

How Does AI Empower the Development of Cities and Enterprises? A Literature Review and Pathway Analysis

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Abstract: As a key driving force behind the new round of technological revolution, artificial intelligence (AI) is reshaping urban systems and the operational logic of enterprises at an unprecedented pace. In the urban context, it has revolutionized public governance and administrative models, driving the upgrading of smart infrastructure and the transformation of fiscal systems. In the corporate domain, AI has exerted far-reaching impacts on operational performance, corporate governance, and financing activities. However, issues such as the “algorithmic divide” and new financial risks have also become prominent. Through a comprehensive review and analysis of relevant literature, this study reveals the complex mechanism by which AI influences urban and corporate development. From the perspective of enabling pathways, the technological mechanism has altered cost structures and production models, the principal-agent mechanism has reconstructed organizational relationships, and the market allocation mechanism has reshaped market order—yet each of these mechanisms faces unique challenges. In the future, establishing a balance between AI capabilities and institutional frameworks, as well as strengthening regulatory and ethical norms, will be crucial to achieving efficient transmission across the “urban-corporate” dimension and promoting digital transformation.

Keywords: Artificial Intelligence; Urban Development; Corporate Governance; Pathway Mechanisms

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1.Introduction

Artificial intelligence (AI), as a core force in the new round of technological revolution, is empowering urban systems and enterprise operational logic at an unprecedented pace. Since 2010, breakthroughs in key foundational technologies such as big data, cloud computing, and deep learning have extended AI functional boundaries from perception and prediction to automated decision-making and institutional control, shifting its economic impacts from the technical efficiency level to the institutional structural level. This transformation has elevated AI from a mere technological variable to a critical productive factor, significantly influencing urban governance and corporate governance structures.

On one hand, concepts like the “smart institutional environment” in the urban dimension have drawn increased attention to AI role in enhancing urban system resilience (Schintler & McNeely, 2022). In urban governance, AI transcends traditional management tools, actively shaping resource allocation—from water/electricity scheduling and traffic route planning to influencing local fiscal budgeting and regulatory capacity enhancement. On the other hand, in the corporate domain, AI-

driven empowerment of corporate governance and digital transformation has substantially improved production efficiency (Wamba-Taguimdje et al., 2020). For example, AI-led risk assessment systems have revolutionized risk evaluation processes, enabling enterprises to establish intelligent end-to-end risk management.

Despite the exponential growth of AI research and its extensive exploration in urban governance and corporate management, the academic landscape remains notably fragmented. Urban governance studies predominantly focus on technical applications like “smart cities” and “digital platforms,” emphasizing efficiency improvements in traffic scheduling and public services (Yigitcanlar et al., 2020), which limits insights to isolated “governance function modules.” Corporate research largely concentrates on AI optimization of “overt economic indicators” such as productivity and management performance (Wamba-Taguimdje et al., 2020), with preliminary discussions on its role in reorganizing corporate structures and driving digital transformation. More critically, the urban and corporate research dimensions have long operated in parallel, lacking systematic linkages—making the exploration of how AI empowerment transmits across the “urban-corporate” continuum a pivotal research gap (Liu et al., 2024).

Consequently, systematically understanding the impacts of AI empowerment on urban and corporate development has become a key concern for both academia and policymakers. While existing studies address application outcomes in specific domains, a comprehensive synthesis of literature is lacking, and a unified explanatory framework for transmission pathways and action mechanisms across urban and corporate levels remains underdeveloped. This paper therefore systematically reviews AI empowerment application scenarios and economic performances within multi-level institutional logics of cities and enterprises, aiming to fill theoretical gaps in the “AI-institution-performance” relationship and provide insights for policymakers and corporate managers during digital transformation.

2. Economic Impacts of AI on Urban Systems

2.1 AI Empowerment of Urban Public Governance and Digital Government

AI most direct transformation of cities lies in its reshaping of the technical foundations and organizational logic for public governance and administrative capabilities. In a systematic review of smart city practices, Yigitcanlar et al. (2020) argue that AI is evolving from a technical support layer to an “institutional hub,” assuming multiple roles in data-driven governance—including prediction, scheduling, early warning, and feedback. Notable examples include real-time urban traffic signal scheduling, rapid emergency response systems, and automated governance performance feedback mechanisms. Take Singapore’s “Virtual Singapore”—a digital twin city project that uses AI to integrate geospatial, traffic, and demographic data, enabling policy simulation and risk assessment to provide scenario models for urban planning and emergency response. This governance paradigm marks a shift from “reactive decision-making” to “predictive governance.”

Das (2025) studying cities in the Global South, found that after introducing an AI data platform in São Paulo, Brazil, urban work order processing time decreased by over 40%, yet the system feedback accuracy was significantly lower in impoverished areas. This reveals the “algorithmic divide” issue: without institutional foundations and data equity mechanisms, the governance optimization effects of AI platforms (AI administrative platforms) will exhibit pronounced spatial disparities, potentially even reinforcing existing governance inequalities. Deng et al. (2021) further note that AI systems under the “digital twin city” concept not only enhance response speed but also embed decision preferences and governance process standards. For instance, Shenzhen’s deployment of AI risk identification algorithms in urban safety has enabled “full-domain sensing-adaptive response” across subway stations, communities, and buildings. This governance model, emphasizing a closed-loop of pre-judgment-scheduling-feedback, is termed the “governance-nested AI model”. Additionally, Schintler and McNeely (2022) characterize AI’s role in urban governance as an “institutional resilience reinforcement mechanism”: AI not only provides real-time information but also helps government agencies construct “multi-scenario adaptive strategies” through algorithmic simulation, enhancing cities’ institutional flexibility and emergency response capabilities amid risks like pandemics and climate disasters.

2.2 AI Empowerment of Urban Smart Infrastructure and Fiscal Efficiency

With the integration of AI technologies, urban infrastructure has evolved from “passive maintenance assets” to “active learning systems”. Traditional urban foundational systems—including transportation, energy, water, and environmental

monitoring—are being reconstructed by AI-driven intelligent systems, whose impacts extend beyond operational efficiency to fundamentally empower urban fiscal logic. AI has reshaped fiscal expenditure patterns, budget allocation principles, and performance evaluation systems, driving urban fiscal institutions toward a more dynamic, data-driven, and outcome-oriented framework.

Korada (2021) notes that in AI-dominated infrastructure systems, urban fiscal resources are shifting from passive repair and periodic maintenance to upfront investments in intelligent systems and algorithmic updates, forming a fiscal transformation mechanism that transitions “from asset maintenance to smart scheduling.” This signifies a fundamental of budget structures and drives fiscal resources from “stock control” to “incremental optimization”. In transportation systems, AI scheduling platforms analyze real-time traffic flow data to accurately identify congestion points, predict peak traffic, and dynamically adjust signal systems, thereby reducing congestion costs and energy waste. In urban budget management, AI plays a crucial role in optimizing government budget allocation: Valle-Cruz et al. (2022) developed a hybrid algorithm model using multi-layer perceptrons and multi-objective genetic algorithms, analyzing open data from 217 countries (1960-2019) to construct a “budget input-policy output” framework. The results show that AI can identify complex nonlinear relationships through massive data processing, uncovering expenditure allocation patterns imperceptible to traditional methods. Its decision-support systems demonstrate significant potential in optimizing resource allocation, promoting economic stability, and enhancing income equity. The study validates the consistency between AI methods and traditional public budget theory, providing a technical pathway for dynamic and precise budget formulation in smart government initiatives, while also offering data-driven policy tools for addressing dynamic challenges such as economic crises and inflationary pressures. AI is driving urban fiscal institutions from “ex-ante static planning” to “in-process dynamic scheduling” and “ex-post outcome orientation.” Fiscal behaviors have become more transparent, real-time, and responsive due to AI’s deep integration, significantly enhancing governance efficiency. However, this technological governance also poses new demands for regulatory capabilities, ethical standards, and algorithmic governance structures. The future development of urban fiscal systems will largely depend on building a balance mechanism between AI capabilities and institutional adaptation.

3.Economic Impacts of AI on Enterprises

3.1 AI Empowerment of Enterprise Operational Performance

From productivity gains to transformations in capital returns, AI, as a general-purpose technology, is to enterprise value creation systems. Brynjolfsson (2021) posits in his “complementary mechanism of intangible capital” hypothesis that AI’s true value does not stem from its computational capabilities alone but relies on deep integration with a firm’s unique intangible capital—including organizational process reengineering, employee skill upgrades, and cross-departmental data-sharing mechanisms. Without these “complementary institutions,” AI not only fails to drive performance leaps but may even exacerbate resource allocation inefficiencies. This “institutional complementarity dependence” has gained empirical support from numerous studies. Wang et al. (2023) utilized panel data from 938 Chinese manufacturing listed firms (2011-2020) and employed fixed-effects models, mediating effect models, and difference-in-differences (DID) models to scientifically examine the impact of artificial intelligence (AI) on TFP. The results show that AI significantly enhances the TFP of Chinese manufacturing enterprises, with the most pronounced improvements observed in firms featuring strong knowledge-sharing institutions and flat organizational structures. Conversely, enterprises with rigid hierarchies and fragmented management information flows often experience minimal performance gains due to the “digital silo effect,” even after AI system investments.

Kuang and Zhou (2025) identifies an inverted U-shaped relationship between enterprise digital transformation—especially the adoption of advanced technologies like AI and cloud computing—and ESG performance. At the profitability level, the study notes that digital technologies initially reduce operational costs and boost profits through automated process optimization, intelligent forecasting, and improved resource allocation. However, in the deepening phase of transformation, firms that fail to align organizational structures, management mechanisms, or business models with technological upgrades may face increased technical path dependence, sunk costs, and organizational inertia, which can suppress profitability and weaken overall ESG performance. This finding underscores that AI’s effectiveness is not automatic; its performance benefits are heavily contingent

on institutional environments, managerial responsiveness, and cultural adaptability. Sokolowska and Zargartalebi (2024) further argue that some enterprises, under financing constraints and labor informality, treat AI as a “cost-cutting tool” focused solely on labor substitution rather than systematic upgrades or organizational restructuring. Such “myopic deployments,” while effective in the short term, fail to deliver long-term improvements in capital return rates.

The impact of AI on enterprise performance operates through a “structural nonlinear mechanism”: its multiplicative effects are realized only when AI deployment is embedded with institutional, organizational, and cultural elements. Otherwise, it may lead not to performance enhancements but to capital misallocation, resource stagnation, and exacerbated institutional frictions. Therefore, in future policy-making and corporate strategies, AI should be treated as an institutional variable rather than a mere tool, requiring holistic transformation to address its challenges to production and organizational models.

3.2 AI Empowerment of Corporate Governance

As artificial intelligence deepens its integration into enterprise management, the logic of corporate governance is undergoing a profound shift from “human governance” to “algorithmic rule-based governance.” This transformation not only redefines the roles and responsibilities of managers but also poses new challenges to internal power structures, organizational forms, and employee behavioral norms. AI’s core roles in corporate governance can be categorized into three dimensions: algorithmic decision substitution, strengthened internal controls, and facilitated organizational restructuring.

AI is reshaping corporate decision-making logic and power distribution. Agrawal et al. (2022) argue that AI economic value stems from a substantial reduction in “prediction costs,” enabling automated probabilistic reasoning and scenario screening in domains where mid-to-top managers historically held information judgment monopolies. This erodes the “monopoly of judgment” in traditional management hierarchies, driving power structures toward flattening and fostering “decentralized” governance models rooted in data-driven algorithms. Shao et al. (2022) in an empirical study of Chinese fintech platforms, found that non-state-owned enterprises experienced significantly improved financing transparency and efficiency after adopting AI credit mechanisms. This change arises from algorithmic models conducting dynamic credit evaluations based on transaction data and operational performance, reducing the role of “relationship capital” and indirectly promoting a shift in governance structures from “power-dependence” to “rule-transparency”.

AI also plays an increasingly pivotal role in internal control mechanisms. Traditional financial control, performance evaluation, and compliance processes rely heavily on post-hoc audits and supervisory oversight, whereas AI integration enables “process control.” Enterprises deploy AI and IoT to establish automated compliance tracking, real-time risk alert systems, and abnormal data detection mechanisms (Mahmood et al., 2022), achieving preemptive “digital governance” even before formal institutionalization. This “digital incubation model” has become a common pathway for emerging corporate governance under AI influence.

However, AI governance mechanisms are not without controversy. Yu and Li (2022) identify a complex mechanism through which AI decision transparency affects employee trust: while higher transparency enhances perceived effectiveness and fosters trust, it also triggers employee discomfort, potentially inhibiting trust. Mishandling this parallel multiple-mediation effect may lead to algorithmic distrust and “technological domination” anxiety, weakening organizational cohesion and institutional identification. Thus, enterprises must deeply understand the relationship between AI decision transparency and trust, balancing effectiveness with comfort to enhance employee acceptance and promote human-AI collaboration.

3.3 AI Empowerment of Corporate Financing Behavior

As artificial intelligence deeply penetrates financial systems, corporate financial behaviors, especially financing mechanisms, are undergoing a structural transformation. AI applications in credit allocation, risk management, and credit assessment are dismantling the structural discrimination and information asymmetry in traditional finance, which historically relied on human-defined labels such as identity, firm size, and property rights. Particularly for small and medium-sized enterprises (SMEs), AI empowerment is opening new channels for capital acquisition while presenting novel institutional challenges and opportunities for financial governance.

The mitigating effect of AI on financing constraints has been widely validated. Shao et al. (2022), in an empirical study of non-state-owned enterprises in China emerging markets, show that AI financial platforms leverage machine learning models

to collect real-time operational data—including transaction frequency, cash flow volatility, and supply chain transactions—to construct dynamic credit scoring systems. This data-driven approach breaks through the long-standing “scale-ownership bias” of traditional financial institutions, enabling previously marginalized small and medium non-state enterprises to access credit systems more equitably, significantly improving their financing availability and reducing costs. Alao (2024) highlights that AI technologies are reshaping the matching mechanisms of financing markets through fintech platforms. Unlike traditional banks that rely on historical credit records and external rating agencies, AI platforms extract real-time information from diverse “digital footprints”, user behavior data, invoice records, social media feedback, via API interfaces to build dynamic credit evaluation models. This mechanism allows marginalized enterprises lacking traditional credit histories, such as female-led startups and new-energy microenterprises to gain recognition and support from financial institutions through behavioral profiling, thereby enhancing structural inclusivity and equality of opportunity in financing.

AI has also exerted profound impacts on capital structure. Xu and Zhao (2023) notes that AI-driven enterprises are altering how capital structures are constructed. These firms typically feature light asset structures, long R&D cycles, and scarcity of fixed assets, making it difficult for traditional credit institutions to conduct effective valuations. As a result, they tend to favor equity financing over debt financing. Concurrently, AI platforms analyze corporate behavioral data to more accurately predict growth potential, enhancing their financing ratings in capital markets. This shift not only strengthens venture capitalists’ willingness to invest in AI enterprises but also reduces their reliance on high-leverage debt, facilitating more robust capital structure optimization. Chang et al. (2024) through a cross-sectional empirical analysis of digital transformation in China A-share market, shows that the widespread adoption of AI platforms in banking systems is transitioning traditional credit models—based on historical scores and fixed credit limits—toward dynamic credit granting systems rooted in real-time behavioral data and risk early-warning mechanisms. This transformation enhances banks’ responsiveness to corporate credit status and significantly improves the flexibility of enterprise liquidity allocation, thereby shortening capital turnover cycles and boosting overall operational efficiency.

4. Mechanisms of AI Empowerment for Urban and Corporate Development

4.1 Technological Enablement Mechanism

The technological mechanism represents the most direct and foundational layer of AI’s empowerment pathways for cities and enterprises. Core AI technologies—particularly machine learning and deep neural network models, excel at processing unstructured big data, enabling real-time prediction and automated response, thereby drastically reducing marginal decision-making and coordination costs in traditional economic activities. Unlike traditional information technologies, however, the cost structure changes induced by AI are not merely linear optimizations but institutional transformations of production factor boundary conditions.

From a cost structure perspective, AI models require substantial data resources and engineering costs during training and system integration phases, constituting their high fixed costs. Once deployed, however, their inference and application processes demand negligible marginal labor or additional computational resources. This “high initial cost + near-zero marginal cost” structural feature grants AI technologies powerful multiplicative effects across multi-scenario and large-scale expansions, rapidly releasing economic and efficiency dividends (Chang et al., 2025). Nayak and Walton (2024) further argues that the “fixed capital-data training” model structure underpinning AI systems is evolving into a new form of institutional market entry barrier. Unlike traditional economic models where marginal costs decrease with production scale, cost reductions in the AI economy depend on continuous model iteration and synergistic expansion of computational infrastructure. This mechanism inherently favors large AI enterprises, as small and medium-sized enterprises (SMEs) lacking data resources and training capabilities face marginalization risks, being excluded from core technologies and markets. At the industrial level, AI-driven automation is reshaping production models. Liang et al. (2025) made an empirical analysis of AI applications across Chinese industries reveals significant disparities in inter-industry adaptability, exhibiting a typical “asymmetric technological penetration” pattern. Data-intensive, highly standardized industries such as finance, e-commerce, and manufacturing more easily integrate AI systems, achieving substantial marginal efficiency gains. In contrast, labor-intensive or service-oriented sectors, characterized by high automation substitutability and technical integration challenges,

are more prone to structural employment shocks and job reconfiguration risks. This divergence is driving dynamic evolutions in China industrial structure.

The production process reconfiguration enabled by AI has also spurred investment waves in new digital infrastructure. Christou and Piller (2024) in their research on organizational transformation, posit that the core of the AI economy has shifted from “labor-for-output” to “algorithm-for-feedback,” with its fundamental economic units evolving from “capital + labor” to a new paradigm of “computational power + data”. This technological logic has triggered a new round of digital infrastructure construction, making AI an institutional variable that redefines the production function itself rather than merely a technical tool. Platform enterprises like Amazon, Google, and Alibaba have embedded AI into their logistics, finance, marketing, and customer relationship management systems, creating closed-loop ecosystems of production-prediction-feedback. These intra-platform AI coordination mechanisms further reduce marginal transaction costs, enabling enterprises to transcend traditional market specialization and adopt full-process automated management models.

Notably, however, the cost structure changes brought by AI are not inherently benign. In the absence of institutional regulation, AI deployment may induce “scale monopoly” and “algorithmic path dependence” issues. Narechania (2025) highlights that the high fixed costs and extremely low marginal costs of AI systems, once a first-mover advantage is established in a market, enable path dependence and market exclusivity through algorithmic optimization and data feedback mechanisms. As model dominance solidifies, AI not only narrows technological competition but also embeds itself into market rules via its cost structure and learning mechanisms, becoming an institutional variable that reshapes resource allocation and production functions. This structural shift promotes a new infrastructure logic centered on “computational power + data,” systematically influencing the evolution of enterprise behavior patterns and urban economic structures.

4.2 Principal-Agent Mechanism

The principal-agent problem, rooted in information asymmetry and misaligned objectives, is a core driver of organizational governance failures. The deep integration of artificial intelligence fundamentally restructures this relational system, giving rise to a new “algorithmic agency structure” that reshapes not only within enterprises but also the interaction logic among government agencies, urban platforms, and the public.

Möhlmann et al. (2021) argue that AI technologies are profoundly transforming agency relationships in traditional corporate governance. By real-time collecting and integrating dynamic data from both inside and outside organizations, AI effectively mitigates information asymmetry in the traditional principal-agent chain, reducing reliance on cumbersome monitoring and incentive mechanisms. Their data-driven governance model, centered on algorithms, enables top managers to conduct continuous, automated behavioral monitoring of frontline and middle-level operations, significantly enhancing organizational responsiveness and operational transparency. In urban governance, this trend is also emerging: many city governments deploy AI for budget allocation, performance monitoring, and public affairs management, transforming traditional hierarchical authorization mechanisms into algorithm-dominated “real-time response systems.” This breaks down information silos between government departments and establishes a “data-logic-based agency monitoring structure.”

AI-empowered principal-agent mechanisms exhibit unique characteristics and advantages: First, efficiency. AI systems outperform human agents in real-time monitoring and behavioral memory, better identifying deviant behaviors and opportunism; second, transparency, AI-recorded processes provide quantifiable governance data for post-hoc accountability and institutional feedback; third, boundary redefinition, the traditional control system based on hierarchical structures is increasingly replaced by algorithmic data chains.

However, these mechanisms are not without risks. Delacroix and Wagner (2021) caution that as AI becomes a key information processing and decision-making hub, traditional responsibility structures are eroding. When AI systems substantially influence decision-making but lack ethical awareness, legal personality, or institutional ownership, a “non-accountable agency” structure emerges. This can be exploited by top managers to evade accountability, shifting risks to “technical systems” and masking the absence of human judgment, potentially inducing “algorithmic authoritarianism” at the institutional level.

4.3 Market Allocation Mechanism

While AI technological enablement mechanisms reshape production functions and governance mechanisms redefine organizational boundaries, its ultimate impact at the market level is the formation of a new round of institutional market restructuring through platform-dominated network effects and data monopoly structures.

Narechania (2021) dubs AI platforms “natural algorithmic monopolists,” distinguishing their monopoly from traditional fixed-asset-based natural monopolies by attributing it to “increasing returns to data learning”. Larger platforms optimize algorithms more effectively, improving marginal decision precision in a non-linear manner that makes market entry extremely difficult for smaller players, leading to competitive path lock-in. AI platforms construct “intelligent lock-in mechanisms”: on one hand, they make user migration difficult through interface binding, data sedimentation, and habitual behavior guidance; on the other, they deeply entangle enterprise resources via intra-platform ecosystems (e.g., supply chain finance, logistics algorithms, precision advertising), creating institutional dependence. This evolves into “semantic path dependence” and “knowledge monopoly”, platforms control not only traffic and transactions but also semantic categorization, trust mechanisms, and consumer choices.

AI platforms fundamentally construct a new co-creation relationship through data synergy: users serve as both consumers and algorithm trainers, with their behavioral data fueling model optimization. The end result is a shift in market control from price mechanisms to algorithmic mechanisms. Platforms shape user choice spaces through recommendation paths, information ranking, and traffic allocation, establishing new market order. Neumann et al. (2022) highlight that AI platforms implement differentiated pricing via user profiling and behavioral data, so-called “algorithmic discriminatory pricing models”, controlling access and prices to reshape transaction pathways, thereby exacerbating information asymmetry and institutional power concentration. Corresponding regulatory measures must keep pace to ensure the equitable and effective use of AI tools.

5. Conclusion

Artificial intelligence as a critical productive factor, plays a pivotal role in urban and corporate development, exerting far-reaching impacts while presenting substantial challenges.

In urban contexts, AI empowers public governance and digital administration, driving a shift from “reactive decision-making” to “predictive governance.” However, this transformation also exposes issues such as the “algorithmic divide,” highlighting risks of spatial disparities in governance efficiency. Regarding smart infrastructure and fiscal efficiency, AI accelerates the intelligentization of urban infrastructure and fosters fiscal institutional reforms, yet it imposes new demands for regulatory frameworks and ethical standards to address potential governance inequalities.

In the corporate domain, AI’s effects on operational performance exhibit structural nonlinearity, with multiplicative benefits realized only through synergy with institutional, organizational, and cultural elements. In corporate governance, AI reshapes decision-making logic and power structures while strengthening internal controls; however, the absence of complementary mechanisms can erode employee trust due to opaque algorithmic processes and “non-accountable agency” risks. Concerning financing behaviors, AI mitigates financing constraints and optimizes capital structures for enterprises, especially SMEs by reducing information asymmetry, though it also introduces new financial risks tied to data-driven credit models and potential market exclusivity.

From the perspective of enabling mechanisms, the technological pathway alters cost structures and production models, but its “high fixed cost + near-zero marginal cost” feature may lead to “scale monopoly” and market entry barriers for smaller players. The principal-agent mechanism enhances organizational transparency and responsiveness through algorithmic monitoring, yet it risks enabling managerial accountability evasion via “non-accountable agency” structures. The market allocation mechanism restructures market order through platform-driven network effects and data monopolies, but this process raises concerns about “algorithmic discriminatory pricing” and concentrated institutional power, necessitating adaptive regulatory interventions.

AI presents both opportunities and challenges in urban and corporate development. Moving forward, fostering a balance between AI capabilities and institutional adaptation, through enhanced regulatory frameworks, ethical guidelines, and cross-dimensional transmission mechanisms between “urban-corporate” systems, will be crucial. This requires interdisciplinary research to address structural mismatches, ensure equitable technology diffusion, and maximize AI’s potential to drive

sustainable, inclusive digital transformation. By embedding AI within robust institutional ecosystems, societies can harness its transformative power while mitigating risks, laying a solid foundation for the future of urban and corporate development in the digital era.

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