative and coordination burdens - for example through meeting summaries, knowledge retrieval, prioritization, workflow support, and generative drafting assistance - which frees psychological availability for core work [24,25]. Second, AI can increase informational transparency by integrating and summarizing dispersed data, thereby mitigating mutual-knowledge problems in distributed collaboration [17,31]. Third, AI can support rapid feedback and iteration by generating forecasts, alerts, and scenario analyses that improve agility under uncertainty [23,37]. Professionals do not engage AI outputs automatically, however; they are more likely to rely on algorithmic support when organizations reduce opacity, clarify the division of labor, and address algorithm aversion through credible human-AI collaboration arrangements [42–44]. These mechanisms imply an accelerator effect: when AI maturity is high, each incremental improvement in DRISA practices yields a larger gain in engagement. When AI maturity is low, the same practices may still help, but their marginal returns are dampened by coordination frictions.

Hypothesis 2 (H2): AI maturity positively moderates the relationship between DRISA practices and employee engagement, such that the relationship is stronger at higher levels of AI maturity.

2.2.2. Differentiating AI maturity from digital integration

A potential concern is conceptual overlap between AI maturity and broader digital integration. We distinguish the constructs on both conceptual and functional grounds. Digital integration refers to the digitization and integration of information systems and workflows so that data are accessible and processes are standardized. AI maturity, in contrast, reflects whether AI is embedded as an active component of coordination and decision making - whether the organization leverages AI to synthesize information, automate routine coordination tasks, and support planning and prediction. In other words, digital integration provides the informational substrate, whereas AI maturity captures the extent to which that substrate is transformed into algorithmically enabled coordination capacity.

Relatedly, digital maturity or IT capability refers to the broader organizational foundation that makes such integration possible, including infrastructure, data quality, digital skills, and process readiness. AI maturity builds on that foundation but denotes a more specific higher-order capability: the extent to which predictive and generative AI are embedded in workflow execution, knowledge retrieval, decision support, governance, and strategic planning. An organization may therefore be digitally integrated or digitally mature without yet exhibiting high AI maturity if its systems remain informative rather than algorithmically active in coordination.

The difference is in line with STS theorizing: technical infrastructure may be necessary, but it cannot by itself guarantee better outcomes. Value is created when technologies are enacted through routines that transform how work is performed [33]. AI maturity thus represents a higher-order form of socio-technical enactment that can amplify the effectiveness of distributed-work practices.

2.3. Spatial flexibility, coordination costs, and organizational performance

Performance in distributed environments depends on how well organizations transform flexibility into coordinated output. Spatial flexibility-the ability of employees to work effectively across locations-can broaden access to talent and support continuity beyond a single site. Recent evidence also suggests that location-flexible work remains well above pre-pandemic levels, although its performance implications vary substantially across countries, firms, and implementation conditions [4,7,45]. Nevertheless, dispersion also increases coordination costs because of time-zone misalignment, reduced informal communication, and difficulties in building shared context [18].

Telework research highlights that technology can curb some of the risks of dispersion, but not eliminate them. Professional isolation can lower performance and raise turnover intentions, especially when opportunities for face-to-face interaction and communication-enhancing technologies are limited [19]. Distributed-collaboration research similarly shows that coordination failures often stem from divergent interpretations and missing shared context [17].

From an STS perspective, spatial flexibility is a social-system feature that must be matched with technical-system capabilities to produce performance gains [33]. Post-pandemic studies of digital work further suggest that geographic flexibility translates into better results only when organizations reconfigure digital and sociomaterial routines to sustain alignment across dispersed settings [46]. When technical integration is weak, spatial flexibility can create delays and rework that directly harm performance. When coordination capabilities are strong, spatial flexibility can improve responsiveness and continuity, thereby creating performance advantages. Accordingly, we predict an overall positive association between spatial flexibility and organizational performance, while emphasizing that this effect should be contingent on coordination capacity.

Hypothesis 3 (H3): Spatial flexibility is positively related to organizational performance.

2.3.1. AI maturity as an accelerator of the spatial flexibility → performance relationship

AI maturity should be particularly consequential for the performance implications of spatial flexibility. The volume and complexity of information that must be processed across locations increase as spatial flexibility expands. That burden becomes more manageable when AI is used to structure human-algorithm collaboration, surface relevant signals, and support judgment without eliminating managerial oversight [25,32,43]. AI-enabled coordination tools can automate routine handoffs, warn about risks, predict capacity constraints, and support more substantial asynchronous collaboration [24,31]. By contrast, when AI maturity is low, higher spatial flexibility can exacerbate coordination problems because employees face fragmented tools, limited decision support, and slower information flow. Thus, AI maturity increases the organization's ability to convert spatial flexibility into effective output. This implies a strong accelerator effect in the performance domain: AI maturity should not only strengthen the positive relationship, but can also determine whether spatial flexibility is beneficial versus harmful.

By contrast, when AI maturity is low, higher spatial flexibility can exacerbate coordination problems. Employees may face fragmented tools, limited decision support, and slower information flow, increasing the likelihood that spatial flexibility produces misalignment and performance losses. This implies a strong accelerator effect in the performance domain: AI maturity should not only strengthen the positive relationship, but can also determine whether spatial flexibility is beneficial versus harmful.

Hypothesis 4 (H4): AI maturity positively moderates the relationship between spatial flexibility and organizational performance, such that the relationship is stronger at higher levels of AI maturity.

Figure 2 presents the conceptual model.

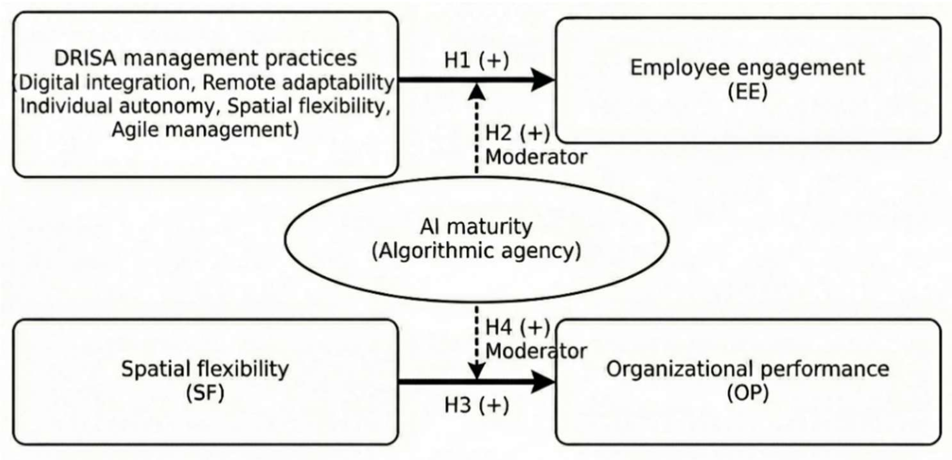

Figure 2. Conceptual model: AI maturity as an accelerator of DRISA practices and spatial flexibility.

3. Materials and methods

3.1. Sample and data collection

We employed a survey design to test the proposed moderation models in a multi-region context. Recruitment combined (a) outreach to digital-nomad and remote-work communities and (b) collaboration with organizations and distributed teams willing to participate in research on distributed work practices. The questionnaire was administered online and disseminated through community channels (e.g., professional groups and forums) and organizational contacts. This approach is appropriate for studying nomad-oriented practices that cut across industries and countries; however, it also implies that the sample is not a probability sample. Accordingly, our inferences focus on theory testing and on identifying boundary conditions (AI maturity) rather than on estimating population prevalence.

The main survey was fielded online in late 2025, using an anonymous, voluntary questionnaire administered through a survey platform. The field design did not collect direct identifiers or sensitive personal information that would reasonably enable re-identification. Respondents could discontinue at any time without penalty, and only anonymized responses were retained for analysis. Given the non-clinical nature of the research, its minimal-risk design, and the use of anonymized survey data without sensitive personal identifiers, the study met the criteria for ethics-review exemption or waiver under institutional norms for low-risk organizational research.

The core sample includes respondents from China (N = 127), the United States (N = 125), and Europe (N = 120), totaling (N = 372). Respondents reported a range of organizational contexts (small, medium, and large firms) and work arrangements (remote, hybrid, and on-site roles with distributed collaboration). The multi-region structure supports greater generalizability than single-country studies and helps mitigate the concern that results are an artifact of one institutional environment. This variable is treated descriptively rather than as a proxy for longitudinal change.

3.1.1. Data screening and quality checks

We implemented three data-quality safeguards. First, the survey was configured as forced-response for scale items, so the dataset contains no missing values for focal variables. Second, there was no time limit for completion. Third, we screened for patterned responding: Cases exhibiting straight-lining across 10 consecutive scale items (i.e., the same response option repeated) were treated as inattentive and removed. Across the full fielding period, six cases were excluded by this rule; the final analytic sample comprises 372 valid responses across China (N = 127), the USA (N = 125), and Europe (N = 120) (see **Table 1**). A supplementary mixed-region dataset (N = 80) was retained for robustness checks.

We also conducted a supplementary pilot test (N = 80) to verify item clarity and reliability before final data collection. Reliability coefficients in the pilot were comparable to those in the main sample (e.g., AI maturity α = .934; employee engagement α = .888; organizational performance α = .915).

Table 1. Sample profile (main validation sample, N = 372).

Characteristic	China (N = 127)	USA (N = 125)	Europe (N = 120)	Total (N = 372)
Gender				
Female	52 (40.9%)	60 (48.0%)	51 (42.5%)	163 (43.8%)
Male	75 (59.1%)	65 (52.0%)	69 (57.5%)	209 (56.2%)
Age				
20–29	53 (41.7%)	45 (36.0%)	41 (34.2%)	139 (37.4%)
30–39	50 (39.4%)	56 (44.8%)	51 (42.5%)	157 (42.2%)
40–49	19 (15.0%)	19 (15.2%)	22 (18.3%)	60 (16.1%)
50+	5 (3.9%)	5 (4.0%)	6 (5.0%)	16 (4.3%)
Education				
Associate	23 (18.1%)	24 (19.2%)	24 (20.0%)	71 (19.1%)
Bachelor	62 (48.8%)	61 (48.8%)	60 (50.0%)	183 (49.2%)
High School	4 (3.1%)	6 (4.8%)	6 (5.0%)	16 (4.3%)
Master+	38 (29.9%)	34 (27.2%)	30 (25.0%)	102 (27.4%)
Company size				
Large	39 (30.7%)	45 (36.0%)	34 (28.3%)	118 (31.7%)
Medium	48 (37.8%)	43 (34.4%)	48 (40.0%)	139 (37.4%)
Small	40 (31.5%)	37 (29.6%)	38 (31.7%)	115 (30.9%)
Work arrangement				
Hybrid	61 (48.0%)	58 (46.4%)	61 (50.8%)	180 (48.4%)
On-site	35 (27.6%)	35 (28.0%)	26 (21.7%)	96 (25.8%)
Remote	31 (24.4%)	32 (25.6%)	33 (27.5%)	96 (25.8%)
Role				
Employee	95 (74.8%)	98 (78.4%)	79 (65.8%)	272 (73.1%)
Founder/Exec	13 (10.2%)	6 (4.8%)	15 (12.5%)	34 (9.1%)
Manager	19 (15.0%)	21 (16.8%)	26 (21.7%)	66 (17.7%)

Note. Percentages may not sum to 100 due to rounding.

3.2. Measures

All items used a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree). Unless otherwise noted, scale scores were computed as the mean of their items.

a) DRISA management practices: DRISA practices capture an organization's management capability system for distributed and nomad-oriented work. The construct comprises five domains: digital integration (6 items), remote adaptability (6 items), individual autonomy (6 items), spatial flexibility (6 items), and agile management (6 items). Domain scores were computed as the mean of their items. Consistent with a configuration approach, we operationalized DRISA practices as the average of the five domain scores. The five domains exhibited strong internal consistency in the main sample (Cronbach's α ranged from 0.884 to 0.935): Digital Integration (α=0.88), Remote Adaptability (α = 0.91), Individual

Autonomy (α = 0.93), Spatial Flexibility (α = 0.93), and Agile Management (α = 0.94). The overall item set shows acceptable internal consistency (α = 0.80) given the multidimensional nature of the construct.

b) AI maturity: AI maturity was measured with five items capturing (a) the extent of AI use in daily workflows, (b) integration of AI into business processes, (c) automation of routine tasks via AI, (d) use of AI for decision support, and (e) use of AI for strategic planning. Cronbach's α for this scale was 0.951. A full list of items is provided in **Appendix A**.

c) Employee engagement: Employee engagement was measured with five items reflecting vigor and dedication (e.g., "At work, I feel energized"; "I am enthusiastic about my job"), consistent with the short form of the Utrecht Work Engagement Scale [39]. Internal consistency in the main sample was strong (Cronbach's a = 0.862; see **Appendix B**).

d) Organizational performance: Organizational performance was measured with five subjective comparative items assessing perceived performance relative to major competitors [47,48]. Objective performance indicators were not feasible in the present design because respondents were drawn from multiple countries, industries, and organizations, making directly comparable archival performance data difficult to obtain under anonymous survey conditions. Subjective comparative performance measures are therefore appropriate in heterogeneous, cross-industry survey settings when the research objective is theory testing rather than audited firm benchmarking, and prior methodological work supports the validity of well-designed subjective performance indicators [47–49]. Internal consistency in the main sample was strong (Cronbach's a = 0.937; see **Appendix B**).

e) Control variables: We controlled for demographic and job characteristics that may relate to engagement and performance perceptions, including region (China, United States, Europe), gender, age, education, company size, work arrangement (on-site, hybrid, remote), and role (employee, manager, founder/executive). Controls were entered as dummy variables in regression models.

3.3. Analytical approach

We used hierarchical ordinary least squares regression with heteroskedasticity-robust standard errors (HC3) to test hypotheses. To reduce multicollinearity and facilitate interpretation, continuous predictors were standardized before creating interaction terms [50]. For H2 and H4, we included main effects (DRISA or spatial flexibility, and AI maturity) and their interaction. We probed significant interactions using simple slope analysis at +/-1 standard deviation of AI maturity.

Given the cross-sectional self-report design, we addressed potential common method variance in two ways. Procedurally, the survey used anonymous participation, practice-focused item wording, and ex post screening for inattentive responses. Statistically, an unrotated principal component analysis of all measurement items showed that the first component accounted for 19.4% of the variance, which is well below conventional heuristic thresholds that typically raise concern [51]. We therefore treat common method bias as unlikely to be the sole driver of the observed effects, while acknowledging that no single diagnostic can fully rule it out in cross-sectional self-report designs. Accordingly, the reported findings should be interpreted as patterned associations rather than definitive causal estimates.

Table 2 provides descriptive statistics and correlations. **Table 3** reports the regression results.

Table 2. Descriptive statistics and correlations.

Construct	M	SD	1	2	3	4	5
DRISA	4.760	0.450					
Agile management	4.681	1.001	.505***				
Spatial flexibility	4.811	0.997	.462***	.020			
AI maturity	4.838	1.009	.073	-.011	.037		
Employee engagement	3.546	0.817	.434***	.175***	.175***	.144**	
Org performance	4.953	1.129	.481***	.294***	.137**	.115*	.290***

Note. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$. Correlations are Pearson's r.

4. Results

4.1. Descriptive statistics and correlations

Table 2 reports mean, standard deviations, and Pearson correlations among the focal variables. DRISA practices are positively associated with employee engagement ($r = .434$, $p < .001$) and organizational performance ($r = .481$, $p < .001$). AI maturity is positively associated with employee engagement ($r = .144$, $p < .01$) and organizational performance ($r = .115$, $p < .05$). Spatial flexibility is positively correlated with organizational performance ($r = .137$, $p < .01$).

Before testing interactions, we confirmed that multicollinearity is unlikely to bias estimates: VIFs for focal predictors were below 1.1. We also assessed common method variance using an unrotated principal component diagnostic; the first component explained 19.4% of the variance across measurement items, below common thresholds used as heuristics of concern [51].

4.2. Hypothesis tests

Table 3 presents the hierarchical regression results. All continuous variables were standardized before analysis; coefficients reported below are standardized betas (β). Control variables (region, gender, age, education, company size, work arrangement, and role) were included in all models but are omitted from **Table 3** for brevity.

Table 3. Hierarchical regression results (standardized coefficients; robust SE in parentheses).

Predictor	Model 1: EE (main)	Model 2: EE (interaction)	Model 3: OP (main)	Model 4: OP (interaction)
DRISA practices (z)	0.412*** (0.047)	0.399*** (0.046)		
AI maturity (z)	0.123* (0.052)	0.129* (0.050)	0.107† (0.063)	0.117* (0.049)
DRISA × AI		0.113* (0.049)		
Spatial flexibility (z)			0.144* (0.056)	0.155*** (0.047)
Spatial × AI				0.360*** (0.045)
R^2	0.289	0.300	0.115	0.232

Note. Controls included in all models: region, gender, age, education, company size, work arrangement, and role. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$. ΔR^2 (Model 2 vs. Model 1) = 0.011; ΔR^2 (Model 4 vs. Model 3) = 0.117.

Hypothesis 1 predicted a positive relationship between DRISA practices and employee engagement. As shown in Model 1, DRISA practices were positively related to engagement ($\beta = 0.412$, $p < .001$), supporting H1.

Hypothesis 2 predicted that AI maturity moderates the DRISA–engagement relationship. In Model 2, the DRISA × AI maturity interaction was positive and significant ($\beta = 0.113$, $p = .022$), supporting H2. The interaction explains incremental variance beyond main effects ($\Delta R^2 = 0.011$). Simple slope analysis (**Figure 3**) showed that the effect of DRISA practices on engagement was stronger when AI maturity was high (+1 SD; $\beta = 0.512$, $p < .001$) than when AI maturity was low (−1 SD; $\beta = 0.286$, $p < .001$).

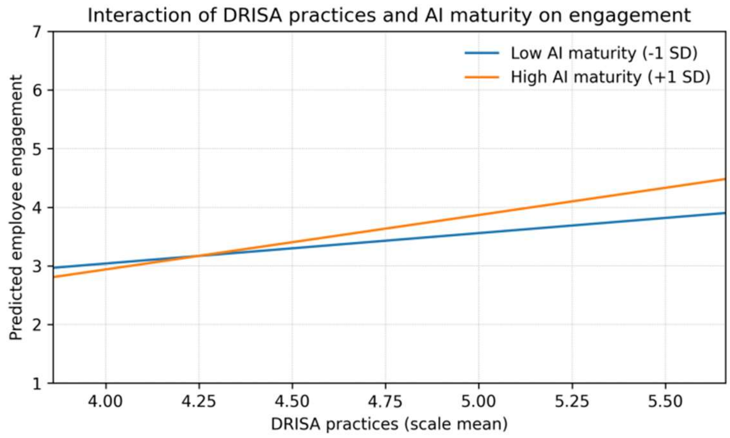

Figure 3. Simple slopes of the DRISA–engagement relationship at low vs. high AI maturity.

Hypothesis 3 predicted that spatial flexibility is positively related to organizational performance. In Model 3, spatial flexibility shows a small positive average association with performance ($\beta = 0.144$, $p < .05$). Given the strong interaction in Model 4, this main effect should be interpreted as an average effect across levels of AI maturity rather than as a uniform performance benefit.

Hypothesis 4 predicted that AI maturity moderates the spatial flexibility–performance relationship. Model 4 shows a strong, positive interaction between spatial flexibility and AI maturity ($\beta = 0.360$, $p < .001$), supporting H4. The interaction explains substantial incremental variance ($\Delta R^2 = 0.117$). Simple slopes (**Figure 4**) indicate a performance penalty of spatial flexibility when AI maturity is low (−1 SD; $\beta = -0.205$, $p = .002$) but a substantial performance benefit when AI maturity is high (+1 SD; $\beta = 0.515$, $p < .001$). This pattern is consistent with the accelerator argument: AI maturity determines whether flexibility produces advantage versus friction.

4.3. Robustness checks and alternative specifications

We conducted additional analyses to assess the robustness of the findings and the stability of the interaction effects. First, because nomad-oriented work is most relevant for employees working remotely or in hybrid arrangements, we re-estimated the interaction models on the remote-plus-hybrid subsample (N = 276). The DRISA × AI maturity interaction remained significant ($\beta = 0.128$, $p = .025$), and the spatial flexibility × AI maturity interaction remained strongly significant ($\beta = 0.342$, $p < .001$).

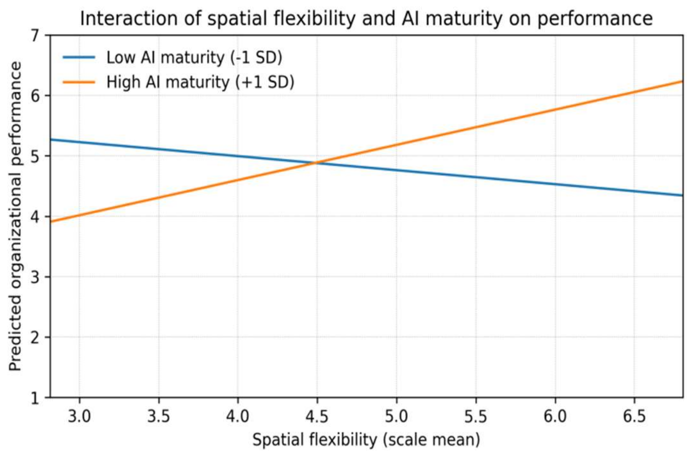

Figure 4. Simple slopes of the spatial flexibility–performance relationship at low vs. high AI maturity.

Second, we estimated the spatial flexibility interaction model separately by region. The spatial flexibility × AI maturity interaction remained positive and significant in China, the United States, and Europe (all $p < .01$). This consistency suggests that the accelerator effect in the performance domain is not driven by a single region.

Third, to rule out the possibility that the observed interactions merely reflect a direct effect of AI maturity, we examined models that included AI maturity as both a main effect and moderator (reported in **Table 3**). The interaction effects remain significant, indicating that AI maturity changes marginal returns rather than simply correlating with outcomes.

Finally, we tested an alternative interaction model in which AI maturity moderates the effect of agile management on organizational performance. In the pooled data, this interaction was not statistically significant when controlling for demographics and region. Accordingly, we treat the spatial flexibility interaction as the primary performance-focused evidence for the AI accelerator effect.

Appendix C reports the distribution of digital-nomad experience in the main sample (<1 year: n = 112; 1–3 years: n = 205; >3 years: n = 55). This information provides additional transparency about respondent heterogeneity, but experience stage remains a cross-sectional descriptor rather than a substitute for longitudinal evidence.

5. Discussion

5.1. Theoretical contributions

This study advances research on AI in management and distributed work by showing that AI maturity functions as a boundary condition that changes the effectiveness of autonomy- and flexibility-oriented management practices. Rather than treating AI primarily as a direct efficiency input, our findings support an "AI accelerator effect": As AI becomes embedded in workflows and coordination routines, the marginal return to distributed-work practices increases.

The moderation of the DRISA-engagement relationship suggests that AI maturity enables employees to realize the motivational benefits of autonomy and digital integration. In nomad-oriented contexts, engagement depends on whether employees can convert autonomy into meaningful and efficacious action without being overwhelmed by coordination friction. AI maturity appears to strengthen this conversion, consistent with theories that emphasize psychological availability [35] and with the JD-R model's focus on the resource conditions that sustain investment at work [36]. It also complements telework research showing that remote and hybrid arrangements yield better outcomes when they are supported by enabling structures and strong work design [3,8].

The moderation of the spatial-flexibility-performance relationship is equally consequential. Spatial flexibility is a hallmark of nomad-oriented organizing, but its performance implications are inherently ambiguous because dispersion can intensify mutual-knowledge problems, conflict, and collaborative siloing [6,17,18]. Our results show that spatial flexibility is not uniformly advantageous: when AI maturity is low, greater spatial flexibility is associated with lower performance, consistent with coordination-cost arguments and telework evidence on isolation and weak communication support [19,45]. When AI maturity is high, however, spatial flexibility becomes strongly performance enhancing. This pattern offers direct evidence that AI maturity is a socio-technical coordination capability that determines whether mobility translates into organizational advantage [46].

These findings also extend STS research by clarifying the role of algorithmic agency. Conventional STS treatments often view technology as infrastructure or as artefacts that people operate. Our results suggest that learning algorithms can become active participants in coordination by summarizing information, generating recommendations, and shaping routines [31,37]. AI maturity captures the extent to which such algorithmic agency has become embedded in organizational coordination [25,33]. In the current AI wave, this organizational layer includes both predictive and generative applications, suggesting that future work should examine how different forms of algorithmic agency - for example generative versus predictive, or opaque versus more interpretable systems - interact with social-system practices to produce divergent outcomes [28,43].

5.2. Practical implications

The results indicate that more autonomy or more mobility is not automatically better when managers design remote or nomad-oriented work systems. Rather, organizations need to treat AI maturity as a complement to flexibility-oriented practices and invest accordingly.

First, organizations that want to support more distributed work should not treat AI as a standalone productivity tool. The empirical pattern implies that workflow integration matters more than isolated tool access. In practical terms, managers should focus on AI-supported coordination mechanisms such as meeting summarization, knowledge retrieval, triage, handoff support, and decision-support routines that reduce information-processing burdens across dispersed teams.

Second, organizations should be cautious about expanding spatial flexibility - for example through work-from-anywhere policies - before adequate coordination capacity is in place. Our interaction results show that spatial flexibility can become performance-reducing when AI maturity is low. A more evidence-linked implication is therefore to sequence investments: strengthen AI-enabled visibility, documentation, workflow support, and governance first, and broaden mobility only once those coordination routines are sufficiently reliable.

Third, organizations should measure AI maturity in a way that is actionable for managers rather than purely symbolic. Useful indicators include whether AI outputs are embedded in recurring workflows, whether employees regularly use AI for knowledge retrieval and synthesis, whether AI-supported recommendations enter planning and prioritization routines, whether governance and human oversight are clear, and whether coordination outcomes such as cycle time, rework, customer response time, and decision latency improve after adoption.

5.3. Limitations and future research

This study has several limitations that also point to fruitful directions for future research. First, the cross-sectional design limits causal inference; longitudinal, quasi-experimental, or field-intervention designs could assess whether increases in AI maturity causally amplify the effectiveness of distributed-work practices over time.

Second, measures rely on self-reported perceptions of practices and performance, and the same respondents reported both predictors and outcomes. Although the Harman diagnostic and the poor fit of one-factor alternatives reduce concern that common method bias is the sole explanation, they do not eliminate the possibility of common source inflation. Future research should therefore incorporate multi-source data, objective indicators (e.g., project cycle time, service quality, financial outcomes), and digital trace data capturing coordination patterns.

Third, AI maturity was measured broadly as embedded use of AI for workflow, process integration, automation, decision support, and planning. Future work could disentangle specific forms of AI-for example generative AI versus predictive analytics-and examine how governance choices such as transparency, explainability, and escalation design shape the accelerator effect and the balance between control and autonomy [23,42,43].

Fourth, although we controlled for region and observed consistent patterns for the spatial flexibility interaction across China, the United States, and Europe, deeper cross-cultural theorizing is needed. Cultural norms around autonomy, uncertainty avoidance, and technology adoption may shape how AI maturity interacts with management practices, calling for multi-level and culturally grounded studies.

Finally, the supplementary experience-stage information reported in **Appendix C** should not be overinterpreted. Experience stage improves transparency about respondent heterogeneity, but it remains a cross-sectional descriptor rather than evidence of within-person adaptation or temporal stability.

6. Managerial guidance

To keep the implications closely tied to the evidence, we distill the practical implications into three action principles.

Principle 1: Diagnose coordination friction before expanding flexibility. Managers should look for recurring approval delays, duplicated work, documentation gaps, and information-hunting costs. In low-maturity environments, these frictions are likely to intensify when spatial flexibility expands.

Principle 2: Build AI maturity in workflow integration, knowledge retrieval, decision support, and governance. The most important acceleration mechanisms are unlikely to come from isolated tool adoption alone. They come from embedding AI in recurrent coordination routines and setting clear rules for verification, escalation, accountability, and human oversight.

Principle 3: Monitor outcome indicators that reveal whether the socio-technical system is actually improving. Instead of assuming that more AI or more flexibility is better, managers should track cycle time, rework, defect rates, decision latency, and customer response time to see whether coordination capacity is rising quickly enough to support autonomy and mobility.

7. Conclusion

This paper positions AI maturity as a boundary condition that alters the marginal productivity of management practices in nomad-oriented work systems. Using cross-regional survey data, it shows that AI maturity strengthens the connection between DRISA practices and employee engagement and fundamentally transforms the consequences of spatial flexibility for organizational performance. More broadly, the findings suggest that digitally flexible work contributes to sustainable social development only when organizations pair autonomy and mobility with sufficient AI-enabled coordination capacity, governance, and employee support.

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Appendix A. Measurement items (abbreviated)

Items were rated on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree).

Table A1. Measurement items used in the study.

Item	Item wording
AI1	Our organization widely uses AI tools (e.g., ChatGPT, Copilot) to support daily work processes.
AI2	AI systems are used to optimize resource allocation, project scheduling, or to automate administrative workflows.
AI3	In key business decisions, AI-based analytics and forecasting provide important support.
AI4	Deployed AI tools automate repetitive tasks, allowing employees to focus on more creative work.
AI5	The organization has a clear AI strategy and encourages employees to explore how AI can improve work efficiency.
EE1	At work, I feel energized.
EE2	I am enthusiastic about my job.
EE3	I am immersed in my work.
EE4	I feel inspired by my work.
EE5	I am proud of the work that I do.
OP1	Compared with major competitors, our organization has an advantage in innovation speed.
OP2	Compared with major competitors, our organization has an advantage in operational efficiency.
OP3	Compared with major competitors, our organization has an advantage in customer satisfaction.
OP4	Compared with major competitors, our organization has an advantage in financial performance.
OP5	Compared with major competitors, our organization has an advantage in market growth.

Appendix B. Measurement model assessment

We report (a) internal-consistency evidence for each multi-item scale, (b) confirmatory factor analysis (CFA) comparisons for the focal psychological/technological constructs used in the moderation models, and (c) a Harman single-factor diagnostic for common method bias.

Harman's single-factor test (unrotated PCA on all measurement items) indicates that the first factor explains 19.4% of the variance, below the conventional 50% heuristic.

Table B1. Internal consistency of multi-item scales (main sample, N = 372).

Scale	Items	Cronbach's α
Digital integration	6	0.884
Remote adaptability	6	0.913
Individual autonomy	6	0.926
Spatial flexibility	6	0.927
Agile management	6	0.935
AI maturity	5	0.951
Employee engagement	5	0.862
Organizational performance	5	0.937

Table B2. CFA model comparisons for focal constructs (main sample, N = 372).

Measurement set	Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
AI–EE–OP	Three-factor	337.69	87	0.944	0.933	0.088	0.038
AI–EE–OP	One-factor	2887.14	90	0.377	0.274	0.289	0.285
SF–AI–OP	Three-factor	485.21	101	0.930	0.917	0.101	0.039
SF–AI–OP	One-factor	3905.49	104	0.307	0.200	0.314	0.314

Note. CFA models were estimated on correlation matrices using maximum likelihood. The three-factor solutions provide substantially better fit than the corresponding one-factor solutions, supporting discriminant validity among the focal constructs.

Appendix C. Supplementary experience-stage composition

To increase transparency about respondent heterogeneity, we report respondents' digital-nomad experience stage as a supplementary descriptor.

Table C1. Digital-nomad experience stage in the main validation sample (N = 372).

Experience stage	**n**	**%**
<1 year (novices)	112	30.1
1–3 years (mainstream cohort)	205	55.1
>3 years (early adopters)	55	14.8

Supplementary interpretation. The sample is therefore not dominated exclusively by novice respondents. At the same time, because experience stage is still observed cross-sectionally, it should not be interpreted as evidence of within-person temporal change or causal stability.