

How digital capabilities shape cultural–tourism development in Chinese cities

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Article

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Abstract

Cities with comparable levels of digitalisation often achieve different cultural–tourism outcomes, yet composite indices reveal little about which digital capabilities account for this variation. This study analyses balanced panel data for 280 Chinese cities from 2011 to 2023. The empirical framework combines city-grouped cross-validation, SHAP attribution, accumulated local effects, spatial autocorrelation diagnostics and geographically local ExtraTrees models. Twelve indicators represent four capability domains: the digital financial environment, digital infrastructure, the digital industrial base and digital innovation capability. ExtraTrees achieved the strongest grouped cross-validated performance ($R^2 = 0.595$, $MAE = 0.0469$ and $RMSE = 0.0615$). Global SHAP rankings placed mobile phone subscriptions first, followed by R&D personnel, patent authorisations, broadband users and R&D expenditure, indicating that infrastructure access and innovation capacity jointly structured the predictions. ALE curves showed threshold-like increases for innovation indicators and diminishing returns for several infrastructure indicators. Local models yielded a mean grouped cross-validated R^2 of 0.579, with values ranging from 0.361 to 0.795. Finance-assisted profiles were most frequent (101 cities), followed by innovation-led (68), infrastructure-driven (66) and industry-supported profiles (45). These findings show that both the composition and local context of digital capabilities matter alongside their aggregate level. The results describe predictive associations and model-based contributions rather than causal effects.

1. Introduction

Digital technologies are increasingly embedded in urban production, services and governance (Shlapak et al. 2025; Yang et al. 2025). Their developmental returns, however, vary markedly across cities. Comparable investments in digital infrastructure can coincide with very different economic and social outcomes (Rydzewski 2025; Wen et al. 2025). This variation raises a question that aggregate digitalisation measures cannot answer: which digital capabilities are associated with stronger local outcomes?

Previous studies link digital transformation to regional development and industrial upgrading (Liu et al. 2024; Cai et al. 2025). Much of this work represents digitalisation with a single composite index (Huang and Lin 2024). Such indices are useful for measuring overall levels, but they combine capabilities with different resource requirements and value-creation processes. Evidence on their relative explanatory importance therefore remains limited (Fan and Wu 2022; Gao et al. 2025).

This aggregate approach is well suited to questions about whether one city is more digitalised than another, but it is less informative about how digital resources are converted into sectoral outcomes. Two cities may receive similar index scores while relying on different combinations of connectivity, finance, industrial services and innovation. Those combinations imply different constraints and routes to value creation. Treating them as interchangeable can therefore conceal why comparable levels of digitalisation coexist with different development trajectories. The present analysis shifts attention from the level of a composite index to the contribution structure within it.

A second limitation concerns functional form. Linear estimates impose a constant marginal association unless nonlinear terms are specified in advance. That assumption is restrictive when digital capabilities are

cumulative and complementary. Basic connectivity may matter most when access is scarce, whereas innovation inputs may become productive only after infrastructure, skills and organisational capacity have reached usable levels. A model that can represent thresholds, plateaus and interactions is consequently needed to distinguish early-stage access effects from later-stage capability effects (Bertschek and Niebel 2016; Romer 1990).

Cultural–tourism development provides a useful setting in which to examine this issue. Digital platforms, destination management systems and online content now influence service provision and visitor experiences. At the same time, cultural–tourism outcomes depend on local resources, innovation systems and market capacity (Zhang 2024; Kallmuenzer and Peters 2023). Persistent differences among Chinese cities make it possible to examine how the composition of digital capabilities relates to uneven development (Yang et al. 2025; Sun et al. 2025).

Digital transformation is therefore represented as a digital capability system (DCS) with four domains: digital infrastructure (DINF), the digital industrial base (DIB), the digital financial environment (DFE) and digital innovation capability (DIC). The analysis asks three questions. Which domains make the largest explanatory contributions to cultural–tourism development? Do their response curves differ across capability levels? How do their relative contributions vary across cities?

The empirical design combines five-fold cross-validation grouped by city with SHAP attribution, accumulated local effects (ALE), Moran statistics and local spatial machine learning. The panel contains 3,640 observations for 280 cities from 2011 to 2023.

The study contributes a disaggregated account of urban digitalisation. It compares 12 indicators within a common predictive model, examines their nonlinear response patterns and maps local contribution profiles. This design distinguishes variation in capability composition from variation in the overall digitalisation level.

The contribution is methodological as well as substantive. Predictive performance is assessed out of sample by keeping all observations from the same city in one fold, which limits the possibility that a model is rewarded for reproducing a city's own temporal profile. Interpretation is then separated into three questions: which indicators contribute most on average, how fitted responses vary across observed feature levels, and whether the contribution structure changes across geographical neighbourhoods. This sequence links model validation to interpretation without treating machine-learning attribution as causal identification.

The study also speaks to cultural–tourism research, where digitalisation is often discussed as a general enabling condition. By distinguishing finance, infrastructure, industry and innovation, the analysis identifies which parts of the digital system are most closely associated with predicted development and where that pattern is not uniform. This provides a more qualified basis for policy than the assumption that a higher aggregate digital score necessarily implies the same development pathway in every city.

2. Literature review and theoretical framework

2.1 Cultural–tourism development in the digital era: from resource dependence to digital empowerment

Cultural tourism links cultural resources, public services, market demand and tourism provision (Richards 2018). As experience-based and creative activities have expanded, cultural resources have also become inputs to local knowledge creation, product development and destination differentiation.

Its development is not simply the sum of cultural supply and visitor demand. Cultural institutions, heritage resources and creative employment shape the content available to visitors, while transport, accommodation, attractions and market demand determine whether that content is converted into tourism activity. Coordination between the two subsystems matters because cultural resources can remain weakly commercialised and tourism growth can occur with limited cultural depth. The coupling-coordination measure used here reflects this joint-development perspective rather than treating one subsystem as a proxy for the other (Xu et al. 2024; Tang et al. 2025).

Digitalisation can affect both the production and circulation of cultural–tourism value. Online information reduces search costs, digital payment systems lower transaction frictions, and platforms can connect attractions with geographically dispersed demand. At the production stage, data systems can improve scheduling and service coordination, while digital media can support interpretation, storytelling and the recombination of cultural content. These mechanisms are related but not identical: access technologies facilitate participation, whereas innovation and industrial capabilities influence the quality and variety of what is produced.

This distinction is especially relevant at the city level. Destinations differ in heritage endowments, institutional provision, market size and the capacity of local organisations to absorb technology. Digital inputs therefore operate through an existing cultural and tourism system rather than replacing it. A broadband connection, a financial service and an R&D workforce each remove a different constraint. Their observed contributions should not be expected to be equal, constant across capability levels or spatially uniform.

Digital technologies affect several parts of this system. They can alter resource allocation, service delivery and visitor access (Yu et al. 2024). Existing studies have mainly asked whether digitalisation is associated with cultural–tourism development. Less is known about how specific digital capabilities differ in their contributions.

2.2 Opening the black box of digital transformation: from aggregate effects to heterogeneous digital capabilities

Digital transformation is widely used to explain regional development, industrial upgrading and urban competitiveness. Lower information and transaction costs can support resource allocation and knowledge diffusion (Goldfarb and Tucker 2019). In tourism, digital platforms and smart service systems can also change how destinations coordinate supply and communicate with visitors (Gretzel et al. 2015).

Most empirical studies nevertheless measure digital transformation as a single index. This approach estimates an aggregate relationship but obscures the separate roles of infrastructure, finance, industry and innovation. The internal contribution structure consequently remains difficult to observe.

Research in digital geography and innovation economics increasingly treats digitalisation as a bundle of related capabilities (Ma and Li 2022; Du and Wang 2024). These capabilities differ in required inputs,

institutional conditions and routes to value creation.

A capability perspective treats technology as something that organisations and places must mobilise, not merely possess. Infrastructure creates the technical possibility of connection; finance supports transactions and access to capital; an industrial base supplies specialised labour and intermediary services; and innovation capability enables experimentation and knowledge production. These domains are complementary because weaknesses in one can limit the returns to another. They are nevertheless analytically distinct because each operates through different actors, time horizons and resource requirements.

DFE mainly reduces financial and transactional barriers. Wider coverage and deeper use can make online purchasing and small-business payments easier, but these services do not by themselves generate cultural content or destination products. DINF provides the communication backbone for search, booking, mobile services and data exchange. Its benefits may be broad but subject to saturation once basic access becomes commonplace. DIB captures a local supply of information-related firms, workers and output that can support platform operation, digital marketing and service integration. DIC represents a further step towards knowledge creation through R&D investment, skilled personnel and patents.

The four domains also differ in the visibility of their effects. Infrastructure and finance may operate as enabling conditions whose contribution becomes less distinctive after diffusion. Industrial and innovation capabilities are more concentrated and may differentiate cities after general-purpose access has expanded. This provides a substantive reason to compare contribution magnitudes and fitted response shapes rather than interpreting the domains as four interchangeable components of a single score (Du and Wang 2024; Gao et al. 2025).

Digital infrastructure supports connectivity and data transmission. The digital industrial base provides firms, employment and platform services. The digital financial environment affects access to payments and finance, while digital innovation capability reflects knowledge creation and technological output (Li and Zhao 2023). These differences imply that the four domains need not make equal contributions (Gao et al. 2025).

2.3 Infrastructure versus innovation: competing perspectives on digital development

Two perspectives are especially relevant. The infrastructure perspective treats communication networks and data facilities as necessary foundations for digital activity (Jin et al. 2024). The innovation perspective argues that technology produces sustained returns only when it is combined with R&D, skilled labour and knowledge production (Romer 1990). Evidence that similar infrastructure levels coexist with different outcomes supports examining both perspectives rather than assuming that infrastructure alone is sufficient (Bertschek and Niebel 2016; Buhalis et al. 2019).

From the infrastructure perspective, networks and data facilities have high fixed costs and broad spillovers. Their initial expansion can connect previously underserved users, reduce communication frictions and allow destinations to participate in digital markets. If coverage approaches maturity, however, an additional unit of

infrastructure may produce a smaller observable change in outcomes. The expected pattern is therefore an early rise followed by weaker returns, not an indefinitely constant slope.

The innovation perspective places greater weight on absorptive capacity and endogenous knowledge production. R&D expenditure does not automatically become a tourism product, but it can support digital content, intelligent services and new organisational routines when skilled personnel and commercial partners are available. Innovation may therefore display delayed or threshold-like associations: returns remain modest at low capability levels and become more pronounced once complementary resources accumulate. Comparing these patterns provides a direct empirical test of whether access or knowledge creation better differentiates cities at the observed stage of development.

2.4 Digital transformation and uneven development

Digitalisation also has a spatial dimension. Knowledge diffusion, industrial linkages and market access can extend beyond city boundaries, but the distribution of these resources remains uneven (Li et al. 2024).

Digital networks reduce some distance-related costs, but they do not eliminate the geography of skills, firms and institutions. Knowledge-intensive employment tends to cluster where specialised labour markets, universities, producers and consumers can interact. Platform services can extend beyond administrative boundaries, yet their design, maintenance and commercialisation remain connected to particular urban ecosystems. Spatial concentration may therefore persist even when digital services are technically accessible from many locations (Ash et al. 2018).

Cumulative causation offers one explanation for this pattern. Cities with stronger initial capabilities can attract additional firms and skilled workers, improve the market for specialised services and generate further innovation. Less-developed cities may gain access to the same general technologies without acquiring the organisational capacity required to use them intensively. The resulting divergence is not proof that digitalisation causes inequality, but it implies that a national average association can mask locally different conversion conditions (Myrdal 1957; Fujita et al. 1999).

For cultural tourism, these conditions include the density of cultural organisations, links between technology firms and tourism providers, and the ability to translate cultural material into marketable experiences. Neighbouring cities may share visitors, transport links and digital service providers, while distant cities with similar index values may operate in very different regional systems. Spatial diagnostics and geographically local models are used to describe this contextual variation rather than to estimate inter-city causal spillovers.

Innovation-intensive firms and skilled workers often concentrate in core cities. Cumulative processes can then reinforce existing advantages (Ash et al. 2018; Myrdal 1957; Fujita et al. 1999). The same measured capability may therefore have different associations across local contexts.

This issue is relevant to cultural tourism because high-value digital content and immersive services rely on specialised knowledge and organisational capacity. Digitalisation may support sectoral development while leaving regional differences intact or, in some cases, widening them (Wang et al. 2025).

2.5 Research framework and theoretical propositions

The theoretical framework treats digital transformation as a capability system rather than a single input. DINF, DIB, DFE and DIC correspond to connectivity, industrial coordination, financial access and knowledge creation. Their contributions may differ in magnitude, shape and spatial distribution (Fig. 1).

The framework implies a sequence rather than a rigid hierarchy. DINF and DFE reduce basic access and transaction constraints; DIB helps coordinate digital production and services; DIC expands the capacity to create and adapt knowledge. Which domain contributes most depends on the constraints already removed in a city and on the complementary resources available there. The propositions therefore concern empirical contribution patterns, not universal technological laws.

P1 establishes the geographical problem, P2 concerns the relative magnitude of capability contributions, P3 concerns their functional form and P4 concerns contextual variation. Together they move from the existence of uneven outcomes to the internal and spatial structure of the fitted relationship. Figure 1 summarises these links while avoiding a causal ordering that the observational design cannot establish.

P1: Digital transformation is associated with uneven cultural–tourism development across cities.

P2: Different digital capabilities contribute unequally to cultural–tourism development, with digital innovation capability expected to play a dominant role.

P3: The developmental returns of digital capabilities are nonlinear.

P4: The influence of digital capabilities is spatially heterogeneous across cities.

The propositions are evaluated with predictive and interpretative evidence. Model performance establishes whether the indicators contain out-of-sample information, while SHAP, ALE and local models describe contribution patterns. These analyses do not identify causal effects.

[Fig. 1. Analytical framework for the predictive association between digital transformation and cultural–tourism development]

3. Research design

3.1 Research background, data sources and analytical framework

The sample comprises 280 prefecture-level and higher-level Chinese cities observed from 2011 to 2023. The balanced panel contains 3,640 city-year observations and covers 30 provincial-level regions. Tibet, Hong Kong, Macao and Taiwan are excluded because comparable city-level series were unavailable.

The city-year design captures both cross-sectional differences and changes over a period in which digital services became widely embedded in urban economic activity. A balanced panel is retained so that model comparison is not driven by changing sample composition. The unit of analysis remains the city-year: provincial indicators are not substituted where city data are unavailable, and the excluded regions are not assigned values by extrapolation.

The source series were checked for consistent units and direction before index construction. Where statistical publications revised labels or reporting formats, conceptually equivalent city-level series were aligned to a common definition. Linear interpolation was limited to gaps within an observed city series; it was not used to create values outside the first and last available years. Retaining imputation flags in the reproducibility data allows the constructed panel to be audited and alternative missing-data rules to be examined.

Cultural–tourism development (CTD) is used as the outcome because it combines cultural provision, tourism demand and the conversion of local resources into market activity. The sector is also exposed to digital platforms, online services and technology-intensive forms of content production.

Data were compiled from Chinese urban, cultural-industry and tourism statistical yearbooks, provincial and municipal yearbooks and statistical bulletins, and the Peking University Digital Inclusive Finance Index (Guo et al. 2020). Missing values within city series were filled by linear interpolation, with imputation flags retained in the analytical data.

The workflow has four stages: spatial diagnostics, grouped cross-validated model comparison, global interpretation with SHAP and ALE, and geographically local modelling. The main predictive and interpretative specification contains the 12 digital capability indicators listed in Table 2.

The stages answer different questions. Spatial statistics first establish whether the outcome and aggregate digital index have a geographical pattern. Candidate models then test whether the 12 indicators contain out-of-sample predictive information. SHAP and ALE are applied only after model selection to describe attribution magnitude and response shape. Finally, local models evaluate whether fit and attribution differ across city neighbourhoods. Keeping these stages separate prevents the spatial maps from being interpreted as a substitute for model validation.

3.2 Measurement of cultural–tourism development and digital capabilities

3.2.1 Measurement of cultural–tourism development (CTD)

CTD represents the joint development of the cultural and tourism subsystems. The index combines cultural-industry employment, cultural institutions, public services, consumption capacity and heritage resources with tourism revenue, visitor demand and attraction supply.

Following prior measurement studies (Xu et al. 2024; Tang et al. 2025), annual entropy weights are calculated separately for the cultural and tourism subsystems. All indicators are positively oriented. The two subsystem scores are then combined with a coupling-coordination measure. Table 1 lists the indicators and average annual weights.

The entropy method is used to calculate the internal weights of the cultural and tourism subsystems. Each positive indicator is first range-normalized:

$$X'_{ijt} = \frac{X_{ijt} - \min_{i,t}\{X_{ijt}\}}{\max_{i,t}\{X_{ijt}\} - \min_{i,t}\{X_{ijt}\}}$$

1

The entropy weight of each indicator is then calculated as follows:

$$p_{ijt} = X'_{ijt} / \sum_i X'_{ijt}; e_j = -k \sum_i p_{ijt} \ln(p_{ijt}), k = 1 / \ln(n); d_j = 1 - e_j; w_j = d_j / \sum_j d_j$$

2

The comprehensive indices of the cultural system and tourism system are obtained as:

$$C_{it} = \sum_j w_j X'_{ijt} T_{it} = \sum_j w_j^T X'_{ijt}$$

3

The coupling degree and comprehensive development index are then calculated as:

$$\begin{aligned} \text{Couple}_{it} &= \frac{2\sqrt{C_{it}T_{it}}}{C_{it}+T_{it}} \\ S_{it} &= \alpha C_{it} + \beta T_{it} \end{aligned}$$

4

Given the equal importance of culture and tourism in integrated development, α and β are both set to 0.5. The final CTD index is calculated as:

$$CTD_{it} = \sqrt{\text{Couple}_{it} \cdot S_{it}}$$

5

Table 1
Evaluation indicator system for CTD

Subsystem	Dimension	Indicator	Average weight	Attribute	Definition
Cultural system	Cultural industry development	Employment share in culture, sports, and entertainment	0.0864	Positive	Reflects the employment foundation and development scale of cultural industries.
Cultural system	Cultural institution provision	Number of museums	0.1167	Positive	Reflects the availability of formal cultural institutions and exhibition facilities.
Cultural system	Public cultural service provision	Public library holdings per 10,000 residents	0.1261	Positive	Reflects the capacity and accessibility of public cultural services.
Cultural system	Cultural consumption capacity	Retail sales per resident	0.0682	Positive	Proxies the consumption capacity that supports residents' cultural participation.
Cultural system	Cultural resource endowment	National intangible cultural heritage projects	0.1026	Positive	Reflects cultural heritage endowment and intangible cultural resources.
Tourism system	Tourism market output	Domestic tourism revenue per resident	0.2238	Positive	Reflects tourism consumption conversion and destination market revenue.
Tourism system	Tourism market demand	Domestic tourist arrivals per 10,000 residents	0.1525	Positive	Reflects tourism demand and destination attractiveness.
Tourism system	Tourism resource supply	Weighted number of A-rated scenic spots	0.1237	Positive	Reflects the quantity and grade structure of tourism attractions.
Note: Average weights are the means of annual entropy weights from 2011 to 2023; all indicators are positive indicators.					

3.2.2 Measurement of the digital capability system

The digital capability system separates four domains that are commonly combined in aggregate digital-economy indices (Li and Zhao 2023; Huang and Lin 2024). This separation permits direct comparison of their model-based contributions.

DFE contains three measures from the Peking University index. DINF covers broadband, mobile communication and telecommunications activity. DIB represents employment and output in information-

related industries. DIC contains R&D expenditure, R&D personnel and patent authorisations.

DFE, DINF and DIB are constructed with annual entropy weights. DIC uses equal weights because the innovation indicators are discrete or highly concentrated. Each domain is standardised before the four domain scores are averaged to form the descriptive digital transformation index (DTI).

Table 2 reports the 12 indicators, their within-domain weights and the equal 0.25 weight assigned to each domain in the DTI.

$$DFE_{it} = \sum_j w_j^{DFE} X'_{ijt}; DINF_{it} = \sum_j w_j^{DINF} X'_{ijt}; DIB_{it} = \sum_j w_j^{DIB} X'_{ijt}$$

6

To avoid weight distortion caused by discrete innovation indicators, DIC is constructed through equal-weight averaging of standardised R&D expenditure, R&D personnel, and patent grants:

$$DIC_{it} = (RDE'_{it} + RDP'_{it} + PAT'_{it})/3$$

7

The four standardised dimensions are then averaged to obtain the comprehensive DTI:

$$TI_{it} = (DFE'_{it} + DINF'_{it} + DIB'_{it} + DIC'_{it})/4$$

8

Table 2
Evaluation indicator system for DTI

Dimension	Symbol	Metric	Within-dimension weight	Dimension weight	Attribute	Definition
DFE	CB	Digital financial coverage	0.3886	0.2500	Positive	Coverage of digital financial services.
DFE	UD	Digital financial usage depth	0.3120	0.2500	Positive	Actual use of digital financial services.
DFE	DL	Digital finance digitalisation level	0.2994	0.2500	Positive	Online and convenient digital financial services.
DINF	BROAD	Internet broadband users per 100 people	0.2651	0.2500	Positive	Fixed internet access infrastructure.
DINF	MOB	Mobile phone subscribers per 100 people	0.2271	0.2500	Positive	Mobile communication infrastructure.
DINF	TEL	Telecommunications revenue per capita	0.5079	0.2500	Positive	Intensity of telecom service supply and use.
DIB	ITEMP	Share of information-service employment	0.1073	0.2500	Positive	Employment base of the digital industry.
DIB	IOUT	Per capita internet-related output	0.2291	0.2500	Positive	Digital industry output foundation.
DIB	IREMP	Internet-related employees	0.6636	0.2500	Positive	Human-resource base of the internet industry.
DIC	RDE	R&D expenditures	0.3333	0.2500	Positive	Digital innovation investment intensity.
DIC	RDP	R&D personnel	0.3333	0.2500	Positive	Digital innovation talent foundation.

Note: DFE, DINF, and DIB weights are derived from the entropy method. DIC is constructed using equal weights, and DTI is calculated by equally weighting the four standardised dimensions.

Dimension	Symbol	Metric	Within-dimension weight	Dimension weight	Attribute	Definition
DIC	PAT	Patents granted	0.3333	0.2500	Positive	Digital innovation output.
Note: DFE, DINI, and DIB weights are derived from the entropy method. DIC is constructed using equal weights, and DTI is calculated by equally weighting the four standardised dimensions.						

3.3 Explainable spatial machine-learning analytical framework

The explainable spatial machine-learning framework is designed for prediction and interpretation rather than causal estimation. Tree-based models can represent nonlinearities and interactions that a linear specification may miss. Spatial statistics describe the geographical patterning of CTD and DTI, while local models examine whether predictive fit and capability contributions vary across neighbourhoods (Mullainathan and Spiess 2017; Athey and Imbens 2019).

3.3.1 Spatial diagnostics and spatial feature construction

Global Moran’s I and local indicators of spatial association (LISA) are calculated before model estimation. They are used to describe spatial dependence and to motivate geographically local analysis, not as causal evidence.

Moran’s I is calculated for 2023 to provide a common cross-sectional snapshot at the end of the study period. Row standardisation gives each city the same total neighbour weight despite differences in absolute distance. The eight-neighbour matrix is the main specification because it maintains connectivity while remaining local enough to identify regional patterning. Recalculation with 12 neighbours tests whether the conclusion depends on a single neighbourhood size.

LISA classifications identify the sign combination between each standardised city value and its spatial lag. High–High and Low–Low categories indicate cities surrounded by values on the same side of the mean; High–Low and Low–High categories indicate spatial contrasts. Figure 2 presents quadrant classifications rather than a significance-filtered cluster map. It should therefore be read as a descriptive account of local spatial configuration, with the permutation tests reported for the global statistics.

The spatial weights matrix contains 280 cities and is based on great-circle distances between city centroids. The baseline matrix links each city to its eight nearest neighbours and is row-standardised. A 12-neighbour matrix is used as a diagnostic robustness check.

The main ExtraTrees, SHAP and ALE specification does not include CTD, its spatial lag or lagged controls as predictors. Restricting the feature set to the 12 digital indicators avoids direct outcome leakage and keeps the contribution comparison aligned with the research question.

3.3.2 Machine-learning identification of nonlinear mechanisms

The predictive relationship between the 12 digital indicators and CTD is represented by the following non-parametric function:

$$\text{CTD}_{it} = f(Z_{it}) + \epsilon_{it}$$

9

Here, X contains the 12 standardised digital indicators and $f(\cdot)$ is the fitted prediction function. ExtraTrees, Random Forest, Gradient Boosting and Ridge are compared using five-fold cross-validation grouped by city. All observations for a city remain in the same fold. Performance is assessed with R^2 , mean absolute error (MAE) and root mean square error (RMSE).

Grouping cross-validation by city is central to the evaluation design. A random split at the observation level would allow earlier or later records from the same city to appear in both training and test sets. Because city observations share persistent institutional, geographical and measurement characteristics, such leakage could overstate generalisation. The grouped split instead asks whether the fitted relationship predicts observations from cities not used to train that fold, which is a more demanding test of transferable predictive structure.

The four candidate estimators provide contrasting benchmarks. Ridge represents a regularised linear relationship. Random Forest averages decorrelated trees, Gradient Boosting builds trees sequentially to correct previous errors, and ExtraTrees adds stronger randomisation when selecting splits. The comparison is not intended to identify a universally superior algorithm; it determines which fitted structure is most suitable for interpreting this dataset under the same grouped validation scheme.

R^2 measures the proportion of held-out variation captured by the predictions, while MAE reports the average absolute prediction error and RMSE gives greater weight to larger errors. Considering all three prevents model choice from depending on a single metric. The selected model must combine strong overall fit with an error profile that is not materially worse than competing estimators.

3.3.3 Explaining uneven development outcomes

SHAP (SHapley Additive exPlanations) decomposes each fitted prediction into feature contributions (Lundberg and Lee 2017). Mean absolute SHAP values are used for importance ranking. ALE curves summarise how predictions change across observed feature levels while reducing the extrapolation problems associated with strongly correlated predictors.

The analysis uses absolute SHAP values to rank the average magnitude of each indicator's contribution. Direction is examined separately through the distribution of signed SHAP values and through ALE curves. This distinction matters because a variable can have a large attribution magnitude while contributing positively at some values and negatively at others. Aggregating absolute contributions by domain provides a common scale for comparing DFE, DINP, DIB and DIC.

ALE is used because the digital indicators are correlated components of a broader capability system. Conventional partial-dependence curves can evaluate combinations of predictors that are sparse or absent in the data. ALE instead accumulates local changes within observed intervals, which reduces extrapolation beyond the joint feature distribution. The curves remain conditional descriptions of the fitted model and do not represent interventions on a city.

$$[ALE_j(x) = \int_{z_0}^x \mathbb{E} \left[\frac{\partial f(Z)}{\partial z_j} \mid z_j = s \right] ds - C]$$

10

The expectation term centres each ALE curve at zero (Apley and Zhu 2020). Solid curves show the ensemble mean, and the bands describe variation across random sub-forests. These curves are descriptive model interpretations, not marginal causal effects.

3.3.4 Diagnosis of spatial heterogeneity

Spatial heterogeneity is examined with a separate local ExtraTrees model for each focal city. Each local sample contains the focal city and its 89 nearest cities (Gu et al. 2024).

The 90-city local sample balances two competing requirements. It must be large enough to support grouped five-fold validation and flexible tree estimation, but local enough to allow the composition of neighbouring urban systems to vary across focal cities. Neighbours are defined by great-circle distance, producing overlapping samples whose results change gradually across space. The method is geographically local in estimation but does not impose a spatial lag as a predictor.

Local contribution profiles are based on relative domain shares, not raw differences in the scale of fitted outcomes. A city is assigned to the domain whose local share exceeds the corresponding national mean by the largest amount. The labels therefore indicate which capability is comparatively prominent in the local model; they do not imply that the other three domains are absent or unimportant.

$$[CTD_i = f_i(Z_i; \Omega_i) + \epsilon_i]$$

11

Predictive performance is evaluated with five-fold cross-validation grouped by city within each local sample. The reported local R^2 is calculated from pooled out-of-fold predictions, and MAE and RMSE are retained as complementary diagnostics. A final model is fitted to the complete local sample only for feature-importance estimation. The resulting profiles are classified as innovation-led, industry-supported, infrastructure-driven or finance-assisted according to their largest relative domain contribution.

4. Results

4.1 Spatial dependence of cultural–tourism development and digital transformation

Both cultural–tourism development (CTD) and digital transformation (DTI) displayed positive global spatial autocorrelation in 2023 (Fig. 2). Under the eight-nearest-neighbour matrix, Moran’s I was 0.2059 for CTD and 0.4736 for DTI. With 12 neighbours, the corresponding values were 0.1596 and 0.4112. All four estimates were significant in two-sided randomisation tests with 999 permutations ($p = 0.001$; $n = 280$). The positive association was therefore robust to the alternative neighbourhood definition and was consistently stronger for DTI than for CTD.

[Fig. 2. LISA quadrant classifications for cultural-tourism development and digital transformation in 2023]

4.2 Machine-learning model performance

Tree-based models produced higher grouped cross-validated R^2 values than Ridge (Table 3). ExtraTrees was selected for interpretation because it had the highest R^2 and supports consistent TreeSHAP attribution.

The performance gap is substantively relevant because all models receive the same 12 indicators and the same city-grouped folds. The lower Ridge R^2 indicates that a common linear surface leaves a meaningful part of held-out variation unexplained. The close performance of ExtraTrees and Gradient Boosting, together with their similar error levels, shows that the predictive signal is not unique to one tree-building procedure. ExtraTrees is retained because it provides the highest R^2 and the lowest RMSE while allowing consistent TreeSHAP analysis.

4.3 Opening the black box: unequal contributions of digital capabilities

ExtraTrees achieved the highest grouped cross-validated R^2 (0.5948), compared with 0.5882 for Gradient Boosting, 0.5671 for Random Forest and 0.4813 for Ridge. ExtraTrees also recorded the lowest MAE (0.0469) and RMSE (0.0615); Gradient Boosting produced the next-lowest errors (MAE = 0.0472; RMSE = 0.0620).

Table 3
Predictive performance of candidate machine-learning models

Model	Obs.	Cities	Features	R^2	MAE	RMSE
ExtraTrees	3640	280	12	0.5948	0.0469	0.0615
Gradient Boosting	3640	280	12	0.5882	0.0472	0.0620
Random Forest	3640	280	12	0.5671	0.0483	0.0636
Ridge	3640	280	12	0.4813	0.0532	0.0696

Mobile phone subscribers per 100 people had the largest mean absolute SHAP value (0.01595), followed by R&D personnel (0.01341), patent authorisations (0.01179), broadband users per 100 people (0.01114) and R&D expenditure (0.01002; Fig. 3). The five leading indicators therefore span digital infrastructure and digital innovation capability. Each of the remaining seven indicators had a mean absolute SHAP value below 0.0070.

[Fig. 3. Global SHAP attribution for the 12 digital capability indicators]

The results support the unequal-contribution component of P2 but qualify the expectation of clear innovation dominance. When mean absolute SHAP values were aggregated by domain, digital innovation capability accounted for 40.06% of total attribution, digital infrastructure for 35.31%, the digital industrial base for 17.25% and the digital financial environment for 7.39%. Digital innovation capability ranked first at the domain level, but its lead over infrastructure was modest.

This ranking indicates that the model distinguishes cities through a combination of connectivity and innovation capacity. Mobile phone and broadband penetration represent the scale of digital access, whereas R&D personnel, patent authorisations and R&D expenditure represent knowledge inputs and technological output. The SHAP values describe the attribution structure of the fitted model. Because the indicators are correlated, the ranking should not be interpreted as a set of independent causal effects.

4.4 Nonlinear developmental returns of digital capabilities

SHAP ranks variables but does not show how predictions vary over their observed ranges. ALE curves were therefore used to examine the shape of the fitted relationships (Fig. 4).

[Fig. 4. Accumulated local effect curves for the 12 digital capability indicators]

The response shapes differed across the four domains. DFE curves were small relative to the innovation curves. Several DINF curves rose at low levels and then flattened or declined, while DIB curves varied across indicators.

Within DINF, broadband and mobile-phone indicators showed early increases followed by weaker or negative slopes at higher levels. IT employment and internet-related employment within DIB increased mainly beyond the lower part of their observed ranges.

Within DIC, the curves for R&D personnel and R&D expenditure remained comparatively flat across much of the lower and middle ranges before rising sharply near the upper end of their observed distributions. Patent authorisations also increased in the upper range, but with a smaller fitted change. These patterns indicate upper-range nonlinearities rather than formally estimated thresholds or causal treatment cut-offs.

The different curve shapes support P3 as a statement about modelled nonlinearity.

Taken together, the fitted responses varied with the observed level of each capability. Broadband and mobile-phone access showed their largest increases between low and middle levels, after which the curves flattened or declined, whereas the innovation indicators changed more strongly in the upper part of their distributions. This pattern is consistent with the possibility that skills and organisational capacity complement R&D inputs. Because ALE is a conditional model interpretation, the curves do not identify a universal threshold or a causal return schedule; they show that a common proportional effect would not describe the fitted relationships well.

4.5 Spatial heterogeneity in digital capabilities and local development pathways

The local models had a mean grouped cross-validated R^2 of 0.579 and a median of 0.561. Values ranged from 0.361 to 0.795; the mean out-of-fold MAE was 0.0450 and the mean RMSE was 0.0590. No local R^2 value was negative or fell outside the $1.5 \times \text{IQR}$ bounds. Figure 5a maps local predictive fit, while Fig. 5b maps mean absolute SHAP contribution intensity.

[Fig. 5. Spatial variation in local predictive fit and global-model SHAP contribution intensity]

Regional aggregation of the national model showed different contribution structures (Table 4). DIC had the largest share in eastern China (43.48%) and northeast China (52.09%), whereas DINF had the largest share in central China (39.85%) and western China (38.65%). Total mean absolute SHAP contribution was highest in the east (0.107) and lowest in the central region (0.068).

The neighbourhood-specific local models classified 101 cities as finance-assisted, 68 as innovation-led, 66 as infrastructure-driven and 45 as industry-supported (Fig. 6). Finance-assisted cities formed the largest category, accounting for 36.07% of the sample rather than a majority.

[Fig. 6. Dominant local digital capability domain by city]

The variation in local fit and contribution profiles supports P4 as a statement about spatially heterogeneous model behaviour. It does not establish that location itself causes the observed differences.

The local results add two qualifications to the national model. First, predictive fit remained positive throughout the mapped range but varied enough to show that the same feature set described some neighbourhoods better than others. Second, no single capability profile characterised most cities: finance-assisted, innovation-led and infrastructure-driven profiles were all common, while industry-supported profiles were less frequent.

Regional averages and local model classifications answer different questions. The regional values aggregate city-level SHAP contributions from the national model: DIC ranked first in the east and northeast, while DINF ranked first in the central and western regions. The local typology instead identifies the domain that is most elevated relative to its average share within each neighbourhood-specific model. A finance-assisted label therefore indicates comparative local prominence rather than the largest absolute contribution at the national or regional level.

Table 4
Regional contribution structure of digital capabilities

Region	Cities	Total	DfE share	DINF share	DIB share	DIC share
East	86	0.107	6.25%	33.72%	16.55%	43.48%
Central	80	0.068	9.90%	39.85%	19.57%	30.69%
West	81	0.086	8.02%	38.65%	16.91%	36.42%
Northeast	33	0.081	8.08%	24.21%	15.63%	52.09%

4.6 Robustness checks

Robustness checks varied the estimator, sample and dependent-variable construction (Table 5).

These checks assess whether predictive performance depends on the estimator, the inclusion of administratively distinctive municipalities, the pandemic period or the construction of CTD. Alternative estimators provide a common benchmark under the same grouped folds. The sample exclusions evaluate sensitivity to the four municipalities and to 2020–2022, while the alternative dependent variable uses equal indicator weights. No single check establishes robustness to every modelling decision, so the results are interpreted as evidence of stability within this specified set of alternatives.

Gradient Boosting and Random Forest achieved grouped cross-validated R^2 values of 0.588 and 0.567, respectively. Ridge produced a lower R^2 of 0.481. The close performance of the two ensemble alternatives supports the presence of nonlinear predictive structure without implying that one tree algorithm is uniquely suitable.

Excluding the four municipalities reduced R^2 to 0.531, while excluding 2020–2022 produced an R^2 of 0.602. Their MAE values were 0.0467 and 0.0463, and their RMSE values were 0.0614 and 0.0613, respectively. The decline after removing the municipalities indicates some sensitivity to the largest urban centres, although out-of-sample performance remained positive.

Using the equal-indicator-weight CTD measure yielded an R^2 of 0.582, an MAE of 0.0479 and an RMSE of 0.0627. Predictive performance was therefore close to the entropy-weighted baseline, suggesting that the main fit was not driven by one weighting rule.

Taken together, the sample and outcome checks produced grouped cross-validated R^2 values between 0.531 and 0.602. These checks support the stability of positive out-of-sample prediction, but they do not test whether the SHAP ranking is invariant across specifications. Attribution claims are therefore based on the prespecified baseline ExtraTrees model.

Table 5
Robustness checks

Robustness check	Model / sample	Target	Obs.	Cities	Group-CV R^2	MAE	RMSE
Baseline	ExtraTrees	CTD	3640	280	0.595	0.0469	0.0615
Alternative model	Gradient Boosting	CTD	3640	280	0.588	0.0472	0.0620
Alternative model	Random Forest	CTD	3640	280	0.567	0.0483	0.0636
Alternative model	Ridge	CTD	3640	280	0.481	0.0532	0.0696
Sample / target robustness	Excluding municipalities	CTD	3588	276	0.531	0.0467	0.0614
Sample / target robustness	Excluding 2020–2022	CTD	2800	280	0.602	0.0463	0.0613
Sample / target robustness	Alternative dependent variable	Alt. CTD	3640	280	0.582	0.0479	0.0627

5. Discussion

5.1 Why does digital transformation lead to uneven development outcomes?

The results distinguish aggregate digitalisation from capability composition. Innovation indicators dominated the fitted contribution structure, whereas finance and infrastructure indicators made smaller contributions. This pattern is compatible with the view that connectivity is necessary but may not be sufficient for converting digital resources into cultural–tourism outcomes.

This distinction helps explain why studies using composite indices can report a positive average association while offering limited guidance about the resources that underpin it. Composite measures are useful summaries, but equal increases in the index can reflect very different changes in underlying capabilities. In the present model, variation in innovation inputs carries much more attribution than variation in individual finance or infrastructure indicators. The finding therefore shifts the explanation from digital access alone towards the capacity to produce, adapt and commercialise knowledge.

The dominance of DIC is plausible in cultural tourism because this sector combines service delivery with symbolic and creative production. Connectivity can bring a destination online, but it does not determine the quality of digital interpretation, immersive content, platform design or the integration of cultural resources into new products. These activities draw on skilled personnel, experimentation and organisational learning (Kallmuenzer and Peters 2023). Patent and R&D indicators are imperfect proxies for that capacity, yet their joint ranking is consistent with an innovation-based account rather than an infrastructure-only account.

At the same time, the smaller attribution of DINF and DFE should not be read as evidence that they are dispensable. General-purpose capabilities often become less differentiating precisely because they have diffused widely. Where broadband, mobile access and digital payment are already common, cross-city variation in them may explain less of the remaining variation in CTD. Their role may be foundational and complementary: innovation can produce larger fitted returns because access and transaction systems are already in place.

The ALE curves add an important qualification. Infrastructure indicators were most strongly associated with prediction changes at lower capability levels, while innovation indicators rose more sharply at higher levels. The data therefore support stage-dependent associations rather than a constant return to digital investment.

The fitted shapes reconcile the infrastructure and innovation perspectives. Infrastructure is associated with larger prediction changes at the lower end of provision, which is consistent with the value of removing basic access constraints. Innovation rises more strongly at medium-to-high levels, which is consistent with cumulative capability formation. Rather than selecting one perspective for all cities, the evidence suggests a sequence in which connectivity enables participation and knowledge capabilities increasingly differentiate higher-capability contexts.

This sequence is not deterministic. The model does not observe organisational quality, collaboration networks or the specific uses of patents and R&D. A high innovation indicator can therefore coexist with weak

conversion into tourism outcomes, and a city can use external technologies effectively without a large local patent base. The curves describe regularities in the sample, not a policy rule that investment in one indicator automatically produces a particular gain.

Local contribution profiles also varied across cities. Differences in industrial structure, knowledge resources and absorptive capacity may help explain this variation, but these mechanisms are not directly tested. The maps should therefore be read as evidence of local model heterogeneity rather than as estimates of place-based causal effects.

Spatial heterogeneity places a further boundary on national recommendations. Capability conversion depends on the surrounding labour market, industrial structure, visitor economy and institutional setting. An infrastructure-driven profile may indicate that connectivity remains a binding constraint, whereas an industry-supported profile may reflect the value of local digital firms and specialised employment. Finance-assisted profiles can arise where transaction access and market participation are more differentiating than locally produced technology.

The local models also caution against equating spatial clustering with causal spillovers. Nearby cities share many observed and unobserved conditions, and the overlapping local samples are designed to describe that context. They do not show that improving one city's capability will raise or lower outcomes in neighbouring cities. Establishing such effects would require a research design based on exogenous changes, temporal diffusion or explicit network transmission.

5.2 Theoretical contributions

The analysis makes three contributions to research on urban digitalisation.

First, the study develops a capability-composition account of urban digital transformation. The conceptual unit is not a single index but a system in which access, transactions, production and knowledge creation remove different constraints. This allows the empirical analysis to retain the convenience of an aggregate DTI for spatial description while avoiding the assumption that its components contribute equally to CTD.

Second, the study connects predictive validation with interpretable machine learning. Grouped cross-validation establishes that the indicators contain information for held-out cities before SHAP or ALE is used to explain the fitted model. The combination of magnitude rankings and response curves separates the question of which variables matter most from the question of how their contributions change across observed levels.

Third, the study extends attribution analysis into geographical context. The local models show that a national ranking can coexist with substantial city-level variation in predictive fit and relative domain prominence. This is a more specific claim than a general statement that regions differ: it identifies how the internal contribution structure of the same model family changes across overlapping urban neighbourhoods.

6. Conclusions and policy implications

6.1 Research conclusions

Composite digitalisation indices show how far a city has advanced, but they cannot show which digital capabilities are associated with stronger local outcomes. This study addressed that gap. It disaggregated urban digital transformation into four capability domains and compared 12 indicators within a single explainable model of cultural-tourism development across 280 Chinese cities from 2011 to 2023. The design separated model validation from interpretation. Predictive performance was assessed with five-fold cross-validation grouped by city, so that no city appeared in both training and test folds. The fitted model was then read through SHAP attribution, accumulated local effects and local spatial models. The evidence supports four conclusions.

First, both cultural-tourism development and digital transformation were spatially clustered in 2023, and digital transformation showed the stronger clustering. These statistics describe geographical concentration and not a causal spillover effect.

Second, the largest contributions were shared between infrastructure and innovation rather than dominated by one domain. Mobile phone subscriptions made the single largest SHAP contribution, followed by R&D personnel and patent authorisations. At the domain level, digital innovation capability ranked first with 40.06% of total attribution, but its lead over digital infrastructure at 35.31% was modest. This result qualifies the common expectation that innovation alone drives digital returns.

Third, the fitted relationships were nonlinear. Several infrastructure curves rose at low levels and then flattened, while innovation curves rose most sharply in the upper part of their observed ranges. A single constant marginal effect would not describe these patterns well.

Fourth, both predictive fit and capability composition varied across city neighbourhoods. Finance-assisted profiles were the most common category at 101 cities, followed by innovation-led at 68, infrastructure-driven at 66 and industry-supported at 45. No single profile described a majority of cities.

These findings support the central claim of the study. The aggregate level of digitalisation conceals two things that matter for cultural-tourism development. One is the composition of digital capabilities. The other is the way that composition changes from place to place. The contribution is therefore both substantive and methodological. Substantively, the analysis shows that infrastructure and innovation contribute at similar magnitudes on average, and that the leading capability differs across regions and neighbourhoods. Methodologically, it shows how grouped validation, attribution and local modelling can be combined to read a predictive model without treating its output as causal. All results describe predictive associations and model-based contributions rather than causal effects.

6.2 Policy implications

The following implications follow from predictive associations rather than causal estimates. They are best read as priorities to test and monitor, and each should be evaluated against measurable outcomes as local data accumulate.

Connectivity and innovation should be treated as complements, not substitutes. Infrastructure and innovation contributed at similar magnitudes, and mobile phone access made the single largest contribution. Investment

that raises innovation capacity should therefore not come at the expense of basic digital access, because both appear to matter for cultural-tourism development.

Investment should be sequenced to the current capability level of each city, because the fitted returns were nonlinear. In cities where digital access is still limited, the steepest gains were associated with basic connectivity, so connectivity is the more relevant early priority. In cities where access is already mature, the stronger returns were associated with innovation inputs, so support for R&D personnel, applied research and the conversion of patents into cultural-tourism services becomes more relevant.

The capability mix should be matched to local conditions rather than to a single national template. The local models produced four distinct profiles, and no profile described a majority of cities. A policy design that works in an innovation-led city may not suit an infrastructure-driven one. Local diagnosis of the leading capability is therefore a useful step before committing resources.

The enabling role of the digital financial environment deserves attention at the local level. Its national contribution share was small, yet it was the most prominent local capability in the largest group of cities relative to its own average. This suggests that local digital finance and payment systems may support cultural-tourism activity in many places, even where they are not the largest absolute contributor. Support here should be modest and monitored rather than treated as a primary lever.

Cross-sector collaboration can be encouraged where it lowers coordination costs. Shared platforms and interoperable services among technology firms, cultural organisations and tourism providers may help, although industry-supported profiles were the least common category, so this is a priority for a minority of cities and its design should reflect local market capacity.

Regional coordination may be useful where tourism markets and digital services cross administrative boundaries. Such coordination should be assessed against service and access outcomes that can be measured, rather than assumed to be beneficial. Taken together, these implications point away from a uniform digital policy and toward one that reflects the level, composition and location of each city's digital capabilities.

6.3 Limitations and future research

Four limitations define the scope of the findings.

First, predictive explanation is not causal explanation. Grouped validation reduces leakage and provides a demanding assessment of out-of-sample fit, but it does not remove omitted-variable bias or reverse association. Cities with stronger cultural–tourism sectors may attract digital firms and skilled workers, while governance quality, education and market size may influence both sides of the relationship. The SHAP and ALE results should therefore be interpreted as model-based associations.

Second, measurement involves unavoidable simplification. City yearbooks differ in reporting practices, entropy weights depend on the observed distribution, and interpolation reduces gaps without recovering unobserved values. Patents, R&D personnel and expenditure capture formal innovation inputs and outputs

but not all forms of creative experimentation or technology adoption. The dominance of DIC should be tested with alternative measures of digital content production, organisational capability and service innovation.

Third, spatial scale matters. Prefecture-level cities combine heterogeneous urban and rural areas, and the 90-city neighbourhood is a modelling bandwidth rather than a naturally bounded regional system. Different distance metrics, adaptive bandwidths or functional economic links could yield different local samples. Future research could compare administrative, transport and tourism-flow networks and evaluate whether local contribution profiles remain stable across these definitions.

Finally, external validity is limited to the institutional and development context represented by Chinese cities between 2011 and 2023. Comparative studies could test whether innovation also dominates in countries with different digital infrastructure maturity and tourism structures. Stronger causal designs could exploit phased infrastructure programmes, policy discontinuities or matched longitudinal shocks, while firm-, attraction- and visitor-level data could examine the organisational mechanisms that aggregate city indicators cannot observe.

Declarations

Competing interests

The author declares no competing interests.

Ethics declarations

Ethical approval

was not required because the study uses aggregate city-level statistics and does not involve human participants, personal data or experimental interventions.

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Author Contribution

H.Y. conceived and designed the study, collected and curated the data, developed the methodology and code, conducted the statistical and spatial analyses, prepared the figures and tables, and wrote and revised the manuscript.

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Code availability

The Python code used for data processing, model estimation, SHAP, ALE, spatial diagnostics and robustness checks is available in the versioned Zenodo record at <https://doi.org/10.5281/zenodo.21927473>.

Data Availability

The processed data and code supporting the findings of this study are available in Zenodo at <https://doi.org/10.5281/zenodo.21927473>. The repository contains the analytical dataset, data dictionary, and Python scripts required to reproduce the reported analyses. Data derived from the original statistical yearbooks and the Peking University Digital Inclusive Finance Index remain subject to the terms of the respective data providers.

References

1. Apley DW, Zhu J (2020) Visualizing the effects of predictor variables in black box supervised learning models. *J Royal Stat Society: Ser B (Statistical Methodology)* 82(4):1059–1086. <https://doi.org/10.1111/rssb.12377>
2. Ash J, Kitchin R, Leszczynski A (2018) Digital turn, digital geographies? *Prog Hum Geogr* 42(1):25–43. <https://doi.org/10.1177/0309132516664800>
3. Athey S, Imbens GW (2019) Machine learning methods that economists should know about. *Annual Rev Econ* 11:685–725. <https://doi.org/10.1146/annurev-economics-080217-053433>
4. Bertschek I, Niebel T (2016) Mobile and more productive? Firm-level evidence on the productivity effects of mobile internet use. *Telecomm Policy* 40(9):888–898. <https://doi.org/10.1016/j.telpol.2016.05.007>
5. Buhalis D, Harwood T, Bogicevic V, Viglia G, Beldona S, Hofacker C (2019) Technological disruptions in services: lessons from tourism and hospitality. *J Service Manage* 30(4):484–506. <https://doi.org/10.1108/JOSM-12-2018-0398>
6. Cai Y, Liang L, Zhang Y, Qi L, Wang C (2025) Does digital inclusive finance promote industrial global value chain upgrading? evidence from China's advanced manufacturing. *Finance Res Lett* 82:107640. <https://doi.org/10.1016/j.frl.2025.107640>
7. Du Z, Wang Q (2024) Digital infrastructure and innovation: Digital divide or digital dividend? *J Innov Knowl* 9(3):100542. <https://doi.org/10.1016/j.jik.2024.100542>
8. Fan HJ, Wu T (2022) New digital infrastructure, digital capability and total factor productivity. *Res Econ Manage* 43(1):3–22. <https://doi.org/10.13502/j.cnki.issn1000-7636.2022.01.001>
9. Fujita M, Krugman P, Venables AJ (1999) *The spatial economy: cities, regions, and international trade*. MIT Press, Cambridge
10. Gao JZ, Hua GH, Huo BF (2025) Digital technology, green innovation, and high-quality economic development: Mechanism analysis and empirical evidence. *J Knowl Econ* 16(3):12011–12047.

<https://doi.org/10.1007/s13132-024-02355-4>

11. Goldfarb A, Tucker C (2019) Digital economics. *J Econ Lit* 57(1):3–43.
<https://doi.org/10.1257/jel.20171452>
12. Gretzel U, Werthner H, Koo C, Lamsfus C (2015) Conceptual foundations for understanding smart tourism ecosystems. *Comput Hum Behav* 50:558–563. <https://doi.org/10.1016/j.chb.2015.03.043>
13. Gu T, Zhao H, Li Y, Guo J, Cui Q (2024) Attribution analysis of urban social resilience differences under rainstorm disaster impact: Insights from interpretable spatial machine learning framework. *Sustainable Cities Soc* 112:106029. <https://doi.org/10.1016/j.scs.2024.106029>
14. Guo F, Wang J, Wang F, Kong T, Zhang X, Cheng Z (2020) Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Q* 19(4):1401–1418
15. Huang CC, Lin BQ (2024) How digital economy index selection and model uncertainty will affect energy green transition. *Energy Econ* 136:107774. <https://doi.org/10.1016/j.eneco.2024.107774>
16. Jin L, Cao K, Li J, Xu Q (2024) Information infrastructure construction and optimization of resources allocation among firms: Evidence from Broadband China strategy. *Int Rev Econ Finance* 91:36–53. <https://doi.org/10.1016/j.iref.2024.01.007>
17. Kallmuenzer A, Peters M (2023) Organisational learning and sustainable tourism: The enabling role of digital transformation. *J Knowl Manage* 27(11):82–98. <https://doi.org/10.1108/JKM-06-2022-0434>
18. Li Q, Zhao S (2023) The impact of digital economy development on industrial restructuring: Evidence from China. *Sustainability* 15(14):10847. <https://doi.org/10.3390/su151410847>
19. Li Y, Guo J, Zhu W (2024) Digital financial inclusion and domestic tourism demand: through the lens of spatial spillover. *Tour Econ* 30(7):1680–1703. <https://doi.org/10.1177/13548166231224578>
20. Liu H, Wang X, Wang Z, Cheng Y (2024) Does digitalisation mitigate regional inequalities? Evidence from China. *Geogr Sustain* 5:52–63. <https://doi.org/10.1016/j.geosus.2023.09.007>
21. Lundberg SM, Lee SI (2017) A unified approach to interpreting model predictions. *Adv Neural Inf Process Syst* 30:4765–4774. <https://arxiv.org/abs/1705.07874>
22. Ma J, Li Z (2022) Measuring China's urban digital economy. *Natl Acc Rev* 4(4):329–361. <https://doi.org/10.3934/NAR.2022019>
23. Mullainathan S, Spiess J (2017) Machine learning: An applied econometric approach. *J Economic Perspect* 31(2):87–106. <https://doi.org/10.1257/jep.31.2.87>
24. Myrdal G (1957) *Economic theory and under-developed regions*. Gerald Duckworth & Co., London
25. Richards G (2018) Cultural tourism: A review of recent research and trends. *J Hospitality Tourism Manage* 36:12–21. <https://doi.org/10.1016/j.jhtm.2018.03.005>
26. Romer PM (1990) Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2), S71–S102. <https://doi.org/10.1086/261725>
27. Rydzewski P (2025) Digital inequality and sustainable development. *Problemy Ekorozwoju / Probl Sustainable Dev* 20(1):96–108. <https://doi.org/10.35784/preko.6691>
28. Shlapak A, Zhavoronok A, Vdovenko N, Bilousov O, Horban D, Krylov D (2025) The impact of digital technologies and artificial intelligence on management of socio-economic processes in the context of

- sustainable development. *RISUS - J Innov Sustain* 16(2):180–193. <https://doi.org/10.23925/2179-3565.2025v16i2p180-193>
29. Sun PP, Lin Z, Chen CF (2025) Unlocking potential: Macro insights into the evolution of a multi-destination tourism innovation network. *J Travel Res* 64(1):139–157. <https://doi.org/10.1177/00472875231209981>
30. Tang Y, Yi K, He Z, Zhang F (2025) What configurational conditions promote the integration of culture and tourism? A fuzzy-set qualitative comparative analysis based on China's provincial data. *SAGE Open* 15(2). <https://doi.org/10.1177/21582440251342504>
31. Wang K, Liu M, Gan C (2025) Lessening or deepening? The effects of digital economy on regional disparities of tourism development. *Economic Change Restruct* 58(2):1–30. <https://doi.org/10.1007/s10644-025-09859-2>
32. Wen HW, Yu HL, Lee CC (2025) Spatial imbalance in the digital era: how the digital economy affects urban sprawl in China. *Appl Econ* 57(38):5992–6005. <https://doi.org/10.1080/00036846.2024.2374459>
33. Xu D, Li X, Yan S, Cui L, Liu X, Zheng Y (2024) A quantitative model to measure the level of culture and tourism integration based on a spatial perspective: A case study of Beijing from 2000 to 2022. *Sustainability* 16(10):4276. <https://doi.org/10.3390/su16104276>
34. Yang SS, Hu L, Lu YG (2025) Regional differences, source decomposition and driving forces of the integration level of digital technology and cultural tourism in Chinese cities. *J Chongqing Univ (Social Sci Edition)* 31(5):32–47
35. Yang Y, Shen L, Sang M, Ding X (2025) The impact of digitalisation on urban sustainable development – An economic perspective. *Technological Forecast Social Change* 212:124005. <https://doi.org/10.1016/j.techfore.2025.124005>
36. Yu M, Ma B, Liu D, Zhang A (2024) Is the digital economy empowering high-quality tourism development? A theoretical and empirical research from China. *PLoS ONE* 19(5):e0303087. <https://doi.org/10.1371/journal.pone.0303087>
37. Zhang JK (2024) Smart city construction impact on destination competitiveness: a time-varying difference-in-differences analysis of Chinese prefectural-level cities. *Tourism Rev* 80(4):966–983. <https://doi.org/10.1108/TR-05-2024-0432>

Figures

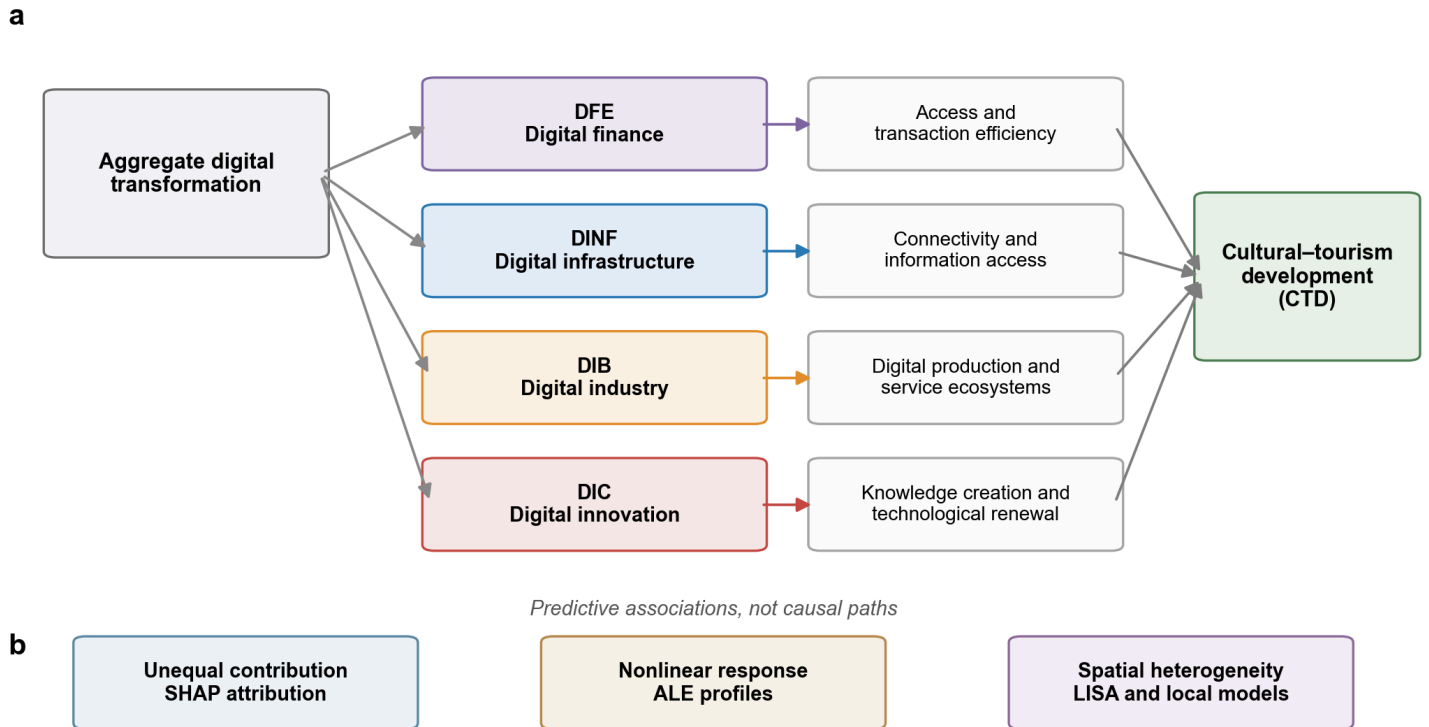
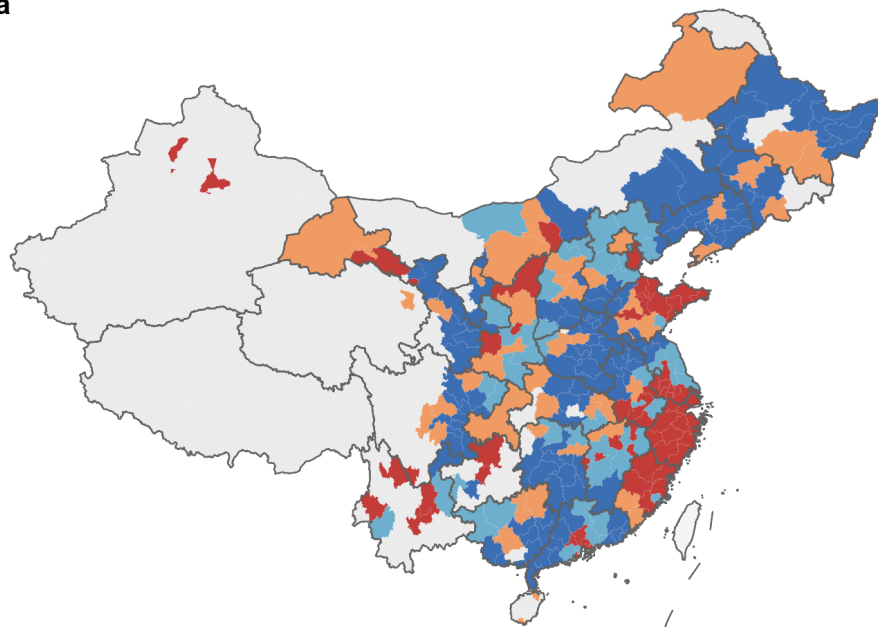


Figure 1

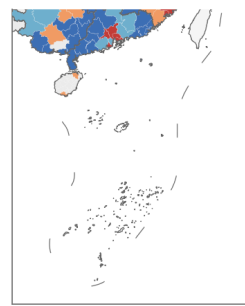
Analytical framework for the predictive association between digital transformation and cultural-tourism development. Aggregate digital transformation is decomposed into the digital financial environment (DFE), digital infrastructure (DINF), the digital industrial base (DIB) and digital innovation capability (DIC). The lower panel summarises the three analytical lenses: unequal contribution, nonlinear response and spatial heterogeneity. Arrows organise the analytical framework and do not represent estimated causal paths.

Cultural-tourism development

a



N

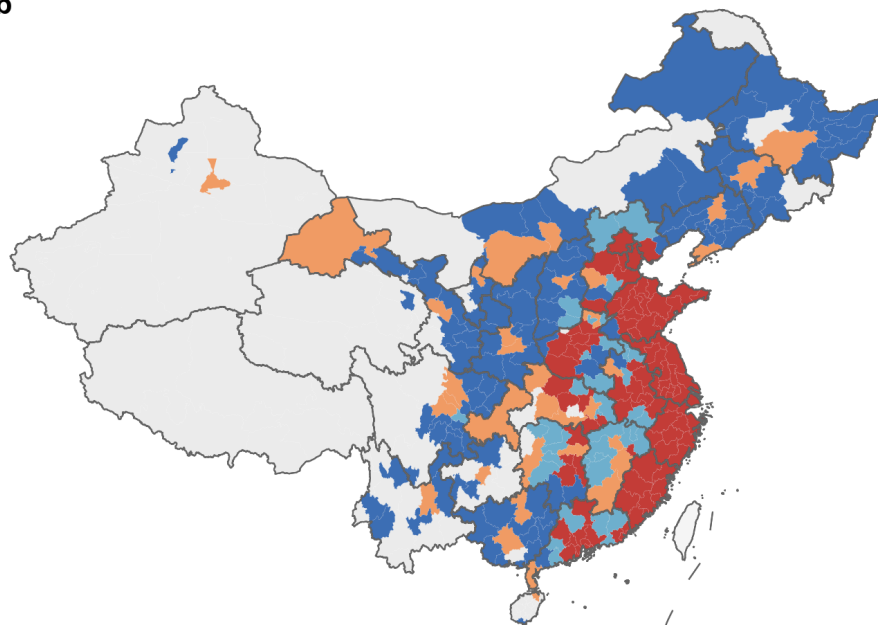


LISA quadrant (k = 8)

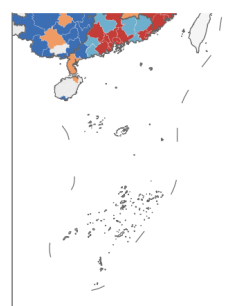
- High-High
- Low-Low
- High-Low
- Low-High
- No data

Digital transformation

b



N



Base map: GS(2024)0650 official administrative-division data; boundary geometry unmodified.

Figure 2

LISA quadrant classifications for cultural-tourism development and digital transformation in 2023. a, Cultural-tourism development. b, Digital transformation. High-High, Low-Low, High-Low and Low-High denote sign combinations of each standardised value and its spatial lag under the primary eight-nearest-neighbour matrix ($k = 8$). All 280 quadrant assignments are shown; the maps are not filtered by local permutation significance. Base map: official administrative divisions, GS(2024)0650; boundary geometry unmodified.

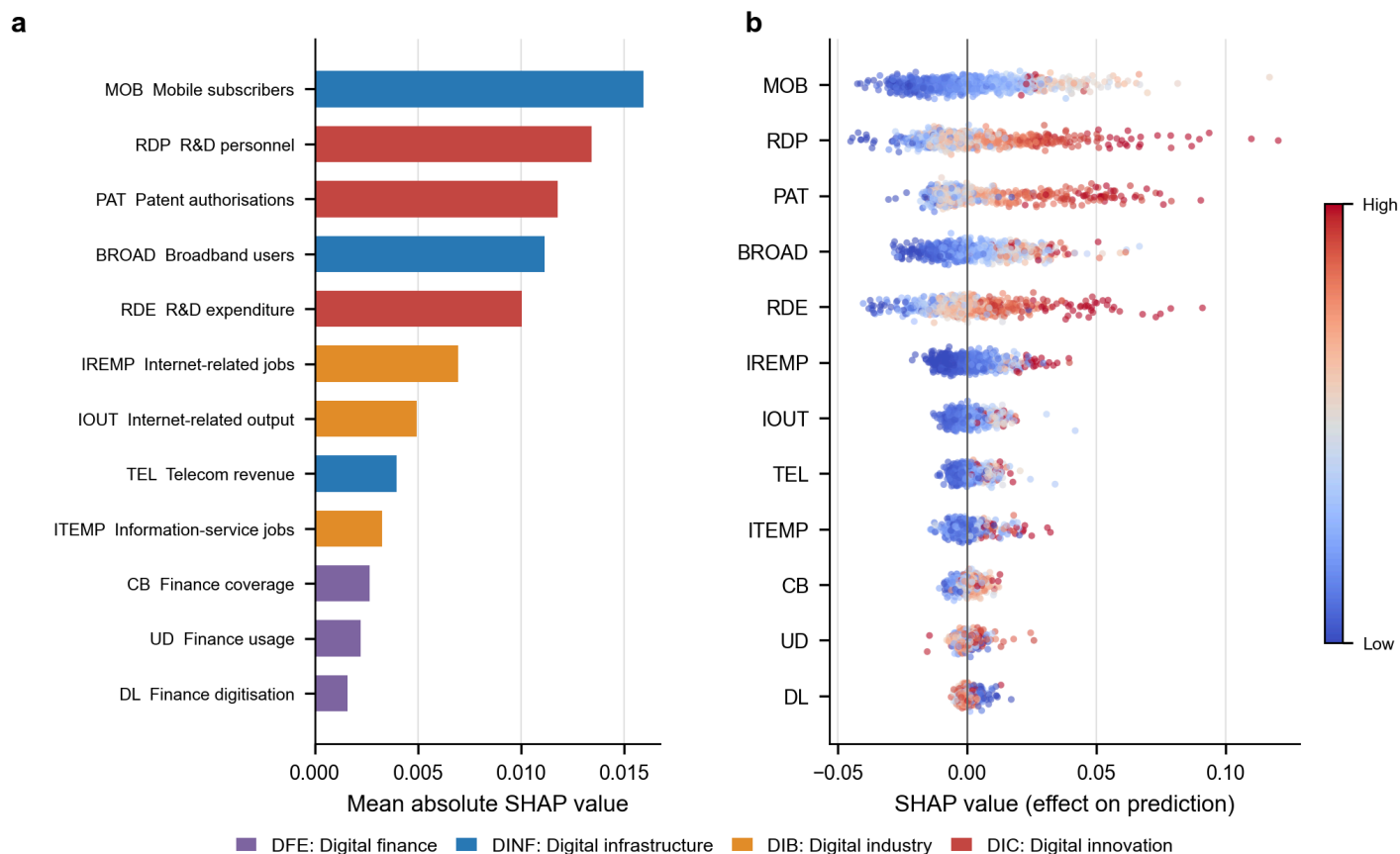


Figure 3

Global SHAP attribution for the 12 digital capability indicators. a, Mean absolute SHAP values used for the global importance ranking. b, Observation-level SHAP values, with colour indicating the standardised feature value from low to high. SHAP values were computed for 900 city-year observations sampled from the 3,640-observation panel. Indicator abbreviations are defined in Table 2. SHAP values describe model attribution rather than causal effects.

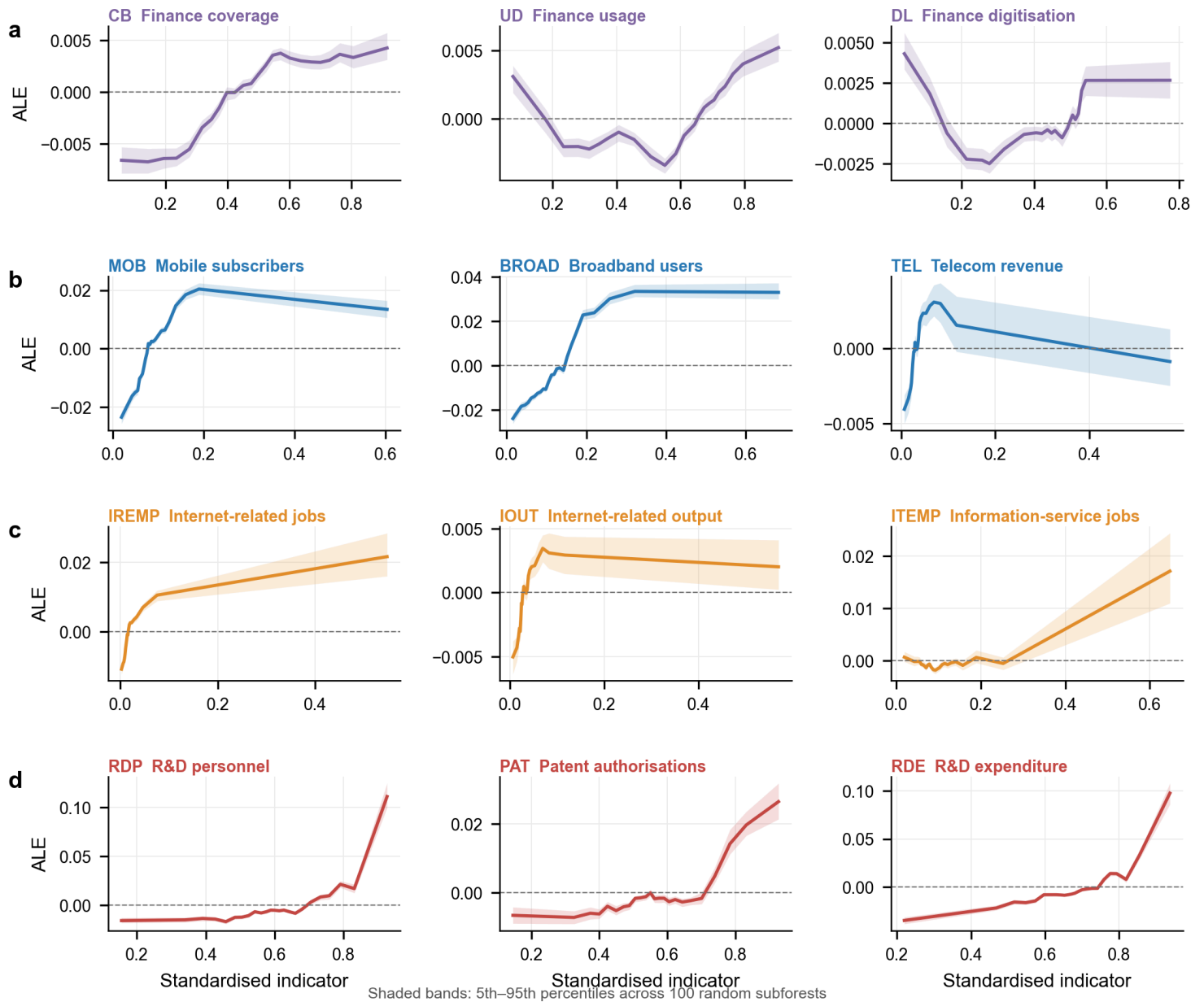
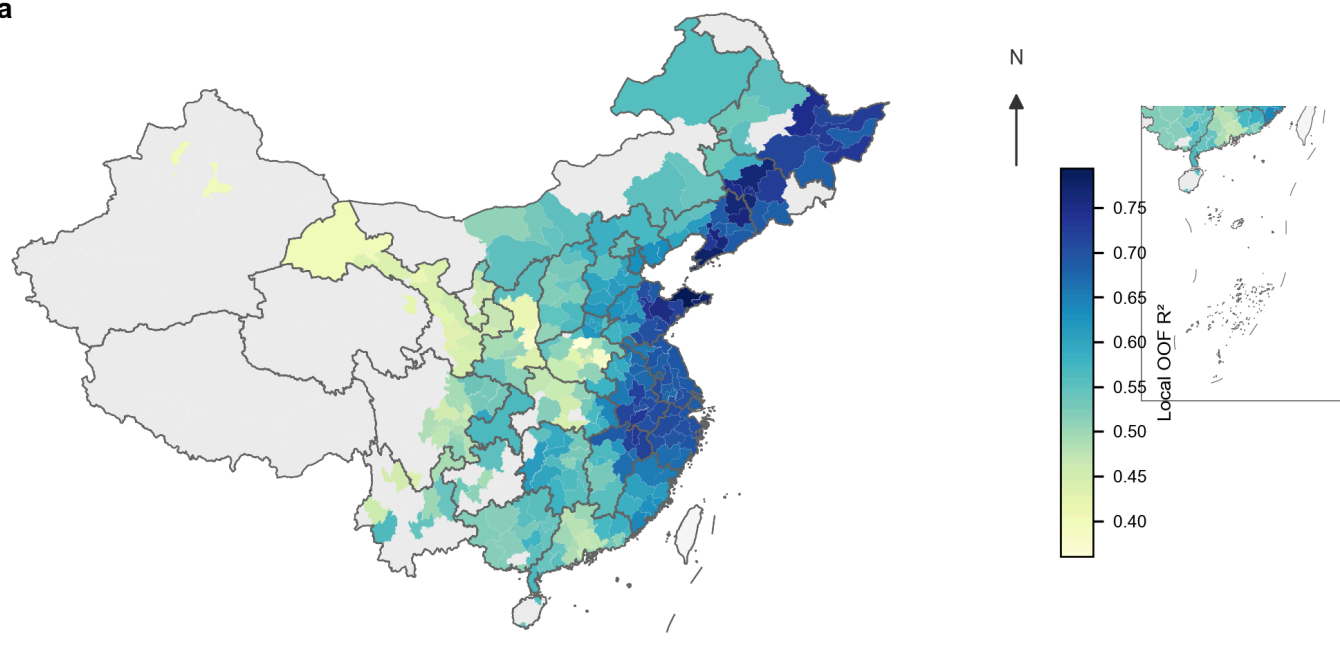


Figure 4

Accumulated local effect curves for the 12 digital capability indicators. a, Digital financial environment. b, Digital infrastructure. c, Digital industrial base. d, Digital innovation capability. Solid lines show mean ALE values and shaded bands show the 5th–95th percentile range across 100 random subforests. The curves represent model-based predictive response patterns rather than causal marginal effects.

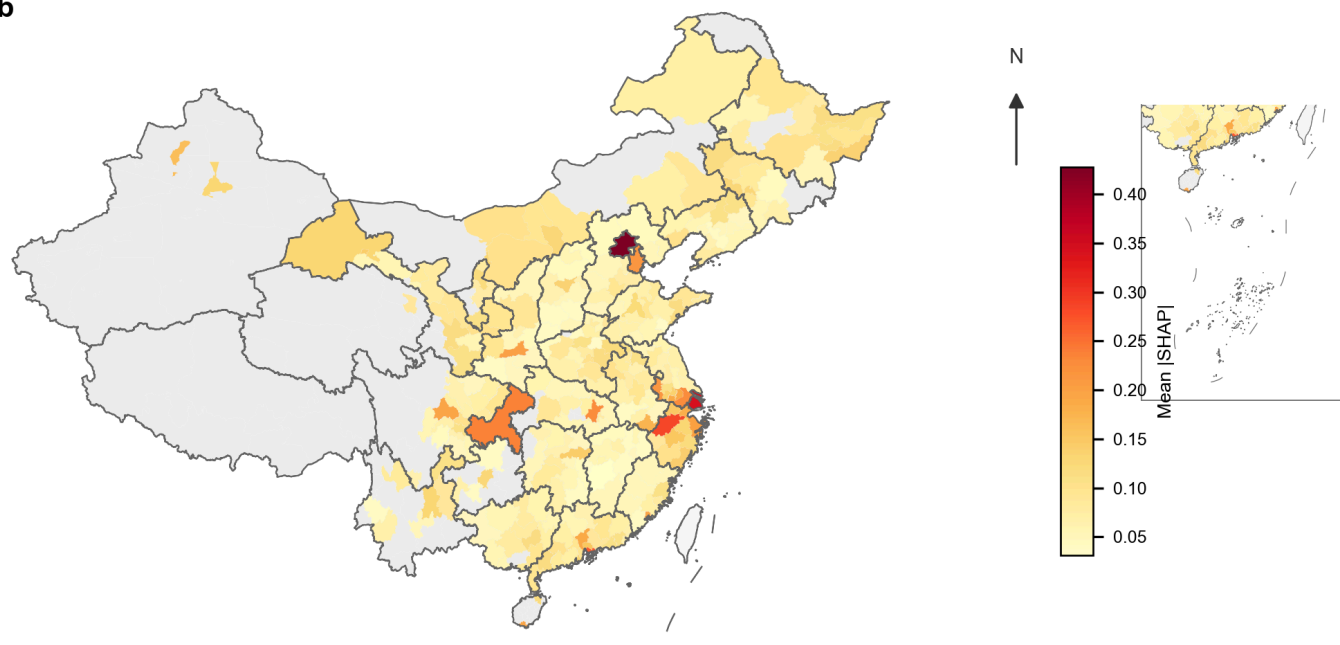
Local out-of-fold model fit

a



Global-model SHAP contribution intensity

b

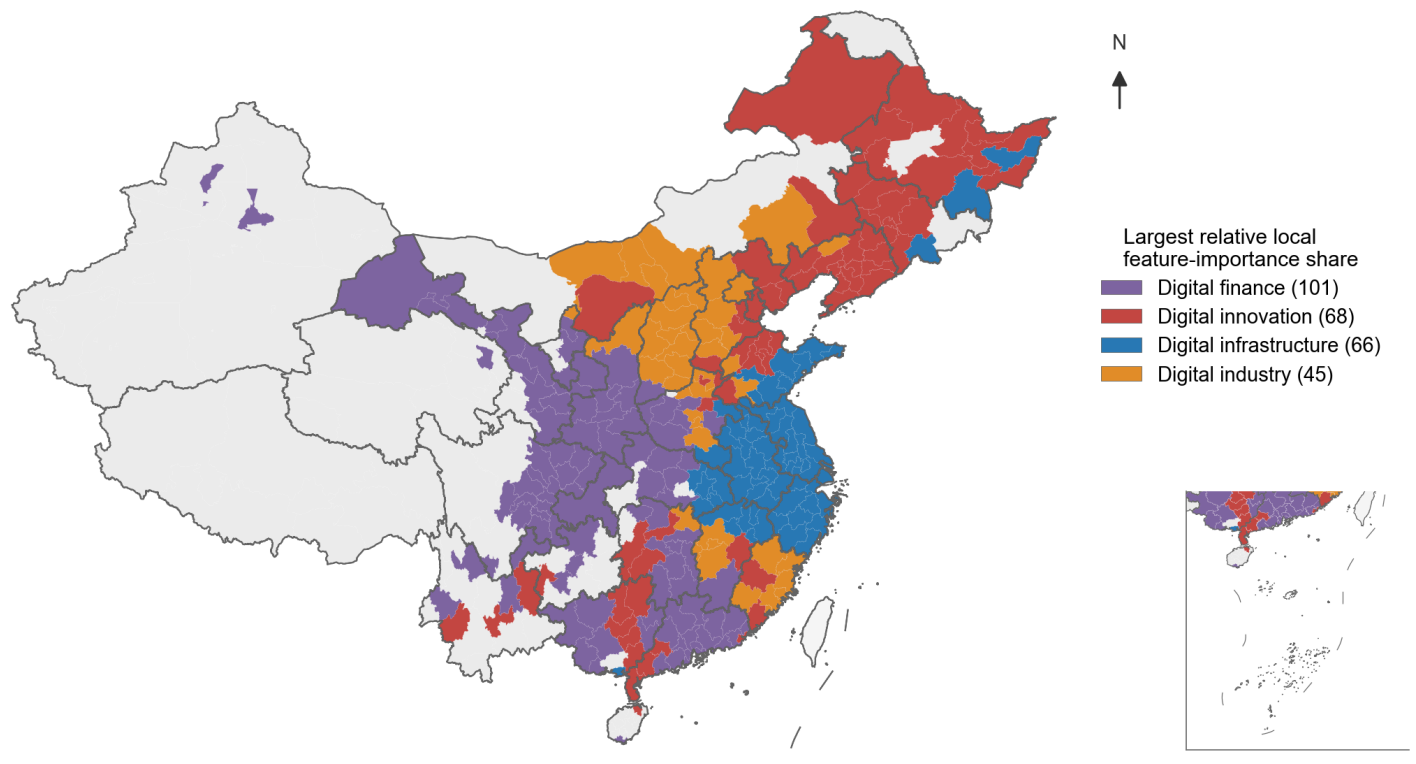


Base map: GS(2024)0650 official administrative-division data; boundary geometry unmodified.

Figure 5

Spatial variation in local predictive fit and global-model SHAP contribution intensity. a, Local predictive fit measured by pooled out-of-fold R^2 from five-fold cross-validation grouped by city in each 90-city neighbourhood model. b, City-level mean absolute SHAP contribution summed across the 12 digital capability indicators in the global ExtraTrees model. Panel b is an aggregation of global-model SHAP values, not local-model SHAP. Base map: official administrative divisions, GS(2024)0650; boundary geometry unmodified.

Dominant local digital-capability domain



Base map: GS(2024)0650 official administrative-division data; boundary geometry unmodified.

Figure 6

Dominant local digital capability domain by city. For each 90-city neighbourhood model, domain shares were calculated from impurity-based ExtraTrees feature importance and compared with the corresponding mean share across all 280 local models. DFE is dominant in 101 cities, DIC in 68, DINF in 66 and DIB in 45. The classification therefore represents relative local feature importance, not local SHAP attribution. Base map: official administrative divisions, GS(2024)0650; boundary geometry unmodified.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [dominantcontributioncounts.csv](#)
- [globalmoran2023.csv](#)
- [alevalues.csv](#)
- [cityshapcontributions.csv](#)
- [cityyearshapcontributions.csv](#)
- [robustnessperformance.csv](#)
- [regionalcontributionstructure.csv](#)
- [shapimportance.csv](#)

- localmodelssummary.csv
- modelperformance.csv
- localdominantcounts.csv
- shapvalues.csv
- lisaquadrants2023.csv
- localmodelcityresults.csv
- shapsample.csv