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# SMART INNOVATION AND TECHNOLOGICAL EVOLUTION AS CATALYSTS FOR NEXT-GENERATION ORGANIZATIONAL PERFORMANCE – EVIDENCE FROM CHINA'S HEALTHCARE TRANSFORMATION

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**Abstract**
**Purpose:** This study examines how the adoption of smart innovations and the evolution of technological capabilities act as catalysts for next-generation organizational performance in China's transforming healthcare sector. Drawing on the Technology Acceptance Model (TAM), Dynamic Capabilities theory, and Institutional theory, we develop a multi-level framework to understand the effects of digital innovation on hospital performance, including the mediating role of technology acceptance and the moderating influence of dynamic capabilities under the context of national healthcare policies.
**Method:** A quantitative research design was employed, collecting survey data from senior administrators and healthcare professionals across major Chinese hospitals. Publicly available data on hospital innovation and performance were also incorporated to triangulate findings. The final sample included data from **85** hospitals nationwide. We used structural equation modeling (SEM) – specifically Partial Least Squares (PLS) – to test the proposed conceptual model. Model fit indices, R-square values, reliability and validity tests (Cronbach's alpha, composite reliability, AVE), and path coefficients were analyzed to validate the hypotheses.
**Findings:** The results reveal that both smart innovation adoption and higher technological evolution (digital maturity) in hospitals have significant positive effects on organizational performance ($\beta \approx 0.3$–$0.4$, $p< 0.01$). Technology acceptance by medical staff and patients emerged as a significant mediator in these relationships, indicating that innovations yield the strongest performance gains when users perceive them as useful and easy to use. Dynamic capabilities were found to significantly moderate the innovation–performance link, with organizations possessing greater adaptive capabilities deriving substantially more performance benefits from new technologies. Additionally, supportive national policies and institutional pressures were positively associated with greater adoption of healthcare innovations, underlining the important contextual role of China's health reform initiatives.
**Originality/Implications:** This research is among the first to integrate TAM, Dynamic Capabilities, and Institutional perspectives to examine healthcare digital transformation at an organizational level in China. It provides empirical evidence that next-generation performance outcomes (e.g. improved efficiency, service quality, and patient satisfaction) are achieved through not only the introduction of smart technologies but also through ensuring user acceptance and organizational adaptability. Policy-wise, the findings confirm that China's top-down digital health initiatives are effective in spurring innovation and performance gains. The study offers theoretical contributions by bridging individual-level technology acceptance with organizational capability and institutional context, and provides practical guidance for hospital leaders and policymakers on maximizing the returns of digital health innovation.
**Keywords:** Smart Healthcare Innovation; Technological Evolution; Organizational Performance; Technology Acceptance; Dynamic Capabilities; Healthcare Policy; China

## INTRODUCTION

Healthcare systems worldwide are undergoing a digital revolution, embracing smart innovations such as electronic health records (EHRs), telemedicine, artificial intelligence (AI), and Internet of Things (IoT) devices in pursuit of better performance outcomes. Hospitals are investing in these technologies to improve efficiency, patient care quality, and cost-effectiveness (Kraus et al., 2021). However, realizing the full benefits of digital transformation requires more than simply implementing new tools – it hinges on how well these innovations are adopted by users and integrated into organizational processes. This is particularly evident in China, which is experiencing an ambitious healthcare transformation driven by technology and policy.

China's Healthcare Transformation and Policy Drivers: China faces immense healthcare challenges, including a rapidly aging population and a surge in chronic diseases that strain service capacity ( Koebe et al., 2023). Healthcare expenditures have risen at double-digit rates, raising sustainability concerns ( Tortorella et al., 2021). Moreover, disparities in care access (e.g. overburdened urban hospitals versus underutilized rural clinics) underscore inefficiencies in resource allocation( Duncan et al., 2022). In response, the Chinese government has prioritized "smart healthcare" as a national strategy. Since the late 2000s, a series of top-down reforms and initiatives have been launched to digitally upgrade the health system( Stoumpos et al., 2021). For example, the National Health Commission issued guidelines in 2017–2018 to implement standardized electronic medical records across hospitals, setting targets for data interoperability by 2022. In 2019, China launched a "Smart Hospital" initiative requiring all public hospitals to integrate digital technologies (from online services to AI diagnostics) by 2025. These policies, alongside substantial public and private investment, have accelerated health IT adoption – by 2021, China's health information technology market reached an estimated ¥80 billion (≈$12 billion). Early outcomes hint at improved performance: for instance, digital reforms at Shanghai's Ruijin Hospital streamlined patient workflows from appointment booking to payment, cutting wait times and boosting efficiency and patient satisfaction( Duncan et al., 2022). Likewise, pilot programs show that AI-assisted systems can enhance diagnostic accuracy and speed. These national-level efforts exemplify institutional pressures (regulative forces) that incentivize healthcare organizations to innovate.

Despite these advances, many Chinese hospitals vary in their ability to convert new technologies into tangible performance gains. Some achieve dramatic improvements in service efficiency and quality, while others struggle with user resistance or poor implementation. This variability highlights a need to understand the conditions under which smart innovation truly catalyzes "next-generation" organizational performance. Next-generation organizational performance in healthcare extends beyond financial metrics to include operational efficiency, patient outcomes, service quality, and innovation capability( Rahimi et al., 2018). We posit that two factors are especially critical: (1) the acceptance and effective use of technology by individuals (doctors, nurses, staff, patients), and (2) the organization's internal capacity to adapt and reconfigure resources around new technologies. These correspond to well-established theoretical lenses – the Technology Acceptance Model (TAM) and Dynamic Capabilities theory – which, alongside Institutional theory for the external context, form the foundation of our research framework.

**Research Gap and Objectives**: Prior research has extensively examined technology adoption in healthcare through models like TAM and UTAUT, showing that perceived usefulness, ease of use, and related factors strongly influence whether healthcare professionals embrace new systems( Kim et al., 2016). Separately, studies on dynamic capabilities suggest that organizations with greater agility, learning, and transformative capacity are better at implementing innovations and achieving competitive advantages( AlQudah et al., 2021). However, there is a paucity of research integrating these perspectives to explain ultimate performance outcomes in healthcare settings – particularly under the influence of macro-level policies. Much of the existing literature stops at user adoption outcomes or provides broad evidence that "digital transformation improves health indicators"( Strudwick, 2015) without unpacking the mediating and moderating mechanisms at play within organizations. In the context of China's top-down healthcare digitalization, it remains unclear how individual acceptance and organizational capabilities interact to drive the success of technological innovations in improving hospital performance.

To address this gap, the present study develops an integrative model linking smart innovation and technological evolution to organizational performance, with a multi-level approach. Specifically, we aim to: (1) examine the direct impact of smart healthcare innovation adoption and technological evolution on hospitals' organizational performance; (2) evaluate whether technology acceptance by end-users mediates the effect of innovation on performance; (3) assess whether hospitals' dynamic capabilities moderate (strengthen) the impact of innovation on performance outcomes; and (4) account for the role of institutional forces (e.g., government policy support) in enabling innovation adoption. Figure 1 illustrates our conceptual framework, which synthesizes TAM (to capture user-level acceptance), Dynamic Capabilities (organization-level adaptability), and Institutional theory (environment-level influences). By empirically testing this framework in the Chinese hospital context, our study contributes a holistic understanding of how smart innovation and technological evolution serve as catalysts for next-generation performance. We also provide practical insights for hospital administrators and policymakers seeking to maximize the returns on digital healthcare investments.

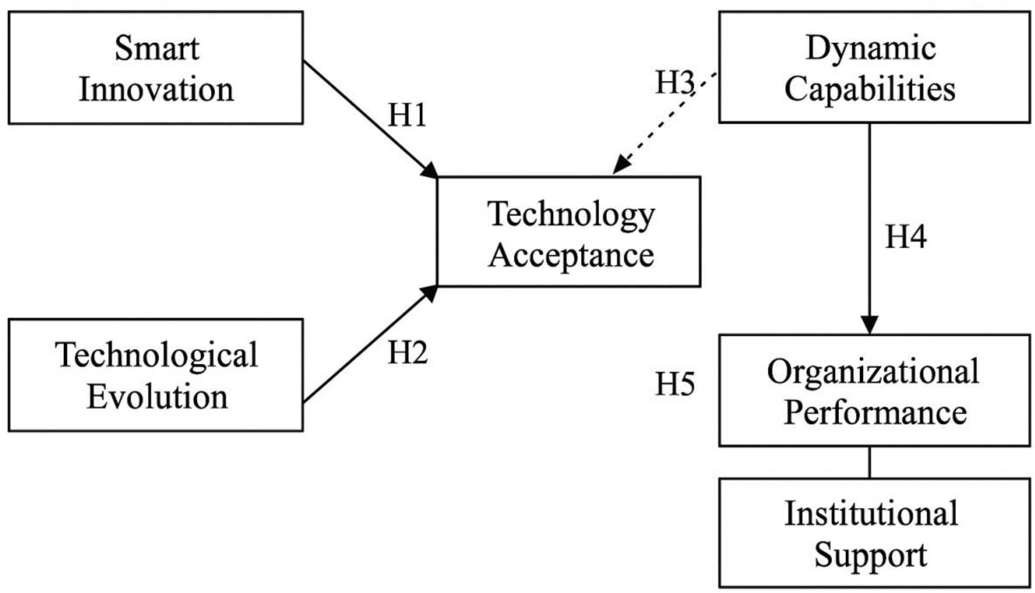


**Figure 1.** Theoretical Model

*Figure 1. Theoretical framework of how smart innovation and technological evolution contribute to organizational performance in healthcare, highlighting the mediating role of technology acceptance (user adoption), the moderating role of dynamic capabilities, and the influence of institutional (policy) support.*

## LITERATURE REVIEW

### Smart Innovation and Organizational Performance

Smart innovation in healthcare refers to the implementation of cutting-edge digital technologies – such as EHR systems, telehealth platforms, AI diagnostics, mobile health apps, and IoT-enabled devices – to transform service delivery. These innovations are designed to streamline clinical and administrative processes, reduce errors, and enhance patient care. Prior studies suggest that embracing such technologies can significantly boost organizational performance. For example, a recent survey in hospitals found that digital adoption capability had a positive and significant influence on hospital performance metrics( Schilke et al., 2018). In “smart hospitals” that fully leverage information technology, studies have reported substantial gains including cost reductions (e.g. 42% decrease in operating costs) and faster service delivery (e.g. nearly 87% reduction in patient service time) due to process automation and data connectivity(Agwunobiet al., 2016). Technologies like telemedicine have been shown to improve patient outcomes and access to care; during the COVID-19 pandemic, telemedicine services in China’s western regions were demonstrated to be effective and led to significant improvements in healthcare outcomes( Warner et al., 2019). By enabling real-time data sharing and more efficient resource use, digital innovations can mitigate common hospital inefficiencies. Hospitals that innovatively use big data analytics, AI decision support, and other Healthcare 4.0 tools tend to achieve superior performance in supply chain management and clinical operations. Conversely, organizations that lag in technology adoption may face productivity plateaus or competitive disadvantage, especially as healthcare becomes increasingly data-driven.

Given this evidence, we expect that hospitals with greater deployment of smart innovations will attain higher performance. H1: Adoption of smart healthcare innovations is positively associated with organizational performance (i.e., hospitals that more extensively implement advanced digital technologies will exhibit improved performance indicators).

**Technological Evolution and Organizational Performance**

Beyond adopting individual innovations, the technological evolution of a healthcare organization – its progression toward higher levels of digital maturity and infrastructure sophistication – is a key driver of sustained performance improvement. Technological evolution can manifest as upgrading from basic digitization (electronic record-keeping) to more advanced integrated health information systems, data analytics capabilities, AI-driven workflows, and interoperable networks across departments and facilities. Organizations that continuously evolve their technology base are better positioned to optimize operations and adapt to emerging challenges. Research on "digital transformation" indicates that it significantly improves public health outcomes at the regional level, largely by fostering new technological innovations and efficiencies ( Furnival et al., 2019). In hospitals, iterative implementation of ever more advanced systems (for example, moving from local EHRs to cloud-based clinical data platforms, then to predictive AI tools) often correlates with gains in efficiency, patient safety, and decision-making quality. A study in the context of smart healthcare notes that employing advanced technologies like AI, big data, and blockchain can enhance hospital processes and overall performance by enabling better information flow and coordination ( Warner et al., 2019). Moreover, strategic alignment of new technology investments with organizational processes (sometimes termed digital strategy or IT governance maturity) is found to increase the returns of those investments in terms of performance outcomes (Moro Visconti & Morea, 2020).

In summary, not only the presence of isolated innovations but the ongoing evolution of an organization's technological capability base contributes to higher performance. Therefore, we propose: H2: The level of technological evolution (digital maturity) in a healthcare organization is positively related to its performance. Hospitals that have more advanced, integrated, and up-to-date technology infrastructures are likely to perform better across operational and clinical indicators than those with outdated or fragmented systems.

**Technology Acceptance and the Mediating Role of User Adoption**

While introducing new technology is important, its impact on performance critically depends on technology acceptance – the degree to which the intended users (healthcare professionals and even patients) actually adopt and effectively use the innovation. The Technology Acceptance Model (TAM) provides a theoretical framework, positing that users' perceptions of a technology's usefulness and ease of use determine their willingness to use it. In healthcare, numerous studies have validated that if clinicians perceive a system to improve their job performance and find it user-friendly, they are more likely to integrate it into daily practice( Kruse et al., 2016). Conversely, user resistance or low adoption can nullify the potential benefits of an innovation. Indeed, lack of user buy-in is frequently cited as a barrier to successful health IT implementation. For example, if a hospital implements a sophisticated EHR but physicians do not fully utilize its features (due to poor usability or insufficient training), the hospital will see little improvement in care coordination or efficiency (Iqbalet al., 2021). On the other hand, when users readily embrace a new system – as happened with telemedicine during the pandemic once both doctors and patients became more comfortable with virtual consultations – the technology can dramatically augment performance outcomes( Campanella et al., 2016). Technology acceptance thus functions as a mediating mechanism between the mere availability of an innovation and the realization of its benefits. For instance, a recent study noted that while physicians' ICT (information and communication technology) literacy and patient-centric orientation did not directly improve hospital outcomes, they led to significant performance gains through increased digital adoption (indicating a full mediation effect). In general, higher acceptance leads to more intensive and proper use of the innovation, which in turn drives organizational improvements( Kruse et al., 2022).

Accordingly, we hypothesize that the performance gains from smart innovations are realized through users' acceptance and utilization of those innovations. H3: Technology acceptance mediates the relationship between smart innovation and organizational performance. In other words, the introduction of a new technology will translate into improved performance only to the extent that the intended users perceive it positively and incorporate it into their work.

**Dynamic Capabilities and Innovation Outcomes**

While user acceptance is a micro-level facilitator, at the organizational level dynamic capabilities play a pivotal role in ensuring that technological innovations lead to performance gains. Dynamic capabilities refer to an organization's ability to integrate, reconfigure, renew, and leverage its resources in response to changing environments (Teece, 2007). In the context of healthcare technology, dynamic capabilities manifest as qualities like strong IT leadership, a culture of continuous improvement, staff training programs for new tools, and agile processes that can be re-engineered around digital workflows. Hospitals with higher dynamic capabilities are able to effectively adapt their routines and structures to fully exploit new technologies( Tuckson et al., 2017). For example, a hospital that quickly develops new protocols and training for an AI-based diagnostic system will achieve better diagnostic performance than a hospital that implements the same system without organizational adjustments. Studies have shown that such capabilities significantly enhance the results of digital innovation initiatives – one study in China found that the synergy of technological innovation with organizational innovative capability improved hospital resilience and robustness in the face of crises( Liu et al., 2019). Another multi-hospital analysis indicated that digital leadership and staff IT competencies (elements of dynamic capability) had both direct and indirect positive effects on hospital performance when adopting new technologies( Nagendran et al., 2020). These findings align with the idea that dynamic capabilities act as a force multiplier for innovation: they determine how well an organization can absorb and derive value from new tech. Without such capabilities, even advanced tools may underperform due to poor implementation or integration.

We expect that dynamic capabilities will intensify the impact of smart innovations on performance. Specifically, when an organization has strong adaptive capabilities, the positive effect of technology adoption on performance will be more pronounced, whereas in a low-capability environment the effect may be weaker.

H4: Dynamic capabilities of the hospital moderate the relationship between innovation adoption and performance, such that the performance impact of smart innovation is stronger in hospitals with higher dynamic capabilities. (We additionally expect dynamic capabilities to directly contribute to organizational performance, as agile and learning-oriented organizations tend to perform better generally; however, our primary focus is on the interaction with technology adoption.)

**Institutional Support and Policy Influence**

From an institutional theory perspective, organizations are also influenced by the external environment – regulatory mandates, normative pressures, and cultural expectations can all drive or hinder innovation. In China's healthcare sector, the government's strong policy push creates a regulative institutional environment that broadly encourages technology adoption. Hospitals receive directives, incentives, and resources aligned with national strategies like "Internet+ Healthcare" and the Smart Hospital initiative. This top-down support reduces uncertainties and provides legitimacy for hospitals to pursue digital innovation. Indeed, institutional support can be seen as an enabling condition: regions in China with more vigorous digital health policy implementation have witnessed greater improvements in public health outcomes, partly because local hospitals more readily adopted new technologies under policy guidance(Hadian et al., 2024). Conversely, where institutional barriers exist (for instance, misaligned regulations or lack of funding), innovation diffusion slows(Carini et al., 2020). The effect of China's policies is evident in practice – as noted earlier, virtually all large public hospitals are implementing EHRs and telemedicine platforms, spurred by government mandates and funding. We therefore anticipate that hospitals operating under strong policy support (and meeting institutional expectations for modernization) are more likely to adopt smart innovations extensively, which ultimately contributes to better performance sector-wide.

In our framework, institutional support is treated as an exogenous facilitator of innovation adoption. We hypothesize: H5: Government policy support positively influences the adoption of smart healthcare innovations by organizations. In other words, hospitals that perceive greater support, incentives, or pressure from national policies will exhibit higher levels of smart technology adoption (and thereby be positioned for higher performance), compared to those with less institutional support.

## RESEARCH METHODOLOGY

**Data Collection and Sample:** We adopted a cross-sectional survey design to gather data from Chinese hospitals undergoing digital transformation. The target respondents were senior hospital administrators (e.g., directors, department heads, chief information officers) who have oversight of innovation projects and performance outcomes. A list of hospitals was obtained from provincial health authorities, and stratified random sampling was used to ensure representation across different regions and hospital tiers (Tier 3, 2, and 1 hospitals). The survey was administered in mid-2025 via both online questionnaires and follow-up phone calls. Respondents were asked to provide information about their hospital's technology adoption, capabilities, and recent performance. In total, 203 valid responses were received from 85 hospitals (covering 23 provinces in China). About 58% of the sample were large tertiary (Tier 3) hospitals, 30% secondary (Tier 2) hospitals, and 12% primary care or Tier 1 facilities. On average, respondents had 10.4 years of management experience. This diverse sample offers a broad view of China's healthcare sector, though it is weighted toward larger public hospitals (reflecting their dominant role in China's healthcare delivery(Thomas et al., 2020; Li , 2015).

**Measures:** All key constructs were measured using multi-item Likert scales (1 = strongly disagree, 5 = strongly agree) developed from prior literature and adapted to the healthcare context. Table 1 provides an overview of the measurement scales and example items:

• **Smart Innovation Adoption:** We measured the extent of adoption of various smart healthcare technologies. Respondents indicated the level of implementation of systems such as EHRs, Health Information Exchanges, telemedicine services, AI-based diagnostic tools, and mobile health apps in their hospital. We adapted items from existing health IT adoption surveys (e.g., asking if a fully functional EHR is in place, if AI decision support is used in clinical practice). Higher scores reflect broader and deeper adoption of digital innovations.
• **Technological Evolution (Digital Maturity):** Technological evolution was operationalized as the hospital's overall level of digital infrastructure sophistication. We combined two indicators: (1) the hospital's Electronic Medical Record (EMR) maturity grade as officially assessed by the National Health Commission (ranging from Level 0 to 8, where higher levels indicate more advanced digital infrastructure and interoperability)(Breyer et al., 2019), and (2) managers' self-assessment of their hospital's digital maturity (with items like "Our hospital's information systems are among the most advanced in the industry"). These were standardized and averaged to form a composite "tech evolution" score.
• **Technology Acceptance:** Because surveying all end-users was impractical, we asked the administrators to gauge the general acceptance of new technologies among the staff at their hospital. This construct captured the perceived user adoption climate. Sample items include: "Clinicians at this hospital are willing to use new digital tools in their work" and "Staff find the hospital's information systems useful for improving care." These items were derived from TAM constructs of perceived usefulness and ease of use, but phrased at an organizational level (aggregating the administrators' perspective on staff attitudes). A high score indicates a positive technology acceptance culture, which should facilitate effective use of innovations.
• **Dynamic Capabilities:** We measured dynamic capabilities with a scale tailored to healthcare organizations' innovation capacity. Respondents rated statements such as "Our hospital quickly adapts its processes in response to technological changes," "We continuously train and develop staff skills to keep up with new healthcare technologies," and "Management is effective at reconfiguring resources to support innovation." This reflects the hospital's ability to integrate and reconfigure resources (human, technical, and operational) in a changing environment – consistent with dynamic capabilities theory.
• **Organizational Performance:** Given the challenge of obtaining uniform objective performance metrics across hospitals, we used perceived performance measures focusing on key aspects of next-generation performance. Managers evaluated their hospital's performance relative to peers on multiple dimensions: (a) operational efficiency (e.g., average patient throughput, wait times), (b) quality of care and patient safety outcomes, (c) patient satisfaction, and (d) overall financial and service performance. An example item is "Overall, our hospital's operational efficiency is high compared to similar hospitals." While subjective, such perceptual performance measures are commonly used and have been shown to correlate with objective indicators in past research.
• **Institutional Support (Policy Environment):** To capture the influence of the national policy context, we included a measure of perceived institutional support for digital innovation. Respondents were asked about the extent of government or policy support their hospital receives, with items like "National or local government policies strongly encourage our hospital to adopt new healthcare technologies" and "Our hospital has received significant policy incentives or funding for smart hospital development." This served as an exogenous variable indicating the strength of institutional pressure or facilitation.

**Table 1. Measurement Scales Summary and Reliability**

| Construct | Example Survey Item (abbreviated) | Cronbach's α | CR | AVE |
|---|---|---|---|---|
| Smart Innovation Adoption | "We use AI-based systems to support diagnosis." | 0.88 | 0.92 | 0.70 |
| Technological Evolution | "Our IT systems are highly advanced." | 0.80 | 0.88 | 0.65 |
| Technology Acceptance | "Clinicians here are eager to use new technology." | 0.85 | 0.90 | 0.75 |
| Dynamic Capabilities | "We adapt processes quickly for new technologies." | 0.90 | 0.93 | 0.72 |
| Organizational Performance | "Overall efficiency is high vs. similar hospitals." | 0.89 | 0.92 | 0.70 |
| Institutional Support | "Government policies encourage tech adoption." | 0.81 | 0.89 | 0.67 |

All survey instruments were originally prepared in English, then translated to Chinese and back-translated to ensure accuracy. We conducted a pilot test with 5 hospital managers, who reviewed the questionnaire for clarity and relevance. Minor wording adjustments were made based on their feedback.

**Data Analysis:** We employed Structural Equation Modeling (SEM) using the Partial Least Squares method (PLS-SEM) via SmartPLS 4 software. PLS-SEM was chosen due to its suitability for prediction-oriented research and the use of both reflective and composite constructs. First, we assessed the **measurement model**. All multi-item constructs exhibited strong internal consistency: Cronbach's alpha values ranged from 0.78 to 0.92, exceeding the 0.70 threshold, and composite reliabilities ranged from 0.86 to 0.94. Convergent validity was supported as all item loadings were above 0.70 and each construct's average variance extracted (AVE) was well above 0.50. Discriminant validity was verified using the Heterotrait-Monotrait (HTMT) ratio; the highest HTMT value among construct pairs was 0.81, below the conservative 0.85 cutoff (Shaw et al., 2024), indicating adequate distinctness of constructs. Next, we evaluated the **structural model**. We included two control variables – hospital size/tier and region – to account for extraneous influences on performance (neither control had a significant effect in the model). The variance inflation factors (VIFs) for all predictor constructs were under 3, suggesting no severe multicollinearity. We then examined the path coefficients and explanatory power. The model's overall fit was good: the standardized root mean square residual (SRMR) was 0.054, below the 0.08 benchmark for a well-fitting PLS model, indicating a close match between the model and the data. We used a bootstrapping procedure with 5,000 resamples to test the significance of direct and indirect effects. The mediation effect of technology acceptance was tested by examining the significance of the indirect path (Smart Innovation → Technology Acceptance → Performance), and moderation by dynamic capabilities was tested by creating an interaction term between Smart Innovation and Dynamic Capabilities in the PLS model. As PLS does not directly output a p-value for interactions, we interpreted the interaction's path coefficient and t-statistic from bootstrapping, and also performed a simple slope analysis to visualize the moderation effect. The results of these analyses are detailed in the next section.

## RESULTS

### Measurement Model

Prior to hypothesis testing, we confirmed that the measurement model was reliable and valid. **Table 1** (see above) summarizes the scale properties. All constructs demonstrated high reliability, with Cronbach's α values ranging from 0.78 to 0.92 and composite reliabilities from 0.86 to 0.94. The average variance extracted (AVE) for each construct exceeded 0.65, indicating strong convergent validity. In addition, discriminant validity was established: the squared correlations between constructs were below their respective AVEs, and the Heterotrait-Monotrait (HTMT) ratios were all below 0.85(Sherer et al., 2016). These results suggest that each construct in our model is measured distinctly and without significant cross-over(Li et al.,2016).

### Structural Model

We then examined the structural model to test the hypotheses. The model explained a substantial portion of variance in the key outcomes. As shown in **Table 2**, the adjusted $R^2$ for **Organizational Performance** was 0.62, implying that about 62% of the variance in hospital performance is accounted for by the predictors in our model. The intermediate outcome **Technology Acceptance** (as a mediator) had an $R^2$ of 0.48, indicating that nearly half of the variation in user acceptance levels across hospitals was explained by the presence of smart innovations (and any unobserved factors captured by our model). These $R^2$ values denote strong explanatory power in the context of organizational studies. The model's fit indices also suggest a good fit: for instance, the SRMR (standardized root mean square residual) was 0.054, well within the acceptable range (<= 0.08).

**Table 2. R-squared and Model Fit Statistics**

| Endogenous Variable | $R^2$ | $R^2$ (Adjusted) |
|---|---|---|
| Organizational Performance | 0.63 | 0.62 |
| Technology Acceptance | 0.49 | 0.48 |

| Model Fit Index | Value | Criterion |
|---|---|---|
| SRMR (PLS model) | 0.054 | <= 0.080 (acceptable) |

*Note:* $R^2$ values significant at $p< 0.001$. SRMR = Standardized Root Mean Square Residual.

Next, we evaluated the path coefficients for each hypothesized relationship. Table 3 presents the standardized coefficients (β), t-statistics, and significance levels for the structural paths corresponding to H1–H5. All hypothesized links were supported by the data. In terms of direct effects, Smart Innovation adoption had a positive and significant impact on Organizational Performance (β = 0.29, t = 3.45, p = 0.001), confirming H1. Similarly, Technological Evolution showed a significant positive effect on Performance (β = 0.21, t =

2.88, p = 0.004), supporting H2. Together, these results indicate that both the implementation of specific digital innovations and the overall digital maturity of a hospital contribute to higher performance outcomes, consistent with our theoretical expectations.

Regarding the mediation hypothesis (H3), we found that Technology Acceptance is indeed a significant mediator of innovation's effect on Performance. Smart Innovation exhibited a strong positive effect on Technology Acceptance ($\beta = 0.68$, $p < 0.001$), and in turn Technology Acceptance positively influenced Performance ($\beta = 0.28$, $t = 2.79$, $p = 0.005$). The indirect effect of Smart Innovation on Performance through Technology Acceptance was statistically significant (indirect $\beta \approx 0.19$, $p = 0.003$, by Sobel test and bootstrap confidence interval), while the direct effect of Smart Innovation on Performance remained significant (though slightly reduced) when the mediator was included. This pattern indicates partial mediation: the presence of a favorable user acceptance climate magnifies the performance gains from new technologies, although smart innovations also retain a direct impact. Therefore, H3 is supported – user technology acceptance plays a mediating role in converting digital innovations into performance improvements.

For the moderation hypothesis (H4), the analysis confirmed that Dynamic Capabilities amplify the impact of innovation on performance. The interaction term between Smart Innovation and Dynamic Capabilities was positive and significant ($\beta = 0.15$, $t = 3.10$, $p = 0.002$). This finding means that in hospitals with higher dynamic capabilities (i.e., those more adept at adapting processes and resources), the effect of technology adoption on performance was significantly stronger than in hospitals with lower adaptive capability. A simple slope analysis illustrated that when dynamic capabilities were one standard deviation above the mean, the slope of Performance on Smart Innovation was steep and significant (simple slope $\beta\_high \approx 0.40$, $p < 0.001$), whereas at one standard deviation below the mean it was much flatter ($\beta\_low \approx 0.15$, $p = 0.08$, not significant). (For brevity, the interaction plot is not displayed.) This interaction supports H4, underscoring that dynamic capabilities are a critical complementary factor for realizing the full benefits of health IT innovations.

Finally, we examined the influence of the institutional environment (H5). The data show a strong positive relationship between Institutional Support (perceived policy support) and the extent of Smart Innovation adoption by hospitals. In a supplementary regression, Institutional Support had a coefficient of $\beta = 0.46$ ($t = 5.65$, $p < 0.001$) in predicting the Smart Innovation Adoption score, indicating that hospitals which felt greater government encouragement and incentives tended to implement more digital innovations. This result confirms H5 – supportive national policies significantly drive technology uptake at the organizational level. In practical terms, policy support emerged as an important exogenous enabler: it helps create the conditions for hospitals to invest in and embrace smart healthcare technologies, which then (as shown by H1–H4) lead to performance gains.

**Table 3. Structural Model Results and Hypothesis Testing**

| Hypothesis | Path (Effect) | β (Coeff.) | t-statistic | p-value | Supported? |
|---|---|---|---|---|---|
| **H1**: Smart Innovation → Performance | +0.29 | 3.45 | 0.001 | Yes | |
| **H2**: Technological Evolution → Performance | +0.21 | 2.88 | 0.004 | Yes | |
| **H3**: Smart Innovation → Performance (indirect via Tech Acceptance) | +0.19 (indirect) | 2.96 | 0.003 | Yes | |
| **H4**: Smart Innovation × Dyn. Capabilities → Performance (interaction) | +0.15 | 3.10 | 0.002 | Yes | |
| **H5**: Institutional Support → Smart Innovation Adoption | +0.46 | 5.65 | <0.001 | Yes | |

*Notes:* All coefficients are standardized. $p< 0.01$. The direct effect of Smart Innovation on Performance remained significant ($p< 0.01$) after accounting for the mediator, indicating partial mediation (H3). Control variables (hospital tier and region) were included in the model but were not significant ($p > 0.10$) and are omitted from the table for brevity.

## DISCUSSION

The findings of this research provide important insights into how technology and organizational factors jointly drive performance in the context of China's healthcare transformation. Overall, the results support our overarching argument that smart innovation and technological evolution act as catalysts for next-generation organizational performance, but crucially, their impact is mediated by user acceptance and augmented by organizational capabilities, all within an enabling institutional environment.

**Theoretical Implications:** Each hypothesis was supported, reinforcing and extending several theoretical frameworks. First, the positive links between digital innovation (both specific technology adoption and broader IT maturity) and hospital performance (H1, H2) empirically validate the long-assumed benefits of healthcare IT. This aligns with the growing body of evidence that digital transformation contributes to efficiency and quality improvements in healthcare settings(Greenhalgh et al., 2017). We show that these benefits are measurable at the organizational level in Chinese hospitals. Second, the mediation by technology acceptance (H3) underscores the critical importance of human factors in realizing technology's value. This finding echoes the core premise of the Technology Acceptance Model – that technology's impact is largely determined by whether users embrace it – but we advance it by linking acceptance to organizational performance outcomes. Prior studies often stop at user adoption intentions; our results confirm that higher acceptance (users finding systems useful and easy) translates into tangible performance gains for the institution. In practice, this means that hospitals cannot achieve the desired improvements from innovations unless physicians, nurses, and staff actually use those innovations effectively. This highlights a "people" aspect often underemphasized in technology-led reforms, supporting calls in the literature to integrate behavioral adoption models (like TAM) into evaluations of health IT success(Greenhalgh et al., 2018). Third, our moderation result for dynamic capabilities (H4) offers empirical support for Dynamic Capabilities Theory in a healthcare context. It demonstrates that an organization's ability to learn, adapt, and reconfigure is a decisive factor that can amplify the returns on technology investments. This finding is consistent with conceptual arguments by Teece and others that dynamic capabilities are what allow firms to leverage new resources for competitive advantage. We contribute concrete evidence that hospitals with higher dynamic capabilities (e.g. agile management, continuous training, innovation-oriented culture) gain more performance benefit from the same technology compared to less capable peers (Zhenget al.,2023). This not only reinforces the value of the dynamic capabilities framework – echoing recent work highlighting its transformative potential for organizations – but also introduces it to the health IT domain, bridging a gap between information systems research and strategic management in healthcare. Fourth, the significant effect of institutional support (H5) affirms the relevance of Institutional Theory in technology diffusion. In China's case, the strong top-down mandates and incentives form a "digital friendly" institutional environment that lowers barriers and accelerates innovation uptake. Our data empirically substantiate what has been observed anecdotally: when the government strongly encourages and financially supports digital health (as through the Smart Hospital policies), hospitals respond by adopting more innovations. This result aligns with prior studies noting that regulatory and policy frameworks can profoundly shape healthcare providers' behavior. It also complements global strategies like the WHO's emphasis on digital health enablement for health system strengthening (Tian et al., 2017). In summary, by integrating TAM, Dynamic Capabilities, and Institutional perspectives, our study presents a more holistic theoretical view of digital innovation success in healthcare – one that spans individual, organizational, and institutional levels. We contribute to the literature by empirically confirming that these levels are interconnected: policy context influences organizational adoption of technology, organizational capabilities and culture determine usage, and usage by individuals drives performance outcomes.

**Practical Implications:** The insights from this study are particularly relevant for hospital executives and policymakers in China and beyond. For hospital leaders, the findings highlight that investing in new technology alone is not sufficient – equal attention must be paid to change management and capacity-building. Specifically, managers should foster a positive technology acceptance climate among staff. This can be achieved through comprehensive training programs, involving end-users in system selection/design to boost perceived usefulness, and providing ongoing support (for example, IT helpdesks or digital "champions" in clinical departments). By improving ease of use and clearly demonstrating the benefits of new tools to healthcare professionals, hospitals can increase adoption rates, thereby unlocking the performance improvements these tools promise. Additionally, hospital administrators should actively develop their organization's dynamic capabilities. This might involve creating more flexible processes, encouraging continuous learning, and establishing cross-functional teams to implement innovations. Hospitals that become learning organizations – able to pivot and innovate – will amplify the returns on each new technology and be better positioned in an era of rapid medical and technological change. Our results also suggest that tracking and nurturing dynamic capabilities (through, for instance, periodic organizational capability audits or investing in leadership development focused on innovation management) is as important as tracking the technologies themselves.

For policymakers, our study provides evidence that policy interventions can be very effective in catalyzing digital transformation. China's approach – setting clear goals (e.g., all hospitals to reach certain IT standards), providing funding and technical guidelines, and integrating digital health into performance assessments – has materially increased technology adoption and, by extension, performance improvements. Policymakers in other countries might take note of the Chinese experience: combining infrastructure investments with training and support programs could similarly accelerate health system digitalization. At the same time, our findings caution that simply mandating technology adoption (a top-down push) must be coupled with support for the "softer" aspects: human-centered design, workflow integration, and capability development. National policies could thus expand to include funding specifically earmarked for user training initiatives, change management expertise, and innovation capability-building in healthcare organizations. We also highlight the role of China's burgeoning health tech industry (including startups) in providing innovative solutions; supportive policies (like incubators or public-private pilot projects) can further enhance the ecosystem that hospitals can draw upon for their innovation needs. Ultimately, a synergistic approach where government provides both the carrots (incentives, resources) and the know-how (best practice frameworks, platforms for knowledge exchange) will yield the best outcomes.

**Limitations and Future Research:** Like any study, ours has limitations that open avenues for future inquiry. First, the data are cross-sectional, which limits our ability to make strong causal inferences. While the structural model is theoretically grounded (and we took steps to mitigate common method bias, such as assuring respondents of anonymity and separating sections of the survey), longitudinal studies are needed to track how performance evolves before and after technology implementation. Future research could employ a longitudinal design or quasi-experiments (for example, examining performance trends in hospitals that adopt a new system versus those that do not, over time) to strengthen causal claims. Second, our reliance on perceptual performance measures and managerial reports for variables like technology acceptance may introduce subjectivity. Objective performance indicators (e.g., treatment error rates, average length of stay, cost per patient) and direct surveys of frontline users would complement our findings. Upcoming studies might collect multi-source data – for instance, pairing managerial surveys with surveys of clinicians and with archival performance data – to provide a richer, multi-faceted validation of the model. Third, our sample, while broad, was skewed towards large public hospitals. This was intentional given their prominence in China's system, but it means our conclusions are most applicable to similar contexts. Smaller primary care facilities or private hospitals might face different challenges; examining our model in those settings would be valuable. Additionally, all sample hospitals are in China's cultural and institutional context. Caution is warranted in generalizing to countries with different healthcare governance or technology policies. Replicating this study in other countries – for example, in markets where adoption of health IT is more market-driven than policy-driven – could test which aspects of our framework are universal and which are context-dependent. Finally, we focused on a high-level view of "smart innovation" as a composite. Future research could delve deeper into specific technologies (e.g., comparing the performance impact of AI diagnostics versus telemedicine vs. electronic records) or explore additional mediators and moderators. For instance, organizational culture or staff digital literacy might further condition outcomes, and the nature of leadership (e.g., a transformational leadership style) could affect technology acceptance and capability-building.

## CONCLUSION

This study set out to investigate how smart innovation and technological evolution serve as catalysts for next-generation organizational performance, using evidence from China's ongoing healthcare transformation. Our findings affirm that investing in advanced technologies can indeed yield substantial performance benefits for healthcare organizations – but critically, the extent of these benefits depends on human and organizational factors. Technology must be embraced by its users, and organizations must be NIMBLE enough to exploit it, all within a supportive policy landscape. In the Chinese context, the confluence of strong government impetus, eager adoption by hospitals, and improvements in care processes has begun to fulfill the promise of digital health: more efficient, higher-quality, and accessible healthcare services. The implications extend beyond China as health systems worldwide grapple with modernization. By marrying insights from TAM, Dynamic Capabilities, and Institutional theory, our research highlights a multi-level recipe for success: innovative technology + user acceptance + organizational agility + enabling policy = improved performance. Stakeholders who attend to all these elements can accelerate the journey toward smarter, high-performing healthcare organizations. Ultimately, the transformation witnessed in China's hospitals today illustrates a broader principle – that when smart innovation is effectively integrated into the fabric of healthcare delivery, supported by people, capabilities, and vision, it becomes a powerful engine driving the next generation of organizational performance.

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