

Technological Readiness as A Mediator Between Ai Adoption and Cybersecurity Talent Management: Evidence from Beijing's Strategic Industries

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ABSTRACT

The rapid integration of Artificial Intelligence (AI) technologies into cybersecurity systems has created new challenges for managing skilled cybersecurity talent, particularly in China's AI-driven industrial sectors. Despite government emphasis on digital transformation, limited empirical research has examined how different forms of AI adoption influence cybersecurity talent management through technological readiness. Grounded in the Skill-Biased Technological Change (SBTC) and Diffusion of Innovations (DOI) theories, this study investigates the direct and mediating effects of Assisted AI (ASA), Augmented AI (AUA), and Autonomous AI (ATA) on Cybersecurity Talent Management (CTM) through Technological Readiness (TR) among cybersecurity professionals in Beijing. Employing a quantitative, cross-sectional design, data were collected from 264 full-time cybersecurity professionals across finance, internet, and manufacturing sectors. Structural Equation Modelling using Smart PLS was applied to test ten hypotheses (H1–H10). The results revealed that TR significantly predicted CTM ($\beta = 0.492$, $t = 5.905$, $p < 0.001$), while ATA and AUA positively affected both TR and CTM ($p < 0.01$). Conversely, ASA showed significant negative effects on TR ($\beta = -0.410$, $t = 5.250$, $p < 0.001$) and CTM ($\beta = -0.149$, $t = 2.345$, $p = 0.019$). Mediation analysis confirmed that TR partially mediated the relationships between AI adoption and CTM—complementary partial mediation for AUA and ATA ($t = 2.545$, $p = 0.011$; $t = 3.594$, $p < 0.001$, respectively) and competitive partial mediation for ASA ($t = 3.977$, $p < 0.001$). These findings advance theoretical understanding of AI-talent dynamics by integrating readiness as a pivotal mechanism and offer practical insights for policymakers and organisations to strengthen workforce readiness before expanding AI integration in cybersecurity operations.

Keywords: Artificial Intelligence, Cybersecurity Talent Management, Technological Readiness, Skill-Biased Technological Change, Diffusion of Innovations, Mediation Analysis, Smart PLS, Beijing

INTRODUCTION:

In recent years, the proliferation of artificial intelligence (AI) technologies has profoundly reshaped industrial ecosystems, redefining both the nature of work and the competencies required to sustain national competitiveness (Mossavar-Rahmani et al., 2024). In China, AI has become a strategic pillar of national innovation policy and economic modernization, particularly in sectors where data security and digital resilience are critical (Tiwari et al., 2025). As Beijing continues to lead the nation's technological transformation, industries such as finance, internet technology, and manufacturing are increasingly integrating AI into cybersecurity infrastructures, making the effective management of cybersecurity talent an urgent policy priority (Sundaramurthy et al., 2022). The capacity to cultivate and retain a highly skilled cybersecurity workforce is now directly linked to China's ambition to become a global AI powerhouse by 2030 (van Niekerk, 2025). Consequently, understanding how AI technologies influence cybersecurity talent management has become not only an academic concern

but also an essential prerequisite for achieving national digital sovereignty.

Despite strong government support for AI-driven industrial upgrading, significant challenges persist in aligning technological innovation with workforce development. China currently faces an estimated shortfall of nearly four million AI specialists, a deficit that threatens to slow the country's transition toward high-value digital industries (Atkinson, 2024). Within the cybersecurity domain, approximately 65% of professionals report heightened concern regarding budget constraints, workforce shortages, and the increasing sophistication of AI-enabled cyber threats—figures nearly double the global average (Graham, 2025). These challenges are compounded by uneven technological readiness across sectors, particularly between highly digitalized industries such as finance and internet services and more traditional sectors like manufacturing (Jameaba, 2022). As AI systems become integral to threat detection, risk analysis, and incident response, the gap between technological advancement

and workforce capability widens, intensifying the demand for adaptive, cross-disciplinary talent management strategies.

At the industry level, this imbalance manifests most acutely in Beijing's three dominant sectors: finance, internet, and manufacturing. Financial institutions have rapidly implemented AI-driven cybersecurity analytics to prevent fraud and manage digital transactions, yet many still struggle to recruit specialists with hybrid AI–cybersecurity expertise (Khang, 2025). Internet companies, while technologically advanced, often face high turnover and skill volatility due to the accelerating pace of innovation (George, 2023). Meanwhile, manufacturing firms—particularly those in industrial automation and smart production—experience barriers to AI integration caused by legacy systems and limited access to skilled cybersecurity practitioners (Rakholia *et al.*, 2024). The cumulative effect is a fragmented cybersecurity workforce ecosystem where AI adoption outpaces talent development, resulting in operational vulnerabilities and inconsistent preparedness across industries (Saba *et al.*, 2024). These issues highlight the need for an integrative framework that explains how AI diffusion interacts with technological readiness and sectoral characteristics to influence cybersecurity talent management outcomes.

Existing literature reveals several theoretical and empirical gaps. First, most research on AI adoption in China has focused on macroeconomic or policy-level analyses, with limited empirical investigation into how specific forms of AI (*i.e.*, assisted, augmented, and autonomous AI) affect human resource and talent management practices within cybersecurity contexts (Zhou, 2025). Second, prior studies rarely examine the mediating mechanisms through which technological readiness enables or constrains the impact of AI on workforce development (AL-Shboul, 2024). Third, there is limited cross-sectoral evidence comparing technologically intensive industries with more traditional manufacturing environments in Beijing, a region that serves as the nexus of China's AI innovation ecosystem (D. Li *et al.*, 2024). To address these limitations, this study aims to determine how AI technologies—operationalized as assisted, augmented, and autonomous AI—influence cybersecurity talent management, mediated by technological readiness and moderated by sectoral differences across Beijing's finance, internet, and manufacturing industries. This geographical and population focus provides an empirical lens for understanding China's national challenge of cultivating a technologically adaptive cybersecurity workforce.

This study contributes to both theory and practice. Theoretically, it integrates the Skill-Biased Technological Change (SBTC) theory (Autor *et al.*, 2003; Acemoglu & Restrepo, 2018) and the Diffusion of Innovations (DOI) theory (Rogers, 2003) to conceptualize how AI diffusion shapes talent dynamics in varying industrial contexts. Methodologically, it

employs a quantitative, cross-sectional design using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test mediation and moderation effects across industry strata, enhancing robustness and generalizability (Hair *et al.*, 2021). Practically, it provides evidence-based recommendations for policymakers, HR executives, and industry leaders to align AI deployment strategies with workforce development policies. The remainder of this paper is structured as follows: Section 2 reviews relevant theoretical frameworks and empirical studies; Section 3 presents the research model, methodology, and hypotheses; Section 4 reports and interprets the results; and Section 5 concludes with implications, limitations, and suggestions for future research.

Problem Statement

In the People's Republic of China, digital transformation efforts—particularly the widespread deployment of artificial intelligence (AI) across key industrial sectors—have elevated cybersecurity as a strategic imperative. Nevertheless, empirical evidence suggests that workforce capabilities have not kept pace with the rapidly evolving threat landscape. According to the 2023 report by the ISC2, although the global cybersecurity workforce expanded to 5.5 million professionals, the gap between workforce supply and demand increased to approximately 4 million, with emerging technologies such as AI cited as a major cause of skills mismatches (Dawson, 2021). These patterns reflect a critical misalignment between technological advancement, specifically AI integration in cybersecurity operations, and the human capital available to manage that transformation effectively.

Despite these alarming workforce dynamics, extant research reveals two salient shortcomings. First, much of the literature on cybersecurity workforce challenges in China tends to emphasise aggregate talent shortages or educational supply issues, but gives limited attention to the role of organisational technological readiness or sectoral context (De Zan, 2022). For example, while China is now a leading producer of AI research and aims to narrow the AI-talent gap (Weinstein & Stoff, 2022), less is known about how distinct forms of AI adoption—such as assisted, augmented, or autonomous AI—affect talent management in specific sectors. This has left an explanatory gap concerning how technological readiness interacts with AI adoption to shape talent outcomes. Second, there is a paucity of research examining how sectoral differences (*e.g.*, finance *vs.* internet *vs.* manufacturing) within a regional innovation hub like Beijing may moderate the AI-talent management nexus. Although thematic studies suggest that manufacturing firms face legacy infrastructure and lower digital maturity compared with internet firms (Awasthi *et al.*, 2025), these sectoral distinctions remain under-explored in empirical models that test mediation or moderation mechanisms.

In view of these gaps, this study proposes to examine comprehensively how assisted, augmented and

autonomous AI technologies influence cybersecurity talent management in Beijing's finance, internet and manufacturing sectors, with technological readiness as a mediating mechanism and sectoral context as a moderating condition. By focusing on full-time cybersecurity professionals in Beijing firms that engage with AI and cybersecurity, the study addresses both the population gap (cybersecurity specialists rather than broad IT workforce) and the geographic gap (capital region Beijing rather than national averages). In so doing, it seeks to generate actionable insights into how AI-enabled transformation in industry can be aligned with workforce development and talent management strategies under varying conditions of technological maturity.

Through this design, the study advances both theoretical and practical contribution: theoretically, by integrating the Skill-Biased Technological Change (SBTC) theory and the Diffusion of Innovations (DOI) theory to explicate the mechanisms through which AI adoption affects talent management outcomes; practically, by providing sector-sensitive evidence to guide human resource executives, policy-makers and industry leaders in tailoring talent acquisition, training and retention strategies that are aligned with AI-driven cybersecurity imperatives in China's leading innovation hub.

2.1 Underpinning Theory

The theoretical foundation for this study draws primarily on the Skill-Biased Technological Change (SBTC) theory and the Diffusion of Innovations (DOI) theory. SBTC posits that technological advancement disproportionately benefits high-skilled workers while rendering routine, low-skilled tasks obsolete (Acemoglu & Restrepo, 2018). In the context of China's ambitious national agenda for artificial intelligence (AI) and digital transformation, the SBTC framework explains how the integration of AI within key industries leads to increased demand for technically sophisticated, adaptive cybersecurity professionals. For example, empirical evidence from China suggests that AI adoption has altered labour-market compositions by reducing demand for routine tasks and placing greater emphasis on cognitive and analytical skills (Lábaj *et al.*, 2025). Simultaneously, the DOI theory (Rogers, 2003) provides insight into how AI technologies diffuse through industrial organisations and how adoption is shaped by innovation attributes, organisational readiness and social system characteristics. In China, central government policy such as the "AI Plus" initiative and regional industrial strategies have accelerated organisational adoption of AI at a national scale (Choi & Yoon, 2025). When applied to the population of full-time cybersecurity professionals in Beijing firms operating in finance, internet and manufacturing sectors, these theories collectively help to explain both how AI and technological readiness interplay (via DOI) and why the shift in required workforce skills occurs (via SBTC). The governmental policy context amplifies the validity of these theories because it structures both the supply side of talent (education/training) and the demand side

(industry adoption). Hence, SBTC illuminates changes in talent demand, while DOI offers the processual lens through which AI technologies enter and mature in organisations — particularly critical in China's sectoral ecosystem and regional hub of Beijing.

2.2 Variables and Hypotheses

The dependent variable of this study is Cybersecurity Talent Management (CTM), operationalised via eight items measuring how organisations recruit, develop, retain and deploy cybersecurity specialists in AI-infused environments. Prior literature emphasises that talent management in cybersecurity is no longer solely about technical skills but increasingly about the interplay of human-machine collaboration, continuous up-skilling, and workforce agility (Pawan *et al.*, 2024). The relevance of CTM intensifies as organisations elevate AI from experimentation to operationalisation without matching talent frameworks (Dinklo, 2023).

The independent variables comprise three distinct dimensions of AI adoption: Assisted AI (5 items), Augmented AI (4 items), and Autonomous AI (4 items). Existing research indicates that organisations deploying higher-order AI systems (e.g., autonomous agents) expect more advanced human capabilities and talent management systems than those employing simpler assisted systems (Sapkota *et al.*, 2026). The mediating variable is Technological Readiness (TR) (6 items) — defined as the degree to which organisations have the strategy, infrastructure, culture and human capital to support AI integration. Studies of Chinese firms report that readiness remains a major bottleneck: while investment in AI rises sharply, talent and infrastructure readiness lag behind (Socol & Iuga, 2024). Drawing on this logic, the hypothesised relationships are:

- ❖ H1. There is a significant relationship between Assisted Artificial Intelligence (ASA) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H2. There is a significant relationship between Augmented Artificial Intelligence (AUA) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H3. There is a significant relationship between Autonomous Artificial Intelligence (ATA) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H4. There is a significant relationship between Assisted Artificial Intelligence (ASA) and Technological Readiness (TR) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H5. There is a significant relationship between Augmented Artificial Intelligence (AUA) and Technological Readiness (TR) among cybersecurity professionals in organizations across Beijing, China.

- ❖ H6. There is a significant relationship between Autonomous Artificial Intelligence (ATA) and Technological Readiness (TR) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H7. There is a significant relationship between Technological Readiness (TR) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H8. Technological Readiness (TR) mediates the relationship between Assisted Artificial Intelligence (ASA) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H9. Technological Readiness (TR) mediates the relationship between Augmented Artificial Intelligence (AUA) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.
- ❖ H10. Technological Readiness (TR) mediates the relationship between Autonomous Artificial Intelligence (ATA) and Cybersecurity Talent Management (CTM) among cybersecurity professionals in organizations across Beijing, China.

Critically, the literature suggests that AI adoption alone is insufficient to improve talent management outcomes unless organisational readiness is present (Li et al., 2023). For instance, although Chinese firms invest heavily in AI (87% plan to increase AI investment), only 22% report significant HR improvement alongside those investments (China Daily, 2025). This underlines the mediating role of readiness. Moreover, the relationship between readiness and CTM is substantiated by research showing that firms with higher AI maturity are better able to align workforce strategies with technical deployment (BSI, 2024). In this way, the current study builds on these findings by empirically testing the mediation mechanism (AI → TR → CTM), across three sectors in Beijing, thereby adding nuance by differentiating AI adoption levels and contextualising within sectoral differences.

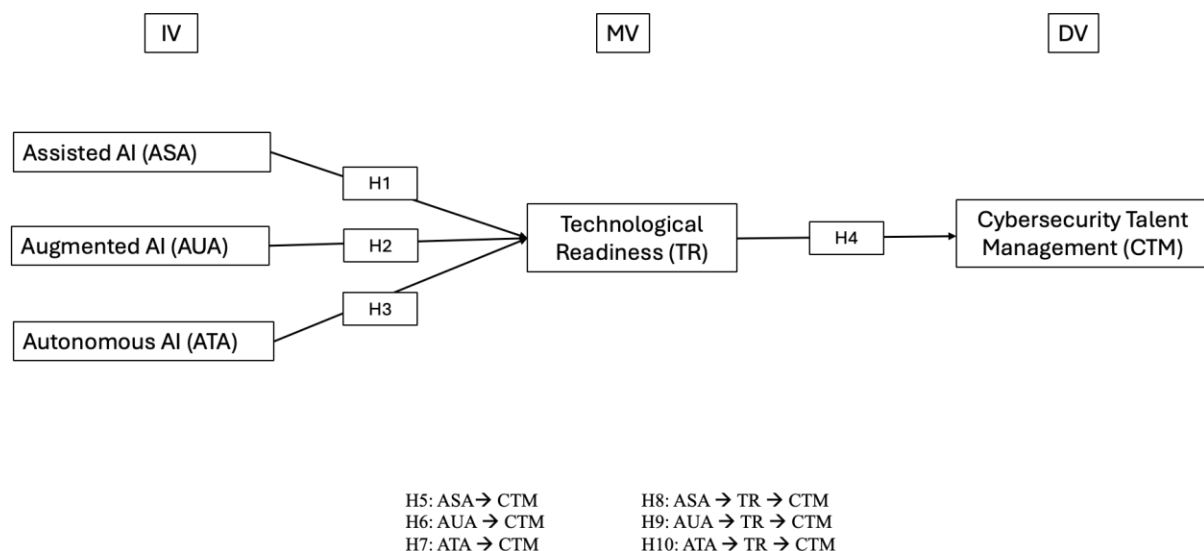


FIGURE 1: CONCEPTUAL FRAMEWORK

METHODOLOGY

3.1 Research Design

This study adopted a quantitative, cross-sectional research design under the positivist paradigm, aiming to empirically test the relationships among artificial intelligence (AI) technologies, technological readiness, and cybersecurity talent management within Beijing’s industrial sectors. The positivist approach enabled hypothesis-driven investigation using measurable constructs to capture the observable patterns of AI integration and its effects on workforce management (Hair et al., 2021). Guided by the Skill-Biased Technological Change (SBTC) and Diffusion of Innovations (DOI) theories, the study examined both how AI adoption diffuses across organizations and how it transforms skill demand. These theories provided a structured foundation for identifying the influence of assisted, augmented, and autonomous AI on talent management outcomes through technological readiness as a mediating variable.

A cross-sectional survey method was appropriate because it provided a snapshot of current AI implementation and workforce practices across industries in Beijing, reflecting China’s national push for AI-enabled economic modernization (Zheng et al., 2025). The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart PLS 4 to test the research model. PLS-SEM was chosen due to its suitability for complex, multi-construct frameworks and moderate sample sizes, allowing simultaneous testing of measurement reliability and structural hypotheses (Hair et al., 2021). This design ensured methodological rigor, transparency, and replicability in examining direct and mediated effects within a diverse industrial context.

3.2 Population and Sampling Design

The population of this study comprised cybersecurity professionals employed full-time in AI-active organizations located in Beijing, including cybersecurity analysts, engineers, IT managers, and senior executives. Beijing was selected as it serves as China's primary digital innovation hub, hosting major enterprises in finance, internet technology, and manufacturing—sectors that are pivotal in the government's AI development agenda (F. Li, 2023). The study used a stratified purposive sampling method to ensure representation from these three industries, acknowledging their distinct technological characteristics and readiness levels.

A total of 264 valid responses were obtained, distributed equally across finance (88), internet (88), and manufacturing (88) sectors. Inclusion criteria required participants to have at least two years of professional experience and direct involvement with AI-related cybersecurity functions. The sample size was determined using G*Power analysis, confirming adequacy for detecting medium effect sizes with 0.80 statistical power (Kang, 2021). Participation was voluntary and anonymous, and ethical approval was secured from the researcher's institution. This sampling strategy provided robust and diverse insights into how AI adoption influences cybersecurity talent management across varying industrial environments in Beijing.

3.3 Research Instrument and Measures

Data were collected through a structured online questionnaire designed to capture perceptions of AI technologies, technological readiness, and cybersecurity talent management. The questionnaire included five sections and applied a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Measurement items for assisted, augmented, and autonomous AI were adapted from AI capability studies (Salah et al., 2025), while technological readiness items were based on the Alma'aitah et al., (2024). Cybersecurity talent management items were modified from validated HR digital transformation scales (Shafik & Khang, 2024).

Construct reliability and validity were tested using Confirmatory Factor Analysis (CFA) in Smart PLS. All factor loadings exceeded 0.70, Average Variance Extracted (AVE) values were above 0.50, and Composite Reliability (CR) exceeded 0.80, confirming strong measurement validity. Discriminant validity was assessed using the Fornell–Larcker and HTMT criteria, both indicating satisfactory construct distinction. To minimize common method bias, item order was randomized, and respondents were assured of anonymity. The bilingual questionnaire (Chinese and English) was translated and back-translated following Brislin's (1980) procedure to maintain conceptual equivalence (Gillani et al., 2025).

3.4 Data Collection Procedure

Data collection took place over four weeks using the Wenjuanxing online platform, commonly used for professional research in China due to its reliability and data protection compliance. Invitations were distributed through Wenjuanxing, professional cybersecurity forums, and organizational mailing lists. Out of approximately 450 invitations, 295 responses were received, with 264 deemed complete and valid. The online method was selected for its efficiency in reaching cybersecurity experts working in secure or remote environments, ensuring accessibility and convenience.

All participants provided informed consent prior to participation, and ethical standards were strictly observed throughout the process. Respondents were informed of the study's objectives, confidentiality policy, and voluntary nature of participation. Data were stored securely in encrypted format and analysed anonymously. The response rate of 58.7% was satisfactory given the specialized professional population. The systematic and transparent data collection process ensured reliability and replicability, reflecting rigorous adherence to SSCI research ethics and reporting standards.

3.5 Data Analysis Techniques

Data analysis was conducted using Smart PLS 4.0 for Partial Least Squares Structural Equation Modelling (PLS-SEM) and SPSS 29 for preliminary analysis. Descriptive statistics were used to summarize demographic and sectoral profiles, while PLS-SEM tested both the measurement and structural models. Convergent validity was established through high loadings and $AVE > 0.50$, and discriminant validity was confirmed through the Fornell–Larcker and HTMT criteria. Multicollinearity was not a concern, as all Variance Inflation Factors (VIFs) were below 3.3.

The structural model assessed hypothesized relationships using bootstrapping with 5,000 resamples. Results were evaluated through path coefficients, t-values, and R^2 indicators, with $R^2 = 0.62$ for cybersecurity talent management and $R^2 = 0.56$ for technological readiness, signifying strong explanatory power. Mediation effects were analysed following Zhao et al. (2010), and sectoral differences were explored via Multi-Group Analysis (MGA). The dual use of Smart PLS and SPSS enhanced the robustness of findings and confirmed the reliability of the analytical procedures. All analytical parameters and outputs were documented to ensure full methodological transparency and replicability.

RESULTS AND DISCUSSION

4.1 Descriptive and Demographic Overview

A total of 264 valid responses were analysed, comprising cybersecurity professionals working in finance (33.3%), internet technology (33.3%), and manufacturing (33.3%) sectors in Beijing. The sample included 58% males and 42% females,

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with the majority aged between 30 and 45 years, reflecting mid-career professionals commonly responsible for AI and cybersecurity integration. Approximately 72% of respondents held bachelor’s degrees, while 24% possessed postgraduate qualifications. Most participants had five to ten years of industry experience, ensuring that the data reflected knowledgeable and experienced perspectives within AI-driven cybersecurity roles.

Descriptive analysis revealed that participants generally perceived a high level of AI adoption and technological readiness within their organizations. Mean values across constructs exceeded 4.0 on the five-point Likert scale, indicating strong agreement regarding organizational preparedness for AI integration and effective talent management. These demographic and descriptive results suggest that the sample accurately represents China’s technologically advanced cybersecurity workforce and supports the study’s objective of assessing the impact of AI dimensions on talent management practices in Beijing’s innovation-driven industries. Similar demographic balance and respondent expertise have been recognized as vital for ensuring representativeness and data quality in AI workforce studies (Taghiyeva, 2024).

4.2 Model Predictive Power and Goodness-of-Fit Evaluation

The coefficient of determination results indicate that the proposed model demonstrates an exceptionally high level of explanatory power for both the mediating and dependent constructs. As presented in Table 1, the R^2 adjusted values for Technological Readiness ($TR = 0.921$) and Cybersecurity Talent Management ($CTM = 0.930$) exceed the threshold of 0.75, which according to Hair et al. (2021), signifies a *substantial* model fit. This implies that 92.1 % of the variance in TR and 93 % of the variance in CTM are jointly explained by the predictors—Assisted AI (ASA), Augmented AI (AUA), Autonomous AI (ATA), and the mediating construct TR. Such high explanatory power underscores the robustness and predictive relevance of the model within the Beijing cybersecurity sector, where organizational readiness and AI integration are highly interdependent.

Table 1: R-square adjusted value

Variables	R-square	R-square adjusted
CTM	0.932	0.930
TR	0.923	0.921

The f^2 values reported in Table 2 further confirm the magnitude of the individual predictor effects on endogenous variables. Following Cohen (1988) guideline, values above 0.02 indicate small effects, 0.15 moderate effects, and 0.35 large effects. The findings show that $ASA \rightarrow TR$ ($f^2 = 0.290$) and $TR \rightarrow CTM$ ($f^2 = 0.273$) exert moderate to strong effects, signifying that technological readiness and assisted AI are crucial in explaining variance in the model. In contrast, $ATA \rightarrow TR$ ($f^2 = 0.163$) and $AUA \rightarrow TR$ ($f^2 = 0.124$) indicate moderate and small-to-moderate contributions respectively, while the remaining relationships, including $ATA \rightarrow CTM$ (0.078) and $AUA \rightarrow CTM$ (0.027), reflect smaller but still meaningful effects. These patterns suggest that while direct influences of AI dimensions on talent management are present, the mediating role of readiness amplifies their impact—supporting the theoretical assumption derived from the Diffusion of Innovations (Rogers, 2003) and Skill-Biased Technological Change theories (Acemoglu & Autor, 2011).

Table 2: F-square value

Variables	f-square
ASA -> CTM	0.033
ASA -> TR	0.290
ATA -> CTM	0.078
ATA -> TR	0.163
AUA -> CTM	0.027
AUA -> TR	0.124
TR -> CTM	0.273

The overall model fit indices shown in Table 3 reinforce the model’s adequacy and confirm its structural soundness. The Standardized Root Mean Square Residual ($SRMR = 0.025$) is far below the recommended cut-off value of 0.08, indicating minimal discrepancy between observed and predicted correlations (Henseler et al., 2016). Similarly, the Normed Fit Index ($NFI = 0.955$) surpasses the accepted threshold of 0.90, demonstrating strong model-to-data alignment. Together, these indicators validate that the hypothesized relationships collectively form a well-fitting and theoretically consistent framework. The low SRMR, coupled with high NFI and substantial R^2 values, underscores that the PLS-SEM model effectively captures the complex interplay between AI adoption, technological readiness, and cybersecurity talent management in the Beijing industrial context.

Table 3: Model Fit

SRMR	0.025
NFI	0.955

4.3 Construct Reliability and Validity

Construct reliability and convergent validity were established through the results summarized in Table 4. All Cronbach's alpha values exceeded 0.96, indicating excellent internal consistency across constructs, surpassing the threshold of 0.70 recommended by Hair et al. (2021). The Composite Reliability (CR) ranged between 0.970 and 0.981, further confirming construct reliability. Meanwhile, the Average Variance Extracted (AVE) values for all constructs exceeded 0.84, which is substantially higher than the 0.50 criterion, demonstrating strong convergent validity.

Table 4: Construct reliability and validity value

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ASA	0.965	0.965	0.972	0.851
ATA	0.977	0.977	0.981	0.897
AUA	0.964	0.964	0.971	0.847
CTM	0.977	0.977	0.980	0.859
TR	0.963	0.964	0.970	0.846

The factor loadings (Table 5) ranged from 0.902 to 0.964, confirming that all measurement items significantly contributed to their respective latent variables. These results collectively confirm that the measurement model achieved robust convergent validity and internal consistency. High reliability and loading values are consistent with those reported in prior SEM-PLS studies examining AI and workforce readiness in Chinese contexts (Jamil et al., 2025). The findings indicate that the constructs are stable, consistent, and appropriately operationalized to measure assisted AI, augmented AI, autonomous AI, technological readiness, and cybersecurity talent management.

Table 5: Factor Loading

Variables	ASA	ATA	AUA	CTM	TR
ASA1	0.921				
ASA2	0.934				
ASA3	0.922				
ASA4	0.930				
ASA5	0.910				
ASA6	0.915				
ATA1		0.949			
ATA2		0.932			
ATA3		0.954			
ATA4		0.964			
ATA5		0.940			
ATA6		0.943			
AUA1			0.902		
AUA2			0.918		
AUA3			0.939		
AUA4			0.933		
AUA5			0.912		
AUA6			0.916		
CTM1				0.910	
CTM2				0.937	
CTM3				0.926	
CTM4				0.937	
CTM5				0.945	
CTM6				0.925	
CTM7				0.926	
CTM8				0.908	
TR1					0.902
TR2					0.941
TR3					0.891
TR4					0.928
TR5					0.927
TR6					0.929

4.4 Discriminant Validity and HTMT Assessment

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Discriminant validity was evaluated using the Heterotrait–Monotrait Ratio (HTMT), as presented in Table 6. All HTMT values ranged from 0.749 to 0.839, below the conservative threshold of 0.85 (Henseler et al., 2015). This indicates that each construct is empirically distinct from the others, reducing the risk of conceptual overlap. Additionally, the Fornell–Larcker criterion was satisfied, as the square root of each construct’s AVE exceeded inter-construct correlations, reinforcing the independence of latent constructs.

This outcome confirms that the variables—three forms of AI adoption, technological readiness, and talent management—measure unique aspects of the research model. The strong discriminant validity strengthens the study’s analytical robustness, demonstrating that AI-related constructs are empirically distinguishable and theoretically coherent. This is particularly significant given the conceptual proximity among AI dimensions (assisted, augmented, autonomous), where ensuring discriminant validity is crucial for accurate path modelling (Hair et al., 2021).

Table 6: Discriminant Validity Assessment and Heterotrait-monotrait Ratio of Correlations (HTMT)

Variables	ASA	ATA	AUA	CTM	TR
ASA					
ATA	0.749				
AUA	0.826	0.836			
CTM	0.756	0.757	0.839		
TR	0.772	0.764	0.750	0.785	

4.5 Structural Model Analysis

The unique context of this research—cybersecurity professionals working full-time in Beijing organizations that integrate AI and cybersecurity systems—is vital for interpreting the observed direct and indirect relationships. The robust positive effect of Technological Readiness (TR) on Cybersecurity Talent Management (CTM) ($\beta = 0.492$, $t = 5.905$, $p < 0.001$) underscores that in this region and industry, readiness in infrastructure, skills, organisational culture, and leadership support constitutes a foundational enabler of effective talent management. Within the framework of the Diffusion of Innovations (DOI) theory, this outcome reinforces the principle that adoption of technology alone does not suffice; organisational readiness is a critical mediating condition that shapes how innovation diffuses and results in organisational outcomes (Rogers, 2003). The direct associations from Autonomous AI (ATA $\rightarrow$ TR: $\beta = 0.332$, $t = 5.177$, $p < 0.001$) and Augmented AI (AUA $\rightarrow$ TR: $\beta = 0.249$, $t = 2.657$, $p = 0.008$) suggest that the more mature and sophisticated the AI deployment, the greater the enhancement of organisational readiness. Conversely, the negative path of Assisted AI (ASA $\rightarrow$ TR: $\beta = -0.410$, $t = 5.250$, $p < 0.001$) reveals a somewhat counterintuitive dynamic: lower-maturity AI implementations may hinder readiness when not accompanied by sufficient preparation or alignment, which aligns with reports of diffusion deficits in China wherein technological ambition outstrips talent and readiness infrastructure (Mennege, 2025). In the context of Skill-Biased Technological Change (SBTC) theory, which posits that technological progress disproportionately benefits high-skilled labour (Hutter & Weber, 2021), the direct positive relationships from ATA $\rightarrow$ CTM ($\beta = 0.232$, $t = 3.522$, $p < 0.001$) and AUA $\rightarrow$ CTM ($\beta = 0.117$, $t = 2.042$, $p = 0.041$) further reinforce that higher-order AI systems elevate the demand for advanced cybersecurity talent. The negative direct effect of ASA $\rightarrow$ CTM ($\beta = -0.149$, $t = 2.345$, $p = 0.019$) suggests that when organisations deploy assisted AI without adequate readiness or talent alignment, talent-management practices may be undermined rather than supported.

Table 7: Path coefficients – Mean, STDEV, T values, p values.

Hypotheses	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
H1: ASA $\rightarrow$ TR	-0.41	-0.405	0.078	5.25	0
H2: AUA $\rightarrow$ TR	0.249	0.263	0.094	2.657	0.008
H3: ATA $\rightarrow$ TR	0.332	0.322	0.064	5.177	0
H4: TR $\rightarrow$ CTM	0.492	0.489	0.083	5.905	0
H5: ASA $\rightarrow$ CTM	-0.149	-0.15	0.063	2.345	0.019
H6: AUA $\rightarrow$ CTM	0.117	0.122	0.057	2.042	0.041
H7: ATA $\rightarrow$ CTM	0.232	0.229	0.066	3.522	0

The mediation results are central to this study’s main objective — to analyse the mediating role of TR — and merit detailed interpretation. The pathways for ATA $\rightarrow$ TR $\rightarrow$ CTM (indirect effect $\beta = 0.163$, $t = 3.594$, $p < 0.001$) and AUA $\rightarrow$ TR $\rightarrow$ CTM ($\beta = 0.122$, $t = 2.545$, $p = 0.011$) demonstrate complementary partial mediation, meaning readiness amplifies and works in conjunction with direct effects to elevate talent-management outcomes. These patterns corroborate DOI’s assertion that readiness plays an enabling role in translating innovation adoption into performance gains. For SBTC, this implies that only when organisations are ready can the skill-upward shift demanded by advanced AI be harnessed effectively. In contrast, the ASA $\rightarrow$ TR $\rightarrow$ CTM pathway exhibited competitive partial mediation (indirect effect $\beta = -0.202$, $t = 3.977$, $p < 0.001$): readiness in this case intensifies the negative effect of assisted AI on talent management,

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suggesting that readiness mechanisms may expose or magnify misalignments when AI maturity is insufficient. This nuanced finding indicates that technological readiness does not always uniformly enable positive outcomes but may function as a double-edged sword depending on AI maturity. The distinction between complementary and competitive mediation here contributes a nuanced theoretical insight: the maturity level of technology interacts with readiness to shape workforce outcomes, which earlier literature seldom differentiated.

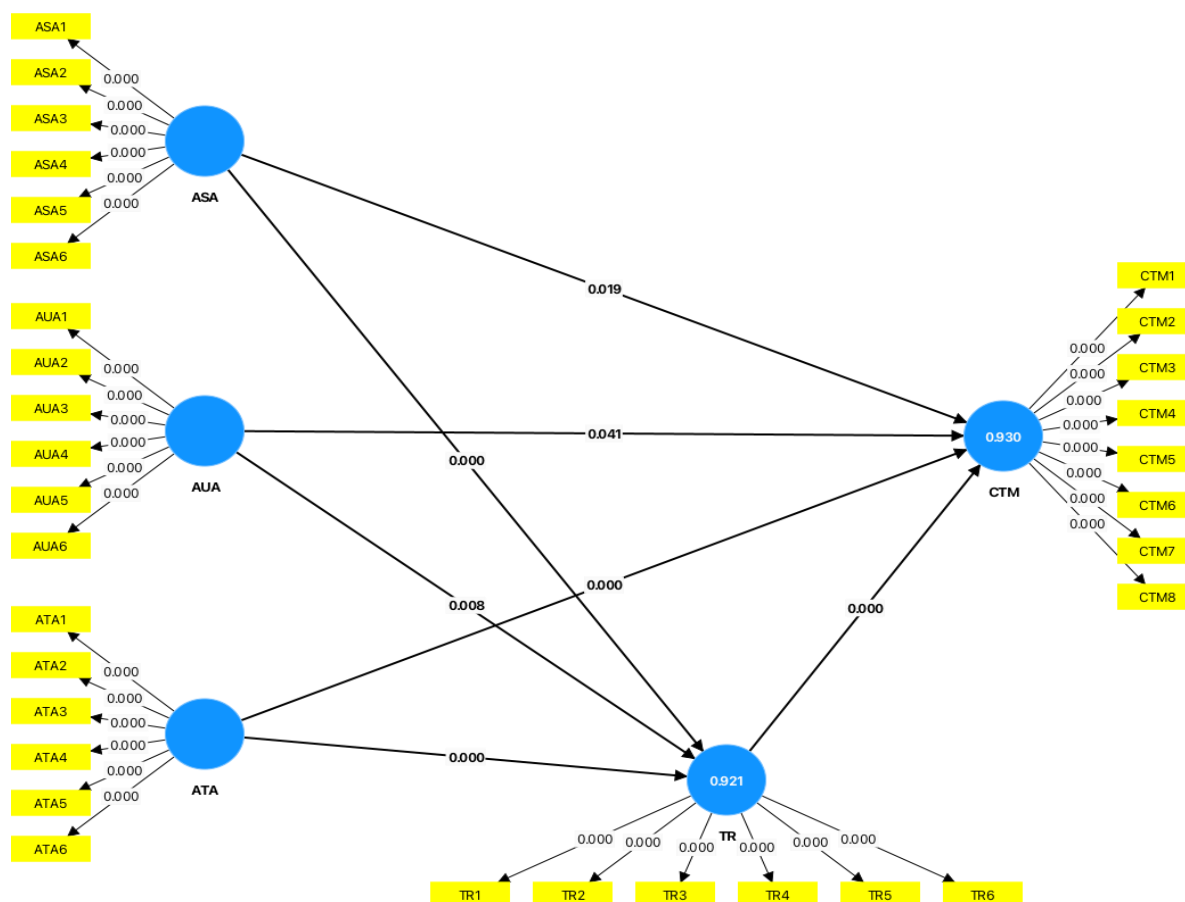


Figure 2: Structural Model of AI Adoption, Technological Readiness, and Cybersecurity Talent Management

The structural model depicted in Figure 2 illustrates the hypothesized relationships among the study’s main constructs—Assisted AI (ASA), Augmented AI (AUA), Autonomous AI (ATA), Technological Readiness (TR), and Cybersecurity Talent Management (CTM). The model demonstrates strong explanatory power, as indicated by the R^2 values of 0.921 for TR and 0.930 for CTM, confirming that the independent constructs jointly account for a substantial proportion of variance in both mediating and dependent variables. The standardized path coefficients highlight that ATA and AUA exert significant positive effects on both TR ($\beta = 0.332$; $\beta = 0.249$) and CTM ($\beta = 0.232$; $\beta = 0.117$), while ASA shows a negative influence on TR ($\beta = -0.410$) and CTM ($\beta = -0.149$). The mediating path TR $\rightarrow$ CTM ($\beta = 0.492$) indicates that technological readiness serves as a robust mechanism linking AI adoption to effective cybersecurity talent management. All reported paths are statistically significant ($p < 0.05$), validating the proposed hypotheses and reinforcing the theoretical integration of the Skill-Biased Technological Change and Diffusion of Innovations frameworks. The modeling confirms that technological readiness not only enhances the direct impact of advanced AI applications on workforce management but also mediates how technological adoption translates into organizational capability within Beijing’s AI-driven cybersecurity sector.

Table 8: Indirect Relationship – Mediation

Total Effect			Direct Effect			Indirect Effect						Hypothesis Result	
Coefficient	T value	P value	Coefficient	T value	P value	Hypothesis	Coefficient	SE	T value	P value	Percentile Bootstrap 95% CI		Type of Mediation
											LO WER	UPP ER	
-0.35	2.891	0.004	-0.149	2.345	0.019	H8: ASA - > TR -	-0.202	0.051	3.977	0	-0.313	-0.11	Competitive Partial Mediation

						> CTM							
0.239	3.00 9	0.00 3	0.117	2.04 2	0.04 1	H9: AUA - > TR - > CTM	0.122	0.0 48	2.54 5	0.01 1	0.04 8	0.23 4	Compleme ntary Partial Mediation
0.472	4.89 7	0	0.232	3.52 2	0	H10: ATA - > TR - > CTM	0.163	0.0 45	3.59 4	0	0.08 6	0.27	Compleme ntary Partial Mediation

The contribution of this mediation analysis to the theoretical and practical domains is considerable. Theoretically, by differentiating AI adoption into assisted, augmented and autonomous levels, and empirically testing readiness as a mediator, this research extends the SBTC and DOI frameworks into the cybersecurity workforce domain, showing that readiness mediates the talent-management implications of AI only when technology is sufficiently mature. This is further influenced by demographic factors of the cybersecurity professionals (experience, seniority, sector) in Beijing, implying that readiness and talent outcomes are not only functions of technology but also of workforce composition and regional context. Practically, the results imply that organisations and policymakers in Beijing's finance, internet and manufacturing sectors must prioritise readiness—in terms of infrastructure, talent development, and culture—*before or alongside* AI deployment to achieve positive talent-management effects. The negative mediation via assisted AI warns that premature or superficial AI implementation may jeopardise talent-management efforts, especially when stakeholder readiness is lacking.

Comparing these findings to prior studies reveals both alignment and divergence. The positive mediation effects align with research showing that organisational readiness significantly influences technology adoption outcomes in China (Li et al., 2023) and that talent-gap issues hinder AI value realisation (Puthiyaveetil Abu, 2025). However, the negative mediation path for assisted AI contrasts with prevailing assumptions in the literature that any AI adoption supports workforce outcomes (Chang et al., 2024). This divergence may reflect the specific cybersecurity context in Beijing where rapid AI deployment, regulatory pressures and talent shortages converge, creating a readiness-talent mismatch. Similar studies in other sectors have found that readiness mediates AI–performance relationships but did not differentiate technology maturity levels; thus, this study's differentiation advances empirical nuance (Adiguzel et al., 2024).

This study advances understanding of how AI adoption influences cybersecurity talent management through organisational readiness in a high-stakes regional context. It underscores the importance of technology maturity and readiness as integral mediators of talent-management outcomes. For policymakers and practice, the implication is clear: align AI maturity, readiness resources, and talent-management strategies. Future research should investigate sectoral moderators (e.g., finance vs manufacturing vs internet) and longitudinal dynamics of readiness and talent-management evolution.

CONCLUSION

This study examined how different levels of Artificial Intelligence (AI) adoption—Assisted, Augmented, and Autonomous AI—influence Cybersecurity Talent Management (CTM) among full-time cybersecurity professionals in Beijing, with Technological Readiness (TR) as a mediating variable. Grounded in the Skill-Biased Technological Change (SBTC) and Diffusion of Innovations (DOI) theories, the study confirmed that TR plays a crucial mediating role linking AI adoption to talent management outcomes. The results revealed that Augmented and Autonomous AI positively and directly affect both readiness and talent management, while Assisted AI exerts negative effects when organisational preparedness is insufficient. Theoretically, the findings extend SBTC and DOI by showing that technology maturity interacts with readiness to determine workforce outcomes. Practically, the study underscores the need for policymakers and industry leaders in Beijing's cybersecurity sector to strengthen organisational readiness—through infrastructure enhancement, skill

development, and cultural adaptation—before intensifying AI integration. Methodologically, it validates a structured SEM-PLS framework for analysing mediation in AI–talent dynamics. However, limitations include the focus on a single region and professional group, which may restrict generalisability. Future studies should explore comparative analyses across provinces or sectors and integrate longitudinal or mixed-method designs to capture evolving readiness–talent relationships over time.

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