

Transforming Talent for Agentic AI-Enabled Services: Developing and Critically Testing a Strategic Human Resource Reskilling Framework

Dr Suman Mathur, Dr Rita Biswas

Technology & Management, Regenesys Business School

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ABSTRACT

Agentic artificial intelligence (AI) is changing service work by enabling systems to plan, coordinate tasks, use tools, and perform actions with limited human supervision. This development changes how employees and AI systems share judgment, responsibility, and control. However, limited empirical research explains how organizations can prepare employees for effective work with Agentic AI. This study develops and evaluates an Agentic AI Talent Transformation Chain by integrating dynamic capabilities theory and self-determination theory. The model links perceived organizational dynamic capabilities, the AI reskilling environment, AI-learning basic psychological need satisfaction, AI reskilling adaptation and mastery, and perceived Agentic AI-enabled service performance. Data collected from professionals working in the Indian banking sector. A total of 161 responses were retained for analysis. A disjoint two-stage PLS-SEM approach was used to assess the measurement and structural models. The pooled analysis showed significant direct and indirect relationships. However, further analysis identified weak reliability in the two-item dimensions, poor discriminant validity, weak redundancy validity for service performance, and substantial response-block heterogeneity. After controlling for the response-block effect, most structural relationships became non-significant, and the full serial pathway was no longer supported. The findings therefore provide preliminary rather than confirmatory evidence for the proposed framework. The study contributes a theoretically grounded model for Agentic AI reskilling and highlights the importance of measurement quality and verified data provenance in emerging AI workforce research.

Keywords: Agentic AI; strategic human resource management; reskilling; dynamic capabilities; self-determination theory; human-AI collaboration; service performance.

INTRODUCTION

Artificial intelligence is moving from systems that classify, predict or generate content toward systems that can pursue goals across multi-step workflows. Contemporary Agentic-AI combines planning, memory, tool use, feedback and coordination so that software can initiate and adapt actions with comparatively limited supervision (Hosseini and Seilani, 2025; Dwivedi et al., 2026). This distinction is consequential for service work. A conventional AI application may recommend a response or produce a draft; an agentic system may identify the next action, access other applications, execute parts of a process, monitor progress and refer an exception to a human. Recent technical reviews accordingly define Agentic-AI through goal-directed autonomy rather than generation alone and emphasize that autonomy exists on a spectrum instead as an all-or-nothing property (Abou Ali et al., 2026; Dwivedi et al., 2026).

The implications of Agentic AI extend beyond faster automation. Agentic systems can change how tasks, decisions, control, and responsibilities are distributed between employees and AI systems. As AI systems gain greater operational autonomy, employees must understand when to delegate, monitor, intervene, and assume responsibility for service outcomes. Leonardi (2025) argues that these distribution loops can displace power and blur responsibility unless employees understand when and how to intervene. Baird and Maruping (2021) argue that agentic information systems challenge the view of technology as merely a passive tool, as rights

and responsibilities can be delegated both to and from information-system artifacts. For human resource management (HRM), therefore, the central question is not simply whether employees can operate an AI interface. It is whether organizations can continually prepare employees to frame objectives, delegate appropriately, monitor autonomous actions, identify errors, correct outputs and remain accountable for service quality.

Evidence from Generative-AI already illustrates both the opportunity and the boundary conditions. Experimental research has found gains in speed and output quality on suitable professional tasks (Noy and Zhang, 2023), while large-scale field evidence from customer support shows that AI assistance can improve productivity and diffuse experienced workers' tacit practices, with particularly strong gains for less-experienced employees (Brynjolfsson et al., 2025). These gains should not be treated as automatic. The automation augmentation paradox highlights the interdependence of automation and human enhancement, showing that they can either reinforce each other positively or negatively based on the choices organizations make (Raisch and Krakowski, 2021). Similarly, human-centered AI research argues that while it's feasible for high automation and meaningful human control to exist side by side, this balance requires careful design focused on reliability, safety, and accountability (Shneiderman, 2020).

This challenge shifts talent transformation from being only a training event to a strategic capability. This challenge moves talent transformation beyond conventional training. It becomes an organizational capability. Research on AI and human resource management identifies skills, role clarity, knowledge sharing, trust, managerial support, and a supportive work environment as important conditions for effective employee-AI collaboration. AI-related reskilling also requires data literacy, digital skills, complex cognitive abilities, decision-making capability, and continuous learning (Chowdhury et al., 2022; Jaiswal et al., 2022; Morandini et al., 2023). However, organizations may still treat reskilling mainly as a collection of training programmes. This approach can separate training from process redesign, career development, managerial support, and operational governance. Such fragmentation may be particularly problematic in Agentic AI environments because technologies, workflows, and delegation arrangements continue to change.

The existing literature explains dynamic capabilities by focusing on how firms sense technological change, seize opportunities and reconfigure resources and routines (Ellström et al., 2022). AI capability demonstrates that organizational value depends on the orchestration of technical and human resources and on changes to processes instead of only technology acquisition (Mikalef and Gupta, 2021; Mikalef et al., 2023). Moreover, self-determination theory (SDT), explains why work environments that support autonomy, competence and relatedness promote high-quality motivation and adaptive functioning (Ryan and Deci, 2020; Gagné et al., 2022). Yet few quantitative models connect these organization-level strategic mechanisms to employees' motivational experience, reskilling mastery and AI-enabled service outcomes in one causal sequence.

This study addresses this gap by developing and evaluating an Agentic AI Talent Transformation Chain. The model explains how perceived organizational capabilities may be translated into employee reskilling and service outcomes through organizational and psychological mechanisms. It links perceived organizational dynamic capabilities, the AI reskilling environment, AI-learning basic psychological need satisfaction, AI reskilling adaptation and mastery, and perceived Agentic AI-enabled service performance.

The study makes three main contributions. First, it integrates dynamic capabilities theory and self-determination theory to connect organizational transformation with employee learning experiences. Second, it distinguishes the organizational reskilling environment from psychological need satisfaction, learning outcomes, and service performance. Third, it shows that measurement quality and data-source heterogeneity can substantially affect the apparent strength of relationships in emerging AI workforce research. The study therefore contributes both a theoretical framework and a methodological caution for future Agentic AI research.

LITERATURE REVIEW AND THEORETICAL DEVELOPMENT

From AI assistance to Agentic-AI enabled services

The term Agentic AI is used inconsistently in the emerging management literature. Clear conceptual boundaries are therefore important. Agentic AI generally refers to goal-directed systems that combine reasoning, planning, memory, tool use, and iterative feedback to perform multi-step activities with a degree of operational autonomy (Hosseini and Seilani, 2025; Abou Ali et al., 2026). Unlike conventional generative AI, which mainly produces content in response to a prompt, Agentic AI can determine and execute intermediate actions within defined constraints. Dwivedi et al. (2026) distinguish these systems from conventional AI agents and stand-alone generative AI by emphasizing self-directed execution of complex goals, shared or persistent memory, orchestration and multi-agent teamwork. The difference is one of operational agencies- an agentic system is designed not only to produce an answer but also to decide and enact intermediate steps within constraints.

In service settings, these capabilities may affect customer support, financial operations, professional services, healthcare administration, travel, logistics, public services and internal shared services. Agentic workflows can route cases, retrieve knowledge, prepare or execute transactions, coordinate specialist agents and escalate exceptions. This changes the employee's role from sole task performer to a combination of goal setter, context provider, exception handler, quality controller and accountable decision-maker. The 'machine as teammate' literature anticipated this shift by arguing that AI can participate in team processes rather than remain a passive instrument (Seeber et al., 2020). The theory of delegation to and from agentic artifacts further clarifies that the human-AI relationship involves transfers of task rights and responsibilities, which must be designed and monitored (Baird and Maruping, 2021).

Agentic autonomy also raises distinctive performance risks. A generated error can remain local; an agentic error can cascade across actions and connected systems. Goal misalignment, inappropriate tool use, weak exception handling and opaque responsibility can undermine service reliability even when throughput improves (Dwivedi et al., 2026). Leonardi (2025) therefore places responsibility circulation and the ability to intervene in agency loops at the centre of organizational expertise. In this study, human oversight is not considered as resistance to automation. It is a service capability that allows organizations to combine machine autonomy with human accountability.

Perceived Organizational Dynamic Capabilities as the Strategic Origin of Reskilling

Dynamic capabilities provide an appropriate organization-facing explanation of continuous talent transformation. Contemporary digital-transformation research operationalizes dynamic capabilities through sensing changes and opportunities, seizing them through commitments and resource allocation, and reconfiguring structures, routines and assets (Ellström et al., 2022). These capabilities are distinct from ordinary operational capabilities. Operational capabilities help an organization perform current activities; dynamic capabilities enable it to change what it does and how it does it as technologies and environments evolve.

This distinction is crucial for Agentic-AI. Sensing requires systematic monitoring of changes in autonomous AI, emerging service requirements and the associated skill implications. Seizing involves allocating time, budget, learning tools and leadership attention, and selecting where human-AI collaboration can create value. Reconfiguring requires redesigning processes, roles, performance management, learning pathways and careers. Digital transformation research consistently argues that successful transformation entails organizational change and malleable designs, not the isolated deployment of a technology (Hanelt et al., 2021; Verhoef et al., 2021). AI capability research reaches a similar conclusion: firms derive value when they orchestrate AI-related resources and transform activities and processes (Mikalef and Gupta, 2021; Wamba-Taguimdje et al., 2020). In this study, dynamic capabilities are examined through employees' perceptions of how effectively their organizations sense AI-related changes, seize emerging opportunities, and reconfigure resources and work practices. The construct therefore represents perceived organizational dynamic capabilities rather than an objective organization-level capability. This distinction is important because the unit of analysis

is the individual employee. Employees may observe organizational practices differently depending on their roles, experiences, and exposure to AI-related transformation. Consequently, the findings reflect how organizational transformation capabilities are experienced by employees rather than verified firm-level capabilities. Establishing organization-level dynamic capabilities would require multiple respondents from each organization together with evidence of within-organization agreement and aggregation validity.

H1- Perceived organizational dynamic capabilities are positively associated with the perceived quality of the AI reskilling environment.

AI reskilling environment as an HR implementation mechanism

A strategic intent becomes meaningful to employees through the environment in which learning occurs. The proposed AI reskilling environment has three components. First, systems and support comprise access to relevant learning resources and assistance from coaches, peers or a help desk. Second, task-aligned training and recognition connect learning content to AI-enabled tasks and signal that progress is valued. Third, an adaptive learning climate combines psychological safety for experimentation with role redesign that reduces avoidable ambiguity.

This configuration reflects recent AI-HRM scholarship. According to Budhwar et al. (2022), AI not only presents new opportunities for organizations but also poses challenges for employees, which calls for a unified HR approach. Chowdhury et al. (2023) argue that the value derived from AI-enabled HRM relies on a comprehensive organizational AI capability framework instead of just isolated tools. In a similar lines, Malik et al. (2023) describe AI-assisted HRM as a strategic system that benefits both the organization and its workforce. At the employee level, elements like knowledge sharing, AI skills, trust, and clarity in roles are essential for enhancing collaboration and overall business performance (Chowdhury et al., 2022). Furthermore, findings from an IT multinational reveal that AI-driven knowledge exchange, when embedded in a culture that prioritizes innovation, can greatly improve the experiences of talent (Malik et al., 2021).

The reskilling environment should not be equated with training volume. Access without task relevance may generate course completion but little transfer. Experimentation without role clarity may increase uncertainty. Recognition without practical support can become symbolic. The construct is therefore specified as a higher-order composite: each component makes a distinct contribution, and weakness in one is not necessarily interchangeable with strength in another.

Self-determination in AI learning

SDT explains the psychological mechanism through which the reskilling environment should influence sustained learning. The theory identifies autonomy, competence and relatedness as basic psychological needs whose satisfaction supports internalization, persistence, performance and well-being (Ryan and Deci, 2020; Vansteenkiste et al., 2020). Autonomy concerns volition and meaningful choice, not independence from others. Competence concerns feeling effective and being able to master challenges. Relatedness concerns belonging, care and connection with significant others.

The application to Agentic-AI is direct. Employees experience autonomy when they have reasonable discretion in how to use AI and a sense of ownership over their learning. They experience competence when they believe they can work effectively with AI agents and can monitor and correct outputs. They experience relatedness when colleagues and managers support skill development. Gagné et al. (2022) argue that SDT is especially relevant to the future of work because digital technologies alter work design, interdependence and control. Parker and Grote (2022) likewise show that the consequences of automation and algorithms are mediated by work design choices such as autonomy, feedback and role structure.

The construct measured here should be called AI-learning basic psychological need satisfaction, not ‘intrinsic motivation.’ The survey does not directly measure intrinsic, identified, introjected or external regulation. Labelling it motivation would overstate content validity. Instead, autonomy, competence and relatedness are

modelled as distinct lower-order components that jointly form a need-satisfaction composite. This approach preserves theoretical specificity while fitting the supplied items.

H2- A stronger perceived AI reskilling environment is positively associated with AI-learning basic psychological need satisfaction.

From need satisfaction to reskilling adaptation and mastery

High-quality reskilling requires more than exposure to learning. It should be visible in sustained effort, transfer to unfamiliar tasks, readiness for autonomous systems and the capacity to maintain service quality. Recent studies find that AI changes both technical and transversal skill requirements, increasing the importance of continuous learning, complex cognition, collaboration and adaptive judgment (Jaiswal et al., 2022; Morandini et al., 2023). Evidence also shows that AI can augment skills in some jobs while increasing pace or reducing autonomy in others, reinforcing the importance of implementation context (Holm and Lorenz, 2022).

SDT predicts that need-supportive conditions promote more autonomous forms of motivation and adaptive functioning. Contemporary meta-analytic evidence shows that more self-determined forms of work motivation are associated with desirable employee outcomes (Van den Broeck et al., 2021). Within the present model, employees who experience choice, efficacy and social support should be more willing to invest effort, persist through difficulty and generalize AI skills beyond their original role boundaries. Competence is particularly important because agentic work requires metacognitive monitoring: employees must know when AI assistance is adequate and when correction or escalation is required.

H3. AI-learning basic psychological need satisfaction is positively associated with AI reskilling adaptation and mastery.

H5. AI-learning basic psychological need satisfaction mediates the positive relationship between the AI reskilling environment and AI reskilling adaptation and mastery.

H6. The AI reskilling environment and AI-learning basic psychological need satisfaction sequentially transmit the positive association between perceived organizational dynamic capabilities and AI reskilling adaptation and mastery.

AI reskilling outcomes and service performance

The final link concerns transfer from learned capability to operational outcomes. AI can increase service speed and quality when employees are able to use it appropriately. Noy and Zhang (2023) show that Generative-AI can raise productivity on suitable professional tasks, while Brynjolfsson et al. (2025) find meaningful productivity gains among customer-support employees and evidence of learning diffusion. At the organizational level, AI capability has been associated with performance through process automation and cognitive insight generation (Mikalef et al., 2023). In service research, knowledge sharing and AI system quality can jointly improve employee service quality and customer satisfaction (Nguyen and Malik, 2022).

However, speed alone is an incomplete criterion for agentic services. The performance composite in this study includes faster service, better handling of complexity and reliable human oversight. These facets need not move in lockstep; an organization can accelerate service while weakening reliability. They are therefore modelled formatively as complementary dimensions of perceived service performance. The global item- 'Overall, Agentic-AI has strengthened service performance outcomes in my organization'- is reserved as a criterion for redundancy analysis rather than treated as another interchangeable indicator.

H4. AI reskilling adaptation and mastery are positively associated with perceived agentic AI-enabled service performance.

H7. AI reskilling adaptation and mastery mediates the positive relationship between AI-learning basic psychological need satisfaction and perceived agentic AI-enabled service performance.

H8. Perceived organizational dynamic capabilities have a positive serial indirect association with perceived agentic AI-enabled service performance through the AI reskilling environment, AI-learning basic psychological need satisfaction, and AI reskilling adaptation and mastery.

Research gap and integrated conceptual logic

The literature reviewed between 2020 and 2026 establishes several pieces of the argument. Existing research provides important but fragmented explanations of AI-enabled organizational transformation. Dynamic capabilities research explains how organizations identify technological change, allocate resources, and reconfigure routines. AI and HRM research explain the importance of employee skills, learning support, role clarity, and human–AI collaboration. Self-determination theory explains how autonomy, competence, and relatedness can support adaptive learning and performance. However, these streams are rarely examined together in a single employee-level model. Limited empirical research explains how perceived organizational transformation capabilities are translated into a supportive AI reskilling environment, psychological need satisfaction, reskilling mastery, and service performance. This study examines this proposed sequence.

Agentic AI Talent Transformation Chain

Strategic capacity becomes dependable service performance through an enabling and need-supportive learning system



DC = dynamic capabilities | ARE = AI reskilling environment | BNS = basic need satisfaction | ARO = adaptation and mastery | ASP = service performance

Figure 1 : **Model . Agentic AI Talent Transformation Chain.** DC = perceived organizational dynamic capabilities; ARE =AI reskilling environment; BNS = AI-learning basic psychological need satisfaction; ARO = AI reskilling adaptation and mastery; ASP = perceived agentic AI-enabled service performance.

Construct	Definition in this study	Lower-order dimensions/facets	Measurement logic
Perceived organizational dynamic capabilities (DC)	Employees' perception that the organization can detect agentic AI-related change, commit resources and redesign routines continuously.	Sensing; seizing; reconfiguring	Higher-order formative composite from three two-item lower-order dimensions.
AI reskilling environment (ARE)	The organizational conditions that make AI learning accessible, task-relevant, supported and psychologically safe.	Systems and support; task-aligned training and recognition; adaptive learning climate and role clarity	Higher-order formative composite from three two-item lower-order dimensions.



AI-learning basic psychological need satisfaction (BNS)	The degree to which AI learning and use support volition, effectiveness and social connection.	Autonomy; competence; relatedness	Higher-order formative composite from three two-item lower-order dimensions.
AI reskilling adaptation and mastery (ARO)	Observable self-reported manifestations of sustained learning, transfer, readiness and quality-preserving capability.	Effort; transfer; preparedness; maintaining service quality	Formative composite because facets are complementary, not interchangeable.
Agentic AI-enabled service performance (ASP)	Perceived improvement in service outcomes arising from AI-enabled workflows and capable human oversight.	Speed; complexity handling; reliable oversight	Formative composite; global overall-performance item used for redundancy analysis.

Table 1 : Summarizes the constructs and their intended measurement logic

RESEARCH METHODOLOGY

The study adopts a post-positivist, explanatory quantitative design and evaluates a theory-derived network of directional associations using a cross-sectional employee survey. The unit of analysis is the individual employee. Organizational practices, motivational experiences, reskilling outcomes, and service performance are therefore interpreted as employee perceptions. The design can identify patterns of association but cannot establish temporal or causal order. Causal language is therefore avoided when interpreting the empirical findings.

PLS-SEM was selected because the model combines reflective lower-order components with reflective-formative higher-order constructs and first-order formative composites. Such hierarchical component models can be estimated using repeated-indicator or two-stage PLS procedures (Becker et al., 2012; Sarstedt et al., 2019). The present analysis uses a disjoint two-stage approach to separate the lower-order measurement assessment from the higher-order structural model.

Data Sampling

The study used purposive sampling to recruit professionals working in the Indian banking sector. Participants were drawn from public-sector, private-sector, and co-operative banking institutions. Eligible respondents were professionals involved in technology development, technology implementation, digital transformation, AI-enabled operations, technology support, supervision, or related operational activities. Participation was voluntary. Respondents were informed about the purpose of the study before completing the questionnaire and could withdraw at any point before submission.

A total of 200 potential respondents were targeted. Of these, 179 responses were received. Eighteen incomplete responses were removed during initial screening. The resulting dataset contained 161 responses before further assessment of measurement quality and response-source heterogeneity. Since the study focuses on perceptions of AI-enabled work, the unit of analysis is the individual employee. Organizational capabilities, reskilling conditions, psychological experiences, learning outcomes, and service performance are therefore interpreted as employee perceptions rather than objective organization-level measures.

Characteristic	Category	n	%
Bank type	Public-sector bank	21	13.04
	Private-sector bank	113	70.19
	Co-operative bank	27	16.77
	Total	161	100
Professional role	Technology development	33	20.5
	Digital transformation	23	14.29
	Technology-enabled operations	105	65.22
	Total	161	100
AI-related experience	Less than 1 year	10	6.21
	1–3 years	28	17.39
	4–5 years	31	19.25
	More than 5 years	92	57.14
	Total	161	100

Table 2. Respondent's Profile

The final sample consisted of 161 banking professionals. Most respondents worked in private-sector banks (70.19%), followed by co-operative banks (16.77%) and public-sector banks (13.04%). Most participants worked in technology-enabled operations (65.22%), while 20.50% worked in technology development and 14.29% in digital transformation. In terms of AI-related experience, 57.14% had more than five years of experience, indicating that a substantial proportion of the sample had considerable exposure to AI-related work.

Data Provenance and Response block assessment

Data provenance was examined because the dataset showed a clear discontinuity in response patterns. Respondents R1–R111 used the full five-point response scale, whereas respondents R112–R161 used only response categories 4 and 5. In addition, several identical response profiles were observed within the second block. These patterns raised concerns about whether the two response blocks were collected under comparable conditions. The following information should therefore be verified for each response block: collection date, recruitment channel, respondent population, questionnaire version, response-scale anchors, institutional source, and data-entry procedure.

The response-block variable was subsequently included in robustness analyses to examine whether the pooled structural relationships remained after controlling for this discontinuity. The block-control analysis is treated as a sensitivity test rather than as proof that the two response groups are equivalent. If the provenance of the second response block cannot be established, results based on the full pooled sample should not be interpreted as confirmatory evidence.

Instrument and construct operationalisation

The questionnaire contains 26 positively worded statements measured on a five-point response scale. The complete item wording and construct mapping are provided in Appendix A. DC, ARE, and BNS are specified as reflective-formative higher-order constructs. Each higher-order construct contains three two-item reflective lower-order dimensions estimated in Mode A. ARO is specified as a four-indicator formative composite, while ASP is specified as a three-indicator formative composite estimated in Mode B. ASP4 is not included in the ASP composite and is used as a global criterion for redundancy analysis.

Reliability coefficients and average variance extracted (AVE) are evaluated for the reflective lower-order dimensions but not for the formative composites (Hair et al., 2020; Hair et al., 2022). Because each reflective lower-order dimension contains only two indicators, the measurement results are interpreted cautiously. This measurement structure is treated as preliminary rather than as a fully established scale.

Code range	Construct/dimension	Items	PLS role	Estimation
DC1-DC2	Sensing	2	Reflective LOC, Mode A	Stage 1
DC3-DC4	Seizing	2	Reflective LOC, Mode A	Stage 1
DC5-DC6	Reconfiguring	2	Reflective LOC, Mode A	Stage 1
ARE1, ARE4	Systems and support	2	Reflective LOC, Mode A	Stage 1
ARE2, ARE5	Task-aligned training and recognition	2	Reflective LOC, Mode A	Stage 1
ARE3, ARE6	Adaptive climate and role clarity	2	Reflective LOC, Mode A	Stage 1
BNS1-BNS2	Autonomy	2	Reflective LOC, Mode A	Stage 1
BNS3-BNS4	Competence	2	Reflective LOC, Mode A	Stage 1
BNS5-BNS6	Relatedness	2	Reflective LOC, Mode A	Stage 1
ARO1-ARO4	AI reskilling adaptation and mastery	4	Formative composite, Mode B	Stages 1-2
ASP1-ASP3	Agentic AI-enabled service performance	3	Formative composite, Mode B	Stages 1-2
ASP4	Global service-performance assessment	1	Redundancy criterion	Validation only

Table 3. PLS-SEM measurement specification.

The dataset was screened for missing values, invalid entries and duplicate identifiers before PLS-SEM analysis. All respondent identifiers were unique. One out-of-range value (45) was identified for ARE5 and treated as missing. Because this represented only 0.024% of the item-level data, the missing value was replaced with the ARE5 mean of 3.356. A complete-case sensitivity analysis excluding the affected respondent was also conducted (n = 160).

Disjoint two-stage PLS-SEM estimation

Stage 1 estimated the nine reflective lower-order constructs including sensing, seizing and reconfiguring; systems and support, task-aligned training and recognition, and adaptive climate and role clarity; and autonomy, competence and relatedness using Mode A. The latent variable scores obtained for these lower-order constructs were then saved for use in Stage 2.

To preserve the theoretical nomological chain during score estimation, the three lower-order components of each upstream higher-order construct were connected to the three lower-order components of the adjacent downstream higher-order construct. The ARO and ASP composites were retained as downstream constructs. In Stage 2, the resulting lower-order construct scores were used as formative indicators of DC, ARE and BNS. ARO1-ARO4 and ASP1-ASP3 remained Mode B formative indicators.

All manifest variables were standardized before estimation. The PLS path-weighting scheme was applied. Mode A weights were estimated using correlations between the indicators and the inner estimates, whereas Mode B weights were estimated using multiple regression within each construct block. The weights were normalized so that the resulting construct scores had unit variance. The primary PLS model converged within 20 iterations using a tolerance criterion of 10^{-6} . Standardized structural path coefficients were then estimated among the PLS construct scores.

Statistical inference was based on 5,000 case-resampling bootstrap samples. The complete two-stage PLS-SEM model was re-estimated for each bootstrap sample. This procedure incorporated uncertainty associated with the lower-order construct scores, formative weights, and structural path coefficients. Two-tailed bootstrap standard errors, p-values, and percentile-based 95% confidence intervals were reported. All analyses were implemented in Python 3.13 using a script-based implementation of the PLS path-modeling procedure described above. The same estimation procedure was applied consistently across the primary, bootstrap, response-block-controlled, and sensitivity analyses. The analytical scripts and model specifications were retained to support reproducibility.

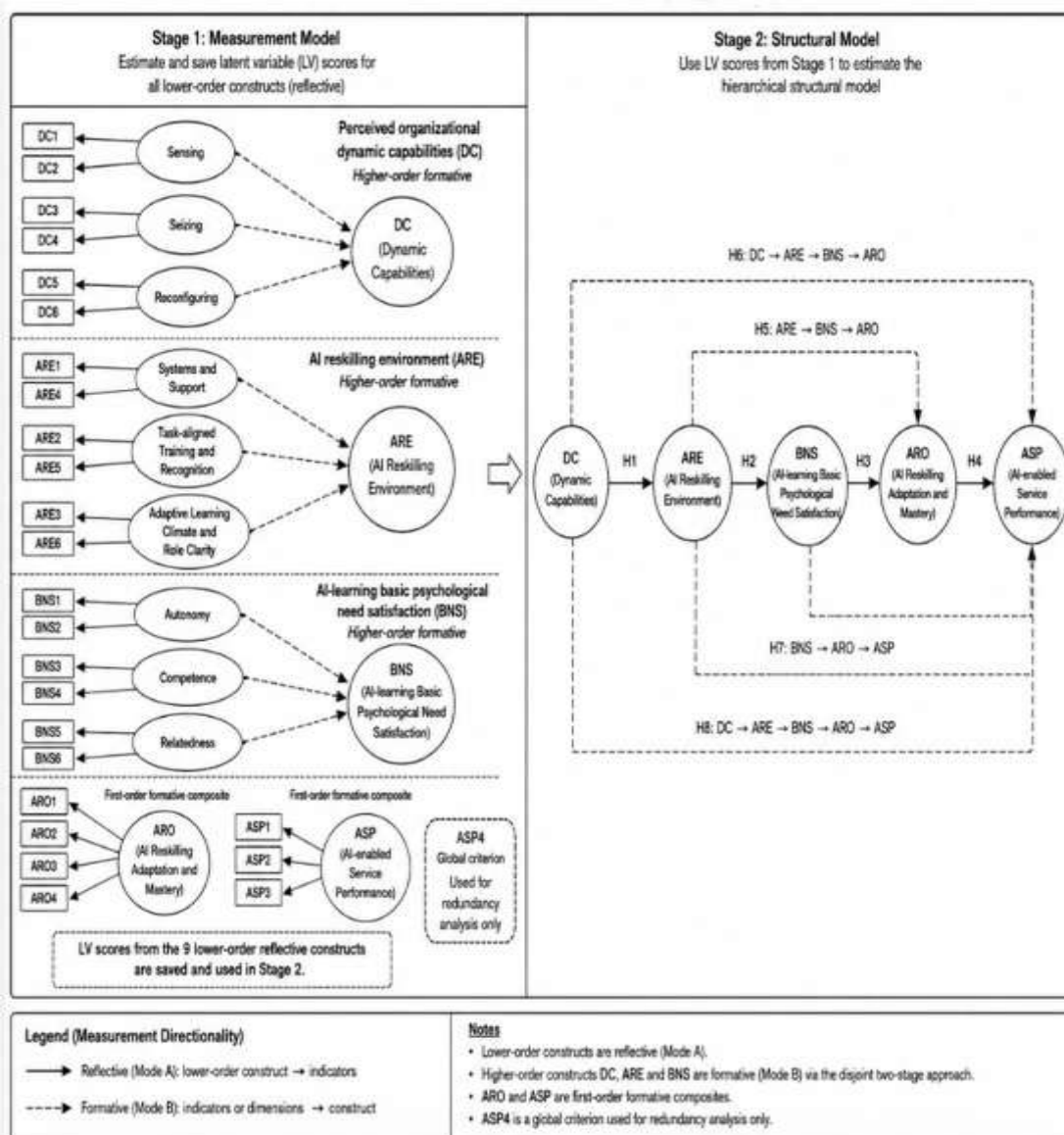


Figure 2. Hierarchical measurement and structural specification of the two-stage PLS-SEM model

Measurement-model assessment

Reflective lower-order components were evaluated using outer loadings, Spearman–Brown reliability for the two-item dimensions, composite reliability (ρ_C), and average variance extracted (AVE). Outer loadings

around .70, rho_C values of .70 or above, and AVE values of .50 or above were used as conventional reference criteria. Greater attention was given to the Spearman–Brown coefficient because two-indicator dimensions can show acceptable PLS loadings even when inter-item consistency is weak.

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT). Values above .90 were treated as evidence of insufficient empirical distinctiveness between conceptually related constructs (Henseler et al., 2015). Formative constructs were assessed using indicator collinearity, outer weights, bootstrap significance, and outer loadings as an absolute-relevance check. VIF values below 3 were preferred. Convergent validity of ASP was assessed through redundancy analysis against the global ASP4 item. A relationship approaching .70 was used as the planned reference criterion. Equivalent global criterion items were not available for DC, ARE, BNS, or ARO. Their redundancy validity could therefore not be directly assessed.

Structural-model and indirect-effect assessment

The structural model evaluated H1–H4 using standardized PLS path coefficients, R^2 values, and f^2 effect sizes. For the single-predictor pooled equations, f^2 was calculated as $R^2/(1-R^2)$. H5–H8 were evaluated as specific indirect effects based on the products of their constituent standardized paths. Evidence of an indirect association was considered present when the 95% bootstrap confidence interval excluded zero. Because the study uses cross-sectional data, these indirect effects are interpreted as statistical mediation patterns rather than evidence of temporal or causal mediation.

Response-block-controlled and sensitivity analyses

A binary response-block indicator was included to assess whether the pooled structural relationships remained after accounting for the observed response-order discontinuity. Respondents R1–R111 were coded 0 and respondents R112–R161 were coded 1. For each endogenous construct, the focal predecessor and the response-block indicator were entered simultaneously. Incremental f^2 for each focal path was calculated by comparing the full equation with a reduced block-only equation. Adjusted indirect effects were then calculated from the block-controlled path coefficients. The complete two-stage PLS model and controlled regressions were re-estimated across 5,000 bootstrap samples.

Additional sensitivity analyses included: (1) complete cases ($N = 160$), (2) exact-response-vector deduplication ($N = 141$), (3) R1–R111 only ($N = 111$), and (4) R112–R161 only ($N = 50$). These analyses examined whether the structural relationships depended on the single invalid cell, repeated response profiles, or the composition of the two response blocks. The block-control analysis is treated as a robustness test. It does not establish that the two response blocks were collected under equivalent conditions or from equivalent populations.

Common-method risk and ethical considerations

All major variables were collected from the same respondent at one point in time. The study is therefore subject to common-method and social-desirability risk. The first unrotated component of the standardized 26-item correlation matrix accounted for 28.7% of the total variance. Although this value is below the commonly used 50% threshold, the result does not establish the absence of common-method bias (Jordan and Troth, 2020; Podsakoff et al., 2024). It is therefore treated only as a preliminary diagnostic and interpreted together with the measurement-validity and response-block sensitivity analyses. Participation was voluntary, and respondents were informed about the purpose of the study before completing the questionnaire.

Empirical results

Initial data screening identified one out-of-range value of 45 for ARE5. This value was treated as missing and replaced with the ARE5 item mean for the primary analysis involving 161 respondents. A complete-case sensitivity analysis was also conducted after excluding the affected respondent ($N = 160$).

More importantly, response-pattern screening identified substantial heterogeneity between the two response blocks. Respondents R1–R111 used the full response scale from 1 to 5, whereas respondents R112–R161 used only categories 4 and 5. Eight clusters of identical response profiles were also observed within the second block. These differences indicate that pooled correlations and structural paths may partly reflect differences between response blocks rather than stable relationships among the theoretical constructs. Therefore, the pooled analysis is presented as an unadjusted baseline. Greater interpretive weight is given to the block-controlled and sensitivity analyses.

Construct	M	SD	1	2	3	4	5
1. DC	3.439	0.910	—				
2. ARE	3.586	0.846	0.687	—			
3. BNS	3.464	0.880	0.618	0.665	—		
4. ARO	3.432	0.938	0.608	0.605	0.637	—	
5. ASP	3.524	0.953	0.563	0.638	0.553	0.532	—

Table 4. Construct descriptives and unadjusted correlations. Note: $n = 161$. ASP uses ASP1–ASP3; ASP4 is the global redundancy criterion. Correlations are descriptive item-mean associations and incorporate the response-block shift.

Reflective lower-order measurement model

Indicator loadings ranged from .644 to .929. Composite reliability ranged from .735 to .818, while AVE ranged from .583 to .693. These values were generally within conventional reference levels. However, Spearman–Brown reliability for the nine two-item dimensions ranged from .290 to .556, and none reached .70. The two-item dimensions therefore show limited internal consistency. The apparently acceptable composite reliability and AVE values should consequently be interpreted with caution.

Dimension	Items	Loading 1	Loading 2	Inter-item r	Spearman-Brown	ρ_C	AVE	Decision
Sensing	DC1, DC2	0.711	0.875	0.282	0.440	0.776	0.636	Below .70
Seizing	DC3, DC4	0.929	0.644	0.316	0.480	0.774	0.639	Below .70
Reconfiguring	DC5, DC6	0.835	0.829	0.385	0.556	0.818	0.693	Below .70
Systems support and	ARE1, ARE4	0.812	0.791	0.285	0.444	0.782	0.643	Below .70
Task-aligned training and recognition	ARE2, ARE5	0.692	0.874	0.255	0.406	0.764	0.622	Below .70
Adaptive climate and role clarity	ARE3, ARE6	0.778	0.822	0.280	0.438	0.780	0.640	Below .70

Autonomy	BNS1, BNS2	0.825	0.697	0.170	0.290	0.735	0.583	Below .70
Competence	BNS3, BNS4	0.771	0.796	0.229	0.372	0.761	0.614	Below .70
Relatedness	BNS5, BNS6	0.798	0.848	0.357	0.526	0.808	0.678	Below .70

Table 5. Reflective lower-order measurement assessment.

Discriminant validity

Discriminant validity was assessed using the HTMT criterion. Of the 36 HTMT values, 20 exceeded the recommended threshold of .90, with the highest value being 1.268. These results indicate that several lower-order constructs were not sufficiently distinct from one another. Therefore, discriminant validity remains an important limitation of the measurement model.

Construct A	Construct B	HTMT	Assessment
Systems and support	Autonomy	1.268	Fails .90
Adaptive climate and role clarity	Autonomy	1.221	Fails .90
Task-aligned training and recognition	Competence	1.140	Fails .90
Systems and support	Task-aligned training and recognition	1.104	Fails .90
Competence	Relatedness	1.095	Fails .90
Autonomy	Competence	1.080	Fails .90

Table 6. Highest HTMT ratios. Full matrix in Appendix C.

Formative measurement model

The formative blocks did not exhibit problematic collinearity: VIF values ranged from 1.077 to 1.436. All 16 outer weights were positive and their 95% bootstrap intervals excluded zero. The strongest relative contributions were ARO4 (quality-preserving mastery; weight = .531), ASP1 (service speed; .518), ARE adaptive climate/role clarity (.502), and DC reconfiguring (.481). These results show that the formative components contribute non-redundant information to their composites in the pooled sample.

The ASP redundancy analysis nevertheless failed the planned convergent-validity criterion. The correlation between the ASP PLS composite and the global ASP4 item was $r = 0.329$, 95% CI [0.184, 0.460], and fell to $r = -0.026$ after response-block adjustment. Thus, statistically significant outer weights should not be interpreted as sufficient evidence that ASP captures the intended global service-performance domain.

Construct	Facet/indicator	Weight	Loading	VIF	t	p	95% CI
DC	Sensing	0.389	0.780	1.393	4.056	<.001	[0.191, 0.565]
DC	Seizing	0.416	0.743	1.252	5.395	<.001	[0.256, 0.557]

DC	Reconfiguring	0.481	0.806	1.321	5.896	<.001	[0.314, 0.635]
ARE	Systems and support	0.458	0.802	1.372	5.785	<.001	[0.294, 0.601]
ARE	Task-aligned training & recognition	0.346	0.707	1.302	4.770	<.001	[0.209, 0.492]
ARE	Adaptive climate & role clarity	0.502	0.774	1.186	6.806	<.001	[0.341, 0.629]
BNS	Autonomy	0.436	0.767	1.268	5.149	<.001	[0.260, 0.585]
BNS	Competence	0.381	0.766	1.376	3.706	<.001	[0.177, 0.581]
BNS	Relatedness	0.454	0.823	1.436	4.397	<.001	[0.238, 0.643]
ARO	ARO1 Learning effort	0.343	0.690	1.244	3.125	0.002	[0.109, 0.538]
ARO	ARO2 Skill transfer	0.336	0.642	1.182	3.227	0.001	[0.121, 0.526]
ARO	ARO3 Preparedness	0.251	0.514	1.098	2.455	0.014	[0.049, 0.445]
ARO	ARO4 Quality-preserving mastery	0.531	0.788	1.177	5.417	<.001	[0.325, 0.709]
ASP	ASP1 Service speed	0.518	0.773	1.167	4.180	<.001	[0.254, 0.740]
ASP	ASP2 Complexity handling	0.404	0.621	1.077	3.275	0.001	[0.142, 0.628]
ASP	ASP3 Reliable oversight	0.474	0.736	1.157	3.600	<.001	[0.201, 0.717]

Table 7. Formative measurement-model results (5,000 bootstrap samples).

Unadjusted Pooled structural model

The unadjusted pooled PLS-SEM model produced positive and statistically significant coefficients for all four adjacent structural paths. DC was associated with ARE ($\beta = .712$), ARE with BNS ($\beta = .668$), BNS with ARO ($\beta = .636$), and ARO with ASP ($\beta = .551$). The corresponding R^2 values were .506, .446, .404, and .304. These coefficients are large according to conventional effect-size benchmarks. However, they were estimated before accounting for the response-block discontinuity. They are therefore treated as unadjusted baseline estimates rather than as robust evidence of hypothesis support.

H	Path	Beta (β)	SE	t	p	95% CI	R ²	f ²	Decision
H1	DC → ARE	0.712	0.038	18.835	<.001	[0.646, 0.794]	0.506	1.026	Significant in unadjusted model
H2	ARE → BNS	0.668	0.051	13.179	<.001	[0.572, 0.772]	0.446	0.806	Significant in unadjusted model
H3	BNS → ARO	0.636	0.046	13.794	<.001	[0.555, 0.733]	0.404	0.678	Significant in unadjusted model
H4	ARO → ASP	0.551	0.057	9.634	<.001	[0.457, 0.679]	0.304	0.437	Significant in unadjusted model

Table 8. Unadjusted pooled PLS-SEM direct effects.

Unadjusted specific indirect effects

The unadjusted pooled model produced positive specific indirect effects for H5–H8. The ARE → BNS → ARO indirect effect was .425. The DC → ARE → BNS → ARO serial indirect effect was .302. The BNS → ARO → ASP indirect effect was .350, while the full DC → ARE → BNS → ARO → ASP serial indirect effect was .167. All four pooled confidence intervals excluded zero.

These results are statistically consistent with the proposed serial pathway in the unadjusted pooled data. However, they were estimated before accounting for response-block heterogeneity. They are therefore interpreted as baseline indirect effects rather than as robust evidence of mediation.

H	Specific indirect effect	Estimate	SE	t	p	95% CI	Decision
H5	ARE → BNS → ARO	0.425	0.051	8.335	<.001	[0.341, 0.541]	Significant in unadjusted model
H6	DC → ARE → BNS → ARO	0.302	0.045	6.751	<.001	[0.236, 0.412]	Significant in unadjusted model
H7	BNS → ARO → ASP	0.350	0.053	6.628	<.001	[0.271, 0.477]	Significant in unadjusted model
H8	DC → ARE → BNS → ARO → ASP	0.167	0.038	4.414	<.001	[0.116, 0.266]	Significant in unadjusted model

Table 9. Unadjusted pooled PLS-SEM specific indirect effects (5,000 bootstrap samples).

Response-block-controlled structural model

The substantive interpretation changes sharply when the observed response discontinuity is controlled. The DC→ARE coefficient falls from .712 to .190 and remains only borderline significant ($p = .049$; 95% CI [.041, .419]). The remaining coefficients fall to .047, .053 and .078, with all three confidence intervals including zero. The incremental f-squared values for H2-H4 are below .01; H1 is .032. The response block itself has large, standardized coefficients in every equation, ranging from .630 to .787.

The block-controlled results do not provide robust support for the full Agentic AI Talent Transformation Chain. Only the DC → ARE relationship retains a small positive association. The remaining direct relationships are not statistically significant, and all adjusted indirect-effect confidence intervals include zero.

The strong relationships observed in the pooled model therefore depend substantially on the composition of the two response blocks. The proposed serial pathway cannot be treated as empirically confirmed using the present dataset.

H	Effect	Adjusted beta (β)	t	p	95% CI	Incremental f^2	Block beta(β)	Decision
H1	DC $\rightarrow$ ARE	0.190	1.970	0.049	[0.041, 0.419]	0.032	0.633	Weak residual
H2	ARE $\rightarrow$ BNS	0.047	0.455	0.649	[-0.128, 0.281]	0.003	0.787	Not robust
H3	BNS $\rightarrow$ ARO	0.053	0.486	0.627	[-0.110, 0.317]	0.002	0.707	Not robust
H4	ARO $\rightarrow$ ASP	0.078	0.721	0.471	[-0.087, 0.339]	0.005	0.630	Not robust
H5	ARE $\rightarrow$ BNS $\rightarrow$ ARO	0.002	0.138	0.890	[-0.023, 0.053]	-	-	Not robust
H6	DC $\rightarrow$ ARE $\rightarrow$ BNS $\rightarrow$ ARO	0.000	0.102	0.919	[-0.006, 0.014]	-	-	Not robust
H7	BNS $\rightarrow$ ARO $\rightarrow$ ASP	0.004	0.181	0.857	[-0.019, 0.073]	-	-	Not robust
H8	DC $\rightarrow$ ARE $\rightarrow$ BNS $\rightarrow$ ARO $\rightarrow$ ASP	0.000	0.038	0.970	[-0.001, 0.003]	-	-	Not robust

Table 10. Response-block-controlled direct and indirect effects. Note: the block control is $R1-R111 = 0$, $R112-R161 = 1$. Indirect effects are products of adjusted direct paths.

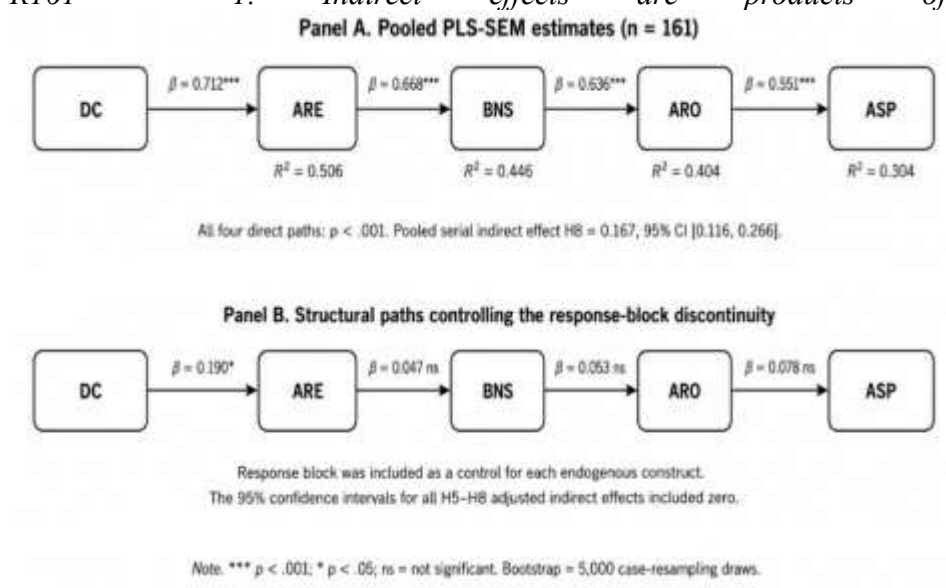


Figure 3. Comparison of unadjusted pooled and response-block-controlled structural estimates.

Sensitivity and common-method diagnostics

The complete-case model ($N = 160$) is almost identical to the primary pooled model, indicating that the single invalid ARE5 value is not responsible for the overall results. De-duplicating exact response vectors ($N = 141$) weakens all four pooled paths. The R1–R111-only model produces substantially smaller positive coefficients, whereas the R112–R161-only model is unstable and produces sign reversals for $ARE \rightarrow BNS$ and $BNS \rightarrow ARO$. This instability reinforces the need to verify the provenance of the second high-rating response block before substantive group comparisons are made.

Analysis	n	H1	H2	H3	H4
Primary pooled	161	0.712	0.668	0.636	0.551
Response-block controlled	161	0.190	0.047	0.053	0.078
Complete case (R121 excluded)	160	0.710	0.664	0.632	0.548
Exact vectors de-duplicated	141	0.634	0.590	0.558	0.465
R1–R111 only	111	0.367	0.274	0.196	0.303
R112–R161 only	50	0.636	-0.671	-0.708	0.708

Table 11. Sensitivity of PLS-SEM direct path estimates.

The first unrotated component accounted for 28.7% of standardized item variance. Because this value is below 50%, a mechanical single-factor explanation is not indicated; nevertheless, this diagnostic does not resolve the much stronger response-block discontinuity, the weak two-item reliability or the HTMT failures.

DISCUSSION

The findings do not provide robust empirical support for the complete Agentic AI Talent Transformation Chain. The unadjusted pooled model produced strong positive direct and indirect relationships. However, most of these relationships became non-significant after the response-block discontinuity was controlled. Only the relationship between perceived organizational dynamic capabilities and the AI reskilling environment retained a small positive association. The remaining direct relationships were not statistically robust, and the adjusted indirect effects did not support the proposed serial pathway.

The theoretical framework therefore remains plausible, but the present study should be interpreted as a preliminary evaluation rather than as confirmatory validation. The findings also show that measurement limitations and response-source heterogeneity can substantially influence structural relationships in emerging AI workforce research.

Measurement limitations constrain confirmatory interpretation

Three measurement findings independently limit confirmatory claims. First, none of the nine two-item reflective dimensions reaches acceptable Spearman-Brown reliability, despite apparently acceptable PLS composite reliability and AVE. This is a warning against relying mechanically on ρ_C and AVE when a construct is represented by only two weakly correlated indicators. Second, discriminant validity is poor: more than half of the HTMT ratios exceed .90 and several exceed 1.00. Third, ASP fails redundancy analysis against its intended global criterion. Taken together, these findings indicate that the current questionnaire does not yet provide sufficiently stable and distinguishable measurements for strong latent-variable conclusions.

The item architecture itself explains part of the problem. Sensing, seizing and reconfiguring are broad dynamic capabilities represented by only two perception items each. Autonomy, competence and relatedness are similarly compressed. ASP3, which captures reliable human oversight, may function more naturally as a governance capability or antecedent of performance than as a coequal outcome facet alongside speed and complexity handling. Future instrument development should broaden each reflective dimension to at least three well-targeted indicators and distinguish oversight capability, oversight behavior and achieved service reliability.

Response-source heterogeneity explains most of the pooled structural strength

The most consequential result is the response-order discontinuity. The high-rating R112-R161 block differs from R1-R111 on every construct and uses only the top two response categories. In the PLS construct scores, block membership explains nearly half to more than two-thirds of the variance. Once that common level shift is controlled, the chain collapses: only the first link retains a small borderline positive coefficient, while the remaining direct and all indirect effects are indistinguishable from zero.

This is an aggregation-induced covariance problem. When one block of respondents answers across the full scale and another block answers almost uniformly at the top, pooled correlations and PLS paths can become large even when within-block relationships are weak or unstable. Bootstrapping does not correct this problem because ordinary case resampling preserves the same heterogeneous mixture. The appropriate next step is not additional significance testing but source verification: collection date, channel, population, questionnaire version, scale anchors and respondent provenance must be established for R112-R161.

The response-block difference should therefore be treated as a data-provenance issue rather than only as a statistical-control issue. Controlling for block membership cannot demonstrate that the two response groups were collected from equivalent populations or under equivalent conditions. The collection date, recruitment channel, questionnaire version, response-scale anchors, institutional source, and respondent provenance of R112–R161 should therefore be verified before the pooled sample is used for confirmatory interpretation. If this information cannot be established, R112–R161 should not be treated as part of the primary confirmatory sample.

Theoretical implications

The findings do not reject the theoretical integration of dynamic capabilities theory and self-determination theory. Instead, they show that the proposed transmission mechanism requires stronger empirical validation. The positive residual relationship between perceived organizational dynamic capabilities and the AI reskilling environment is directionally consistent with the argument that sensing, resource commitment, and organizational reconfiguration may support employee learning conditions. However, the present evidence does not establish the complete psychological and performance pathway.

The distinction between basic psychological need satisfaction and intrinsic motivation also remains important. The questionnaire measures autonomy, competence and relatedness experiences; it does not measure the regulatory forms of motivation specified by self-determination theory. Future studies that make motivational mediation central should measure autonomous and controlled motivation directly rather than relabel BNS as intrinsic motivation. Similarly, learning effort, transfer, preparedness and mastery should be separated empirically if they are theorized as different stages of capability development.

Managerial implications

The Sense-Enable-Motivate-Master-Perform sequence should be viewed as a managerial diagnostic framework rather than as a validated cause-and-effect model. HR and service leaders can use the framework to examine whether their organizations identify Agentive AI-related skill changes, allocate appropriate learning resources, redesign roles and work practices, provide task-relevant training, support employee psychological needs, develop reskilling capability, and evaluate dependable service outcomes.

The present results do not justify numerical claims such as increasing dynamic capability will produce a specific increase in service performance. They do, however, identify measurement priorities for organizations that want to evaluate agentic-AI reskilling credibly: use multiple indicators per capability, retain global outcome criteria, collect operational service evidence, and preserve metadata that allows response sources, sites and collection waves to be separated.

Methodological implications for emerging agentic-AI research

Emerging-technology surveys are particularly vulnerable to source discontinuities because questionnaires may be distributed in multiple waves, channels or populations while the underlying technology and terminology are still changing. This study demonstrates that PLS-SEM can produce a coherent and highly significant serial model even when a large share of the covariance is attributable to response-block composition. Data provenance should therefore be treated as part of measurement validity, not as a clerical issue handled after structural testing.

LIMITATIONS AND FUTURE RESEARCH

This study has several important limitations. First, the dataset shows substantial response-source heterogeneity because R1-R111 used the full five-point scale, whereas R112-R161 used only response categories 4 and 5. Second, the nine reflective lower-order dimensions are measured using only two indicators each and show weak reliability and discriminant validity. Third, the cross-sectional and self-reported design limits causal interpretation and may introduce common-method bias. In addition, purposive sampling within the Indian banking sector limits the generalisability of the findings, and the Agentic AI-enabled service performance construct shows weak redundancy validity.

Future research should therefore strengthen the measurement instrument, use at least three well-targeted indicators for each reflective dimension, and verify data provenance before model testing. Longitudinal or multi-wave designs, larger and more diverse samples, and objective service-performance measures should also be considered. A revised instrument should ideally undergo expert review, cognitive testing, and pilot validation before the framework is tested again.

CONCLUSION

Agentic AI changes the workforce challenge from learning how to use digital technologies to learning how to work effectively and responsibly with increasingly autonomous systems. This study develops an Agentic AI Talent Transformation Chain that proposes a sequence linking organizational transformation capabilities, the AI reskilling environment, employee psychological need satisfaction, reskilling adaptation and mastery, and AI-enabled service performance.

The empirical findings provide preliminary rather than confirmatory evidence for this framework. The unadjusted pooled analysis produced strong direct and indirect relationships. However, these relationships weakened substantially after response-block differences were controlled. The measurement assessment also identified weak reliability in the two-item dimensions, poor discriminant validity, and weak redundancy validity for the service-performance construct.

The proposed framework should therefore not yet be treated as a validated cause-and-effect model. Its main contribution is to provide a theoretically grounded structure for examining how organizations may prepare employees for Agentic AI-enabled service work. Future research should strengthen the measurement instrument, verify data provenance, collect a new and well-documented sample, and evaluate the model across different organizational and service contexts.

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Appendix A: Survey Instrument and Construct Mapping

The following wording reproduces the supplied instrument. Codes were added for analysis.

Code	Construct/dimension	Item wording
DC1	Sensing	Our organization systematically monitors how agentic AI is changing service delivery requirements.
DC2	Sensing	Leaders anticipate the impacts of autonomous AI systems on job responsibilities.
DC3	Seizing	We allocate sufficient resources (time, budget, tools) to AI reskilling.
DC4	Seizing	Management supports changes to processes and roles to capture value from agentic AI.
DC5	Reconfiguring	HR practices (performance, learning, career paths) are updated to reflect AI-enabled work.
DC6	Reconfiguring	Workforce transformation is treated as continuous rather than a one-time initiative.
ARE1	Systems and support	I have access to relevant learning resources to build AI-related skills.
ARE2	Task-aligned training	Training content is practically connected to my AI-enabled tasks.
ARE3	Adaptive learning climate	Employees are encouraged to experiment with AI tools without fear of punishment for mistakes.
ARE4	Systems and support	There is support available (coaching/peers/help desk) when I struggle with AI-related tasks.
ARE5	Recognition	Learning progress in AI skills is recognized and valued by my organization.
ARE6	Role clarity	Role redesign has been managed in a way that reduces confusion and uncertainty.
BNS1	Autonomy	I have flexibility in how I use AI tools to accomplish my tasks.
BNS2	Autonomy	I experience a sense of ownership over my AI learning progress.
BNS3	Competence	I feel capable of working effectively with AI tools or AI agents.
BNS4	Competence	I can monitor and correct AI outputs when necessary.
BNS5	Relatedness	I feel supported by colleagues when learning to work with AI systems.
BNS6	Relatedness	My manager encourages and supports my AI skill development.
ARO1	Learning effort	I consistently invest effort in developing my AI-related skills.
ARO2	Skill transfer	I am able to apply AI skills to new tasks beyond my original job scope.
ARO3	Preparedness	I feel prepared to work in service environments involving autonomous AI systems.



Code	Construct/dimension	Item wording
ARO4	Quality-preserving mastery	I can maintain service quality while working with AI-enabled workflows.
ASP1	Service speed	AI-enabled workflows have improved the speed of service delivery in my unit.
ASP2	Complexity handling	Our team handles service complexity better due to AI support.
ASP3	Reliable oversight	Human oversight mechanisms ensure that AI-driven decisions remain reliable.
ASP4	Global criterion	Overall, agentic AI has strengthened service performance outcomes in my organization.

Appendix Table A1. Survey instrument.

Appendix B: Hypothesis and estimand map

Hypothesis	Estimand	Expected sign	Primary evidence
H1	DC → ARE	Positive	Direct path β and 95% bootstrap CI
H2	ARE → BNS	Positive	Direct path β and 95% bootstrap CI
H3	BNS → ARO	Positive	Direct path β and 95% bootstrap CI
H4	ARO → ASP	Positive	Direct path β and 95% bootstrap CI
H5	ARE → BNS → ARO	Positive	Specific indirect effect and 95% bootstrap CI
H6	DC → ARE → BNS → ARO	Positive	Specific serial indirect effect and 95% bootstrap CI
H7	BNS → ARO → ASP	Positive	Specific indirect effect and 95% bootstrap CI
H8	DC → ARE → BNS → ARO → ASP	Positive	Full serial indirect effect and 95% bootstrap CI

Appendix Table B1. Hypothesis and estimand map.