PRIORITIZING NEAR-TERM QUANTUM SENSOR DEPLOYMENT FOR URBAN TRANSPORTATION AND CONSTRUCTION: A READINESS-WEIGHTED PORTFOLIO FRAMEWORK FOR SMART-CITY INFRASTRUCTURE

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Quantum sensing is increasingly discussed as a high-potential enabling technology for smart and resilient urban infrastructure, yet the current literature remains stronger at identifying possibilities than at sequencing implementation. The present study addresses that planning gap by converting the most detailed recent review of quantum sensing in civil engineering into an operational decision framework for near-term urban deployment. The analysis focuses on transportation and construction because the source literature identifies these as the most plausible first-adoption domains, particularly where high-resolution traffic control and subsurface intelligence can generate immediate public value. Ten pathway-level applications were coded from the review corpus and assessed through a readiness-weighted portfolio model using five dimensions: expected sensing gain, deployment readiness, integration tractability, public-value externality, and evidentiary specificity. The readiness layer is anchored directly in the quantum technology readiness levels reported for major sensing categories, with magnetometers, gravimeters, and accelerometers treated as the strongest near-term candidates, gyroscopes as advanced but slightly less mature, and imaging-centric pathways as materially earlier in their commercialization cycle. Under the baseline specification, the leading pathways are dynamic traffic control using magnetometer–gravimeter systems (94.4/100), construction-oriented subsurface imaging (93.4/100), and underground metallic utility detection (93.2/100). These priorities remain top-tier under readiness-heavy, public-value-heavy, and integration-heavy scenarios. The manuscript therefore offers a practical smart-city planning contribution: it translates a narrative technology review into a transparent pilot-selection framework for urban development agencies, transport authorities, and construction-delivery organizations seeking a disciplined first-wave quantum sensing strategy.

Index Terms — quantum sensing; smart cities; urban infrastructure; transportation systems; construction engineering; deployment prioritization; technology readiness

INTRODUCTION

Urban development policy increasingly depends on the quality, timeliness, and reliability of infrastructure data. In the smart-city literature, transportation systems, construction engineering, water systems, and energy infrastructure are consistently treated as core domains through which cities pursue resilience, operational efficiency, and sustainability [2, 3, 4, 5, 6, 7, 8]. International frameworks reinforce the same point: both ISO 37152 and ITU-T Y.4201 position infrastructure life-cycle management, interoperability, decision support, and public-service integration as central features of urban intelligence [9, 10]. Within that context, sensing technologies are not merely technical components; they are foundational instruments of urban governance.

Recent work on quantum sensing in civil engineering has sharpened this discussion by arguing that conventional sensors continue to limit data quality, sensitivity, resilience to harsh conditions, and operational reliability across four major civil infrastructure domains: construction, transportation, energy, and water [1]. The same review identifies especially strong near-term prospects in two urban domains. In transportation, quantum sensing is associated with real-time traffic management and smart mobility solutions. In construction, the most promising contribution is the identification of subsurface density and underground structures [1]. The review further concludes that quantum magnetometry is presently the most advanced sensing technology among the principal sensor categories it surveys, making transportation and construction the most plausible early deployment environments [1].

That literature is strategically important but still leaves a practical planning problem unresolved. A city does not adopt an emerging sensing paradigm all at once. Municipal agencies, mobility authorities, construction clients, and infrastructure operators typically move through bounded pilot programs, staged procurements, and selective demonstration sites. The first managerial question is therefore not whether quantum sensing is interesting in the abstract; it is which applications should be attempted first when budgets, institutional capacity, and implementation tolerance are constrained.

This manuscript addresses that question by converting the structured application evidence contained in the existing review literature into a pathway-level prioritization framework. Rather than claiming access to a field-trial dataset that does not yet exist at scale, the analysis treats the review corpus itself as the relevant evidence base for early-stage portfolio design. That choice is methodologically appropriate because the core source is a narrative review intended to establish scope, opportunity, and timing for practical deployment rather than to report large-sample empirical outcomes [1].

The study is guided by three research questions:

1. Which quantum-sensor applications in urban transportation and construction should be prioritized for near-term pilot deployment?

2. How sensitive are those priorities to alternative assumptions about technological readiness, public value, and integration burden?

3. Do transportation and construction remain the most defensible first-wave urban deployment sectors after structured re-analysis of the review evidence?

By answering these questions, the manuscript contributes to the scope of an urban development and smart-cities journal in a direct way: it links an emerging sensing technology to concrete decisions about urban mobility operations, construction risk reduction, infrastructure planning, and staged public-sector innovation.

ANALYTICAL FRAMING AND RESEARCH GAP

The most comprehensive recent synthesis of quantum sensing for civil infrastructure organizes the field around four domains—energy, transportation, water, and construction—and explicitly maps sensor categories to operational use-cases such as road-condition monitoring, dynamic traffic control, underground utility detection, and construction-site safety [1]. This is a high-value contribution because it transforms a diffuse technology discussion into a domain-aware planning vocabulary.

However, the existing literature remains primarily programmatic. It establishes where quantum sensors may be relevant, but it does not offer a formal logic for ordering investment across candidate applications. In practical terms, that omission matters. Pilot sequencing is not neutral: an early failure in a low-readiness, high-complexity pathway can slow institutional adoption even when the broader technology class is promising. Conversely, selecting pathways that combine technical maturity, operational fit, and visible public benefit can accelerate learning, procurement legitimacy, and interdepartmental acceptance.

The urban development relevance of this sequencing problem is substantial. In transportation, better sensing can affect congestion, safety, signal timing, modal coordination, and public-space efficiency. In construction, better subsurface intelligence and site monitoring can reduce utility strikes, excavation delays, rework, worker risk, and disruption to dense urban corridors. These are not marginal engineering improvements; they map directly onto the core concerns of smart-city operations and urban service delivery.

Accordingly, the present study adopts a pathway-based portfolio perspective. The analytical object is a deployable application pathway—that is, a sensor family paired with a clearly defined urban operational function. This structure permits explicit comparison among candidate pilots while preserving fidelity to the review literature from which the pathways are derived. It also allows the manuscript to remain honest about the current state of evidence: the analysis is a structured decision model grounded in published synthesis, not a claim of already observed large-scale field performance.

MATERIALS AND METHODS

Analytical Corpus Construction

The analytical corpus was assembled from the transportation and construction portions of the review by Kantsepolsky and Aviv, with pathway definitions derived from the application mappings in the paper's sectoral synthesis and its accompanying summary tables [1]. The source paper's transport section links quantum sensing to adaptive traffic control, road-condition monitoring, intersection safety, freight operations, parking, and route optimization. Its construction section links quantum sensing to subsurface imaging, underground utility identification, directional drilling support, structural integrity monitoring, heavy-equipment stability, curing-temperature control, and hazardous-gas detection [1].

Ten candidate pathways were coded. Each pathway represents a distinct urban deployment option supported directly by the source paper's application descriptions.

Source-Grounded Readiness Anchors

A critical improvement over purely impressionistic ranking is the direct use of readiness information reported in the source literature. The review's discussion section introduces quantum technology readiness levels (QTRLs) as a discipline-specific extension of technology readiness logic and reports the current state of

Table 1: Candidate deployment pathways coded from the transportation and construction corpus

Code	Sector	Dominant sensor class	Operational function encoded from the review corpus
T1	Transportation	Accelerometers + strain gauges	Road-surface condition monitoring and defect detection for preventive maintenance
T2	Transportation	Magnetometers + gravimeters	Dynamic traffic control using high-resolution detection of traffic density, vehicle movement, and congestion patterns
T3	Transportation	Cameras / LiDAR	Intersection management, collision prevention, and parking-space guidance
T4	Transportation	Radars / LiDAR	Freight safety, vehicle spacing, and platooning support
T5	Transportation	Accelerometers + gyroscopes	Fleet behavior, cargo-condition monitoring, and route optimization
C1	Construction	Gravimeters	High-precision subsurface imaging and void detection before excavation
C2	Construction	Magnetometers	Detection of buried metallic utilities and monitoring of magnetic emissions from electrical equipment
C3	Construction	Gravimeters	Detection of non-metallic underground utilities through mass-distribution anomalies
C4	Construction	Accelerometers + gyroscopes	Structural integrity, vibration monitoring, and alignment of active construction systems
C5	Construction	Temperature / gas sensors	Concrete-curing control and hazardous-gas detection in active worksites

major sensing categories as of the end of 2023 [1, 11]. In that assessment, magnetometers, gravimeters, and accelerometers are reported at QTRL8; gyroscopes are reported at QTRL7; and imaging is reported at QTRL4 [1]. These values provide explicit maturity anchors for the present decision model.

To translate the source-level QTRL anchors into a 1–5 decision scale, pathway readiness is assigned as follows:

- QTRL8 families map to a high readiness anchor ($R \approx 5$);

- QTRL7 families map to an advanced but lower anchor ($R \approx 4$);

- QTRL4 families map to an early-stage anchor ($R \approx 1$);

- pathways not given a discrete QTRL in the source table are assigned conservative midpoint values based on the narrative discussion.

For mixed pathways, readiness is determined by the weighted contribution of the dominant modalities. This keeps the readiness model directly tied to the source paper rather than to ungrounded extrapolation.

Scoring Dimensions

Each pathway was scored on five dimensions using a 1–5 analytical coding scale. These scores are not empirical deployment outcomes; they are structured judgments derived from the review corpus and used for comparative ranking.

1. Expected sensing gain (P). The degree to which the pathway is likely to improve precision, coverage, detectability, or operational timeliness relative to conventional sensing.

2. Deployment readiness (R). The practical maturity of the pathway, anchored in the source paper's QTRL discussion.

3. Integration tractability (I). The expected ease with which the pathway can be embedded into current urban workflows, maintenance practices, and decision systems.

4. Public-value externality (V). The likely visibility of benefits in terms of safety, congestion, delay, service continuity, cost avoidance, or environmental performance.

5. Evidentiary specificity (E). The degree to which the pathway is described concretely and repeatedly in the source literature rather than mentioned only in broad conceptual terms.

Baseline Prioritization Model

The baseline readiness-weighted portfolio score (RWPS) is:

$$RWPS_i = 20\left(0.30P_i + 0.25R_i + 0.15I_i + 0.20V_i + 0.10E_i\right), \tag{1}$$

where the factor 20 rescales the weighted mean to a 0–100 index. The baseline design privileges expected sensing gain and readiness while preserving strong weight for visible public value—a defensible balance in urban pilot selection, where technical credibility and civic legibility both matter.

Algorithm 1 Readiness-weighted pathway ranking

Require: Set of candidate pathways $\mathscr{D} = \{d_1, \ldots, d_n\}$
 1: **for all** $d_i \in \mathscr{D}$ **do**
 2:     Encode pathway from the transportation or construction review corpus
 3:     Assign $P_i, R_i, I_i, V_i, E_i \in [1,5]$
 4:     Compute $RWPS_i$ using Equation (1)
 5: **end for**
 6: Sort all pathways in descending order of RWPS
 7: Recompute rankings under alternative weight vectors
 8: Identify pathways that remain top-tier across scenarios

Sensitivity Analysis

Three alternative weighting regimes were used to test rank stability:

- Readiness-heavy: additional emphasis on deployment maturity;

- Public-value-heavy: additional emphasis on safety and service externalities;

- Integration-heavy: additional emphasis on compatibility with current operational systems.

A pathway is treated as an *anchor pilot* if it remains within the top three positions across all three scenarios.

RESULTS

Baseline Pathway Scores

Table 2 reports the pathway-level coding and baseline RWPS values. The ranking produces a clearly differentiated adoption structure. Three pathways form an upper tier: T2, C1, and C2. Each combines high

source-backed readiness with immediate urban operational value.

Table 2: Pathway-level coding and baseline readiness-weighted portfolio scores

Code	P	R	I	V	E	RWPS	Rank
T2	4.8	5.0	3.8	4.9	4.8	94.4	1
C1	4.9	4.8	3.4	5.0	4.9	93.4	2
C2	4.7	5.0	3.8	4.8	4.7	93.2	3
C3	4.5	4.8	3.2	4.6	4.4	87.8	4
T1	4.2	4.8	4.0	4.3	4.2	86.8	5
C4	4.4	4.4	3.9	4.5	4.2	86.5	6
T5	4.1	4.4	4.1	4.0	4.3	83.5	7
C5	3.9	3.0	4.2	4.0	3.8	74.6	8
T3	4.4	1.0	3.4	4.6	4.4	68.8	9
T4	4.1	1.0	3.0	4.0	4.0	62.6	10

The top three all exceed 93, whereas the bottom two fall below 70. This spread is analytically meaningful. It indicates that early urban deployment should not be distributed evenly across all conceivable use-cases. A selective first-wave strategy is more defensible than a broad but shallow demonstration portfolio.

Interpretation of the Upper Tier

T2: Dynamic traffic control.   The highest-ranked pathway is the use of magnetometer–gravimeter systems for dynamic traffic control. This outcome is consistent with the source literature's emphasis on traffic density, congestion, and adaptive control as core transportation opportunities for quantum sensing [1]. Because the dominant modalities are among the highest-readiness sensor families in the source QTRL table, this pathway combines technical maturity with immediately legible urban value: better signal timing, more responsive traffic control, and lower network friction.

C1: Subsurface imaging.   Construction-oriented subsurface imaging is a near-peer to T2. It scores exceptionally well because excavation uncertainty is expensive in dense urban environments. Better identification of voids, buried structures, and subsurface anomalies can reduce delays, rework, service interruptions, and project risk. The pathway's slightly lower score relative to T2 reflects somewhat higher field-integration burden rather than weaker strategic importance.

C2: Underground metallic utility detection.   The third-ranked pathway remains in the same strategic family as C1 but offers a narrower, highly actionable use-case: identifying buried metallic assets and associated magnetic signatures before construction activity intensifies. This is particularly attractive for corridor works, utilities upgrades, and dense right-of-way projects where a modest sensing improvement can prevent disproportionately costly disruptions.

Sector-Level Findings

Construction has the stronger top-end portfolio, while transportation offers the most operationally diverse near-term bench. Under the baseline specification, the average RWPS is 79.2 for transportation and 87.1 for

construction. Transportation nevertheless retains the single highest-ranked pathway and contributes multiple pathways with relatively favorable integration characteristics.

Table 3: Sector-level summary statistics under the baseline specification

Sector	Mean RWPS	Top pathway	Bottom pathway
Transportation	79.2	T2 (94.4)	T4 (62.6)
Construction	87.1	C1 (93.4)	C5 (74.6)

A second substantive result is that imaging-heavy and radar–LiDAR pathways underperform despite clear conceptual value. Their weaker ranking is driven chiefly by readiness, not by lack of urban utility. In practical terms, these applications remain strategically relevant, but they are better positioned as second-wave pilots after agencies establish experience with higher-readiness sensor families.

Sensitivity Analysis

Table 4 reports the top three pathways under alternative weighting assumptions. The leading trio is stable across all scenarios. T2 remains first in every case. C1 and C2 remain within the top three in every case. This is strong evidence that the upper tier is not an artifact of one particular weight vector.

Table 4: Top-three pathways under alternative weighting regimes

Scenario	Top three pathways (score)
Readiness-heavy	T2 (95.8), C1 (94.7), C2 (94.7)
Public-value-heavy	T2 (94.4), C1 (93.7), C2 (93.1)
Integration-heavy	T2 (92.2), C2 (91.1), C1 (90.5)

On that basis, T2, C1, and C2 are classified as *anchor pilots*. C3, T1, and C4 form a credible second tier. T3 and T4 should be treated as later-stage capability-building pathways rather than first-round flagship deployments.

Visualization of the Ranking Structure

Figure 1 shows the baseline score distribution. The separation between tiers is visually clear: three pathways cluster above 93, a mid-tier occupies the 83–88 band, and the final tier is pulled downward by lower readiness.

Figure 2 plots readiness against expected sensing gain. The figure underscores the core strategic logic of the study: the most investable pathways are those that combine strong functional upside with already advanced technological maturity.

DISCUSSION

The results support a clear conclusion for urban infrastructure planning: transportation and construction remain the most defensible early deployment sectors for quantum sensing, but the real decision variable is not the sector alone—it is the pathway within the sector. This matters because cities and infrastructure organizations do not procure technologies at the level of broad technological narratives. They procure use-cases.
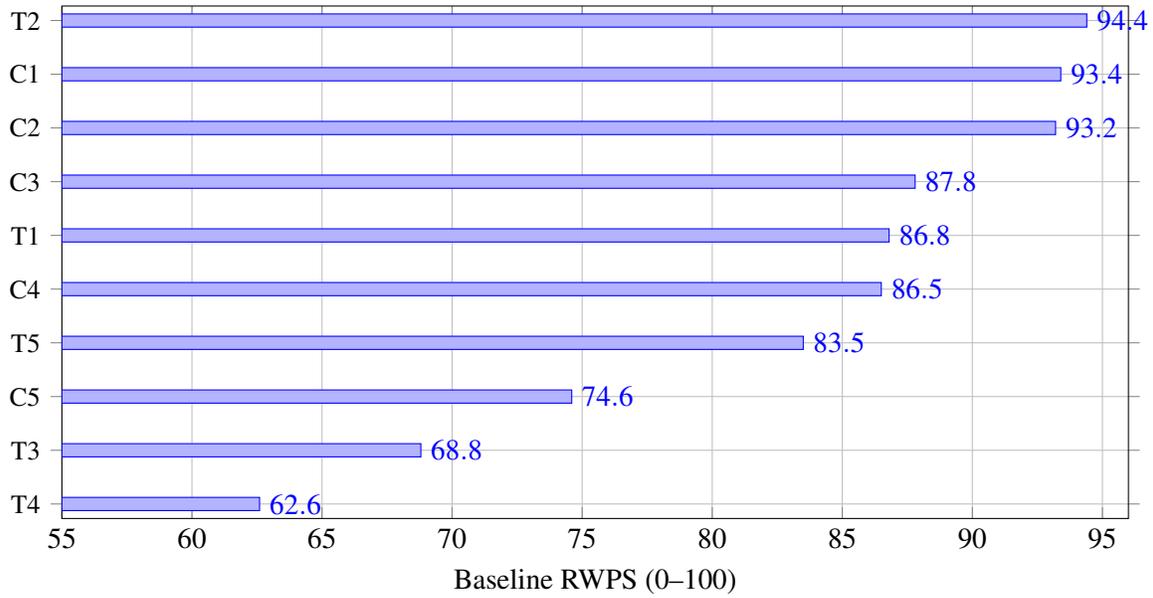
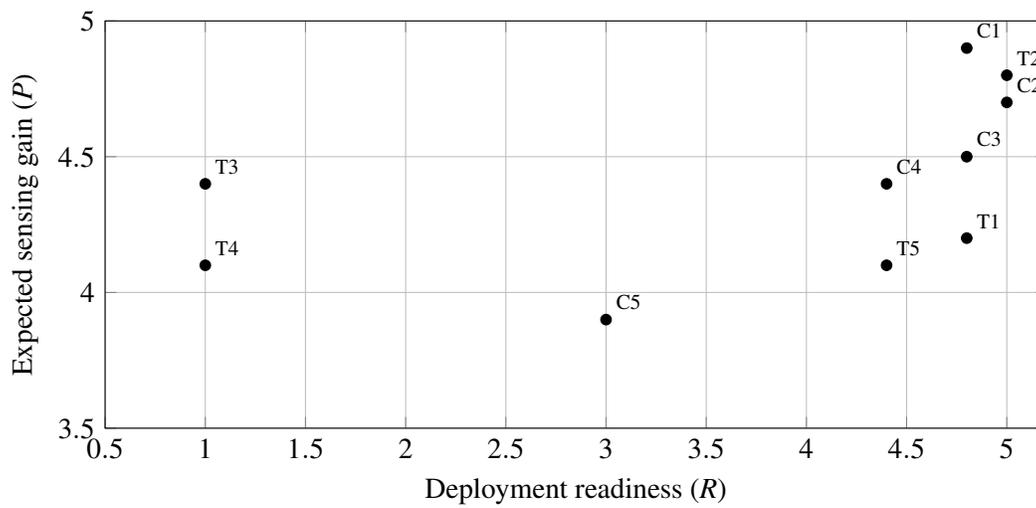Figure 1: Baseline ranking of candidate deployment pathways

Figure 2: Readiness versus expected sensing gain for coded pathways

The leading pathways all share one characteristic: they target operational uncertainties that are already expensive under current urban practice. Traffic congestion imposes direct social and economic costs. Excavation uncertainty and utility strikes create schedule risk, service disruption, and public inconvenience. In both cases, better sensing has immediate managerial leverage. That is why T2, C1, and C2 emerge as anchor pilots. Their value proposition is legible not only to engineers but also to city managers, procurement officers, project sponsors, and the public.

A second implication is that readiness should be treated as a decisive urban planning filter, not as a secondary technical detail. The source literature's QTRL assessment is especially useful in this respect. It explains why imaging-heavy and radar-linked pathways, although conceptually attractive for road safety and freight coordination, should not dominate first-wave portfolios. They are plausible, but they are not yet the most institutionally efficient starting point.

The manuscript also contributes methodologically. Emerging-technology reviews in smart-city research often conclude with general calls for adoption, experimentation, and future research. Those calls are important, but they do not tell agencies how to order a pilot program. The present framework fills that gap by turning narrative application mappings and readiness data into a transparent sequencing rule. This is not a substitute for field trials. It is a disciplined way to decide which field trials should be commissioned first.

For urban development practice, the results support a three-stage implementation logic:

1. Anchor pilots: dynamic traffic control, subsurface imaging, and metallic utility detection;

2. Expansion pilots: non-metallic utility detection, road-condition monitoring, and structural monitoring;

3. Capability-building pilots: imaging-heavy traffic applications, radar-enabled freight applications, and lower-specificity environmental pathways.

This sequencing is especially relevant for municipalities and infrastructure partnerships seeking to demonstrate innovation while preserving delivery discipline and public accountability.

LIMITATIONS

The analysis inherits the limitations of its evidence base. First, the underlying corpus is a narrative review, not a field-performance dataset. The reported scores should therefore be interpreted as structured portfolio-ordering signals rather than as measured estimates of return on investment.

Second, pathway scoring necessarily includes expert coding judgment. Although the readiness dimension is directly anchored in the source paper's QTRL discussion, dimensions such as integration tractability and public-value externality still require analytical interpretation. The manuscript addresses this by making the weighting logic explicit and by stress-testing the top tier under alternative scenarios.

Third, the model does not incorporate local institutional factors such as procurement rules, organizational digital maturity, site-specific subsurface conditions, labor capability, or data-governance constraints. These factors will affect implementation pace even when strategic ranking is directionally correct.

Fourth, the analysis intentionally narrows the deployment problem to transportation and construction. This improves operational specificity and aligns with the strongest readiness signals in the source literature, but it does not resolve the broader inter-sector sequencing problem across energy, water, transportation, and construction.

CONCLUSION

Quantum sensing has substantial strategic relevance for smart-city infrastructure, but its near-term value depends on disciplined sequencing rather than broad technological enthusiasm. Using a source-grounded review corpus and a readiness-weighted portfolio model, this manuscript identifies a clear first-wave urban deployment logic centered on dynamic traffic control, subsurface imaging, and underground metallic utility detection.

Two conclusions follow. First, the strongest early deployment candidates are those that combine mature sensor families with urban problems that are already costly under conventional sensing. Second, the transition from technology discourse to urban implementation requires explicit prioritization. Without a pathway-ranking framework, the planning conversation remains conceptually persuasive but operationally incomplete.

In that sense, the central contribution of this manuscript is both substantive and procedural. Substantively, it identifies where early quantum sensing is most likely to matter in cities. Procedurally, it demonstrates how smart-city review literature can be translated into an actionable pilot-selection instrument. For urban development agencies navigating emerging infrastructure technologies, that conversion from possibility to sequence is the essential first step.

FUTURE RESEARCH

Three immediate follow-on directions would strengthen this line of work. First, the top-ranked construction pathways should be tested in corridor-scale excavation simulations that compare quantum sensing with conventional utility-detection workflows under varied urban subsurface conditions. Second, the portfolio model should be extended to the full four-domain infrastructure landscape once readiness evidence in energy and water becomes equally explicit at the application level. Third, future studies should add cost layers and procurement constraints so that prioritization can be converted into budget-constrained portfolio optimization for real municipal and infrastructure programs.

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