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A Proposed UAV-BIM-Integrated Earned Value Management Framework with a Climate-Adjusted Schedule Performance Index for High-Rise Construction Project Control: A Conceptual Framework and Illustrative Demonstration

Md. Rafsan Jany[1*], Mst. Shamima Shirin[2], Shariful Islam[3], Nahil Nimeri[1], Abu Hasnat Neloy[4], Rezaul Karim[5], Redwanul Haque Jami[1]

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ABSTRACT

Earned Value Management (EVM) is the dominant method for integrated cost and schedule control in construction, yet its Schedule Performance Index (SPI) does not distinguish delay caused by contractor inefficiency from delay caused by unavoidable climate hazards such as monsoon rainfall or cyclones. In climate-vulnerable, monsoon-affected markets, this conflation risks misrepresenting project performance and weakening EVM-based decision-making. This paper proposes a UAV–BIM-integrated EVM framework whose central contribution is a composite metric, the Integrated Digital Construction Index (IDCI), intended to combine a Climate-Adjusted Schedule Performance Index (CASPI), a Climate-Adjusted Cost Performance Index (CACPI), a UAV-BIM Verification Confidence score (UBVC), and a Digital Maturity Score (DMS) into one dashboard-ready decision metric. The framework specifies how Earned Value could be derived bottom-up from UAV-photogrammetric progress reconciled against a cost-loaded Building Information Model rather than subjective percentage-complete estimates, and defines a companion Climate Delay Ratio (CDR) that quantifies the schedule baseline share falling within climate-hazard periods. Following a design-science research approach, the framework is derived analytically from earned value, earned schedule, and UAV–BIM progress-monitoring theory, and is illustrated - not empirically validated - through a fully hypothetical 18-month high-rise case built on a synthetic dataset; no real project, UAV, or cost-accounting data are used. All reported figures demonstrate only the mathematical behavior of the proposed indices under assumptions chosen by the author, not their real-world accuracy. In the illustrative case, conventional SPI falls to 0.66 during a simulated cyclone month while CASPI remains at 0.89, and IDCI rises from 0.68 to 0.92 as UAV-BIM verification coverage and framework maturity increase in the synthetic scenario. The paper's contribution is conceptual and methodological a reusable metric set, an explicit and reproducible computational procedure, a dashboard architecture, and a phased empirical validation agenda rather than a demonstrated improvement in project-control outcomes, which remains to be established on real, instrumented projects.

INTRODUCTION

Earned Value Management (EVM) has been the dominant method for integrated cost and schedule performance measurement in construction and engineering projects since its formalization by the United States Department of Defense and its later standardization as ANSI/EIA-748 (Fleming & Koppelman, 2016). By comparing Planned Value (PV), Earned Value (EV), and Actual Cost (AC) at a common reporting date, EVM produces the Schedule Performance Index (SPI) and Cost Performance Index (CPI), two of the most widely used single-number diagnostics in construction project control. The subsequent development of Earned Schedule (ES) by Lipke (2003) and its later validation (Lipke *et al.*, 2009; Vanhoucke & Vandevoorde, 2007) extended EVM's schedule diagnostics from cost units into true time units, substantially improving the reliability of duration forecasting.

A persistent limitation of both classical EVM and Earned Schedule, however, is that SPI treats all schedule variance as informationally equivalent: a week of lost progress caused by a subcontractor's poor sequencing is indistinguishable, in the index itself, from a week lost to monsoon flooding or a cyclone-driven site shutdown. Weather and climate hazard exposure is repeatedly identified in the construction management literature as a major, but analytically unseparated, driver of schedule variance (Aziz, 2013; Panchal, 2023). In climate-vulnerable, monsoon-affected construction markets such as Bangladesh, where a substantial share of the working calendar falls within a defined monsoon and cyclone-exposure window, this conflation is not a marginal measurement issue: it can materially distort how project teams are evaluated, how contractual excusable-delay claims are substantiated, and how corrective management action is prioritized.

A second, related limitation concerns how Earned Value itself is determined. In common practice, EV is estimated from subjective percentage-complete assessments made by site engineers, which are known to be inconsistent

[1] Department of Civil Engineering, Ahsanullah University of Science and Technology (AUST), Dhaka, Bangladesh
[2] Department of Civil Engineering, Khulna University of Engineering and Technology (KUET), Khulna, Bangladesh
[3] Department of Civil Engineering, University of Asia Pacific (UAP), Dhaka, Bangladesh
[4] Department of Civil & Environmental Engineering, Islamic University of Technology (IUT), Gazipur, Bangladesh
[5] Department of Civil Engineering, World University of Bangladesh (WUB), Dhaka, Bangladesh
[*] Corresponding author's email: trafsan@gmail.com

and difficult to audit. The construction management literature has increasingly proposed replacing subjective percentage-complete estimation with UAV-based photogrammetric or LiDAR surveys reconciled against a Building Information Model (BIM), enabling EV to be computed bottom-up from geometrically verified, cost-loaded model elements rather than top-down from a single estimated percentage (Golparvar-Fard *et al.*, 2011; Freimuth & König, 2018; Pour Rahimian *et al.*, 2020). BIM's expanding role as a condition-monitoring and defect-detection tool for structural assets more broadly (Ferdous *et al.*, 2025) further supports the feasibility of treating BIM as an auditable, element-level data source rather than a static design record. This UAV–BIM reconciliation approach improves the auditability of EV, but the literature has not yet connected it to a climate-hazard-aware schedule performance index, leaving two well-developed research strands UAV–BIM progress monitoring and EVM/Earned Schedule theory largely disconnected from one another and from climate resilience considerations specifically.

This paper addresses both gaps by developing a UAV–BIM-integrated EVM framework built around three contributions: (i) a data architecture in which Earned Value is derived bottom-up from UAV-photogrammetric reconciliation against a cost-loaded BIM model; (ii) a Climate-Adjusted Schedule Performance Index (CASPI) and companion Climate Delay Ratio (CDR) that decompose conventional schedule variance into climate-excusable and managerially controllable components; and (iii) the paper's central novel contribution, a composite Integrated Digital Construction Index (IDCI) that combines CASPI with a parallel Climate-Adjusted Cost Performance Index (CACPI), a UAV-BIM Verification Confidence score (UBVC), and a Digital Maturity Score (DMS) into a single, dashboard-ready decision metric, packaged into a proposed real-time decision support dashboard architecture. The framework is developed following a design-science research approach (Hevner *et al.*, 2004) and demonstrated through a fully hypothetical, illustrative 18-month high-rise case constructed specifically to show how the metrics behave under a simulated monsoon and cyclone exposure window; no real project data are used or claimed. The paper's objective is to contribute a reusable, testable metric set, dashboard architecture, and implementation pathway that can subsequently be validated empirically on real, instrumented projects, particularly in monsoon- and cyclone-exposed construction markets.

Because CASPI's diagnostic and contractual value depends on cause being separated correctly, three related terms are used with deliberate precision throughout this paper. A climate event is an observed meteorological or hydrological occurrence (for example, rainfall exceeding a defined intensity threshold, flood inundation, or a declared cyclone warning). A climate-attributable delay or cost is the portion of observed schedule or cost variance that can be causally associated with a climate event, whether or not that association is contractually recognized. A contractually excusable delay is the subset of climate-attributable delay that satisfies the notice, threshold, and documentation requirements of the governing contract and is therefore recognized as excusable by the client or engineer. CASPI and CDR, as defined in Section 3.5, are operationalized using contractually excusable days specifically, not the broader and harder-to-verify category of climate-attributable delay; this choice trades some conceptual completeness for auditability and is revisited as a limitation in Section 4.5.

This paper is organized around three design objectives, addressed respectively in Sections 3.4–3.6, 3.7, and 3.8–3.9: (RQ1) how Earned Value can be derived bottom-up from UAV–BIM reconciliation rather than subjective estimation, and how a schedule performance index can be decomposed into climate-excusable and managerially controllable components using only contractually auditable data; (RQ2) how climate-adjusted schedule and cost performance can be combined with data-verification coverage and digital-maturity measures into a single composite index without conflating constructs that are conceptually distinct; and (RQ3) how these metrics can be packaged into a decision-support dashboard architecture that keeps climate-hazard governance, EVM reporting, and digital-maturity tracking mutually consistent. These objectives are addressed analytically and illustrated on a synthetic case in this paper; their empirical validation is identified as future work in Section 5.

The remainder of the paper is organized as follows. Section 2 reviews the literature on EVM, Earned Schedule, and UAV–BIM progress monitoring. Section 3 presents the materials and methods, including the design-science research approach, the proposed UAV-BIM-EVM framework, the composite IDCI, and the decision support dashboard architecture. Section 4 presents the results and discussion, demonstrating the framework through an illustrative worked example and discussing implications and limitations. Section 5 concludes and outlines an empirical validation agenda.

LITERATURE REVIEW

Earned Value Management and Earned Schedule

EVM integrates three time-phased data series Planned Value (the budgeted cost of work scheduled), Earned Value (the budgeted cost of work actually performed), and Actual Cost (the realized cost of work performed) into a small set of diagnostic indices, most notably SPI = EV / PV and CPI = EV / AC (Fleming & Koppelman, 2016). Values below 1.0 indicate unfavorable schedule or cost performance, respectively. A well-documented limitation of SPI is that it converges to 1.0 near project completion regardless of actual lateness, since PV eventually equals the full budget at completion (BAC); Earned Schedule addresses this by re-expressing schedule performance in time units, using the point on the PV curve at which cumulative EV should have occurred, denoted ES (Lipke, 2003; Lipke *et al.*, 2009). Subsequent work has validated Earned Schedule-based duration forecasting across simulated and real project datasets, generally finding it more reliable than classical, cost-based SPI forecasting as projects approach completion (Vanhoucke & Vandevoorde, 2007).

Neither classical SPI/CPI nor Earned Schedule formally separates schedule variance by cause. Delay-analysis literature outside the EVM tradition has long recognized weather and force-majeure events as a distinct, typically contractually excusable, delay category, alongside management-controllable causes such as coordination failures, resource shortages, and design changes (Aziz, 2013). The proposed framework in Section 3 formalizes this cause-based separation directly within the EVM index itself, rather than treating it as an external delay-analysis exercise conducted separately from routine performance reporting.

UAV-BIM-Based Progress Monitoring

A parallel literature has developed methods for deriving construction progress directly from reality-capture technologies rather than manual estimation. UAV-based photogrammetry and LiDAR surveys, processed into 3D point clouds and registered against BIM models, allow as-built conditions to be compared element-by-element against the design-intent model (Zhang *et al.*, 2024). Camera-equipped UAVs have been used for visual monitoring of civil infrastructure and construction progress for over a decade (Ham *et al.*, 2016), and more recent frameworks combine UAV imagery, computer vision, and BIM into semi-automated conformance-checking and progress-update pipelines (Freimuth & König, 2018; Pour Rahimian *et al.*, 2020). Because each BIM element can carry both geometric and cost (5D) attributes, the completion status detected from UAV–BIM reconciliation can, in principle, be aggregated into a cost-weighted percentage complete that is materially more auditable than a site engineer's subjective estimate a linkage that has been noted conceptually in the BIM–5D–EVM integration literature (Cárdenas *et al.*, 2018) but has not, to the author's knowledge, been formally combined with a climate-hazard-adjusted schedule index. A closely related conceptual review by the author separately examines UAV-integrated monitoring for high-rise construction in the Bangladesh context and identifies regulatory, economic, and organizational adoption barriers, but stops short of a climate-adjusted EVM index (Jany, 2026), underscoring that the integration proposed here has not previously been formalized even within that closely related line of work.

The underlying premise of a live, bidirectionally updated physical–virtual model is not unique to construction: digital twin architectures combining real-time sensing, virtual simulation, and predictive fault detection have been demonstrated in adjacent asset-heavy domains such as mine hoist monitoring, where a multi-layered digital twin integrating physical systems, real-time data collection, and virtual simulation was shown to improve early-warning accuracy for structural and mechanical faults (Basher *et al.*, 2025). Similarly, IoT-enabled sensing integrated with electrical systems and construction materials has been proposed as a route to smart, resilient urban infrastructure more broadly (Mahmud *et al.*, 2025), reinforcing that the sensor-to-model data architecture underlying the framework in Section 3 draws on a well-established cross-domain pattern rather than a construction-specific novelty.

Climate Exposure and Construction Schedule Risk

Cost and schedule overrun in construction and infrastructure projects is a persistent, well-documented phenomenon across both developed and developing markets (Flyvbjerg *et al.*, 2018). In monsoon-affected and cyclone-exposed regions, a substantial share of a project's working calendar can fall within a season in which excusable weather delay is contractually anticipated; national building codes such as the Bangladesh National Building Code already incorporate wind- and flood-related design provisions reflecting this exposure. Despite this, routine EVM reporting in such markets typically reports a single SPI value that does not indicate what portion of an observed delay was climate-driven versus management-driven, limiting the diagnostic and contractual usefulness of the index during and immediately after the monsoon and cyclone season.

This measurement gap has practical consequences beyond internal project reporting. Standard construction contracts in monsoon- and cyclone-exposed markets typically contain excusable-delay clauses that entitle contractors to time extensions, and in some cases cost relief, for weather events exceeding a defined threshold; however, substantiating such claims conventionally requires a separate, retrospective delay-analysis exercise conducted outside routine EVM reporting, often after a dispute has already emerged. A schedule performance index that is climate-aware by construction, rather than requiring a post-hoc forensic analysis, could in principle reduce the frequency and severity of such disputes by making the climate-excusable component of schedule variance visible in the same reporting cycle in which it occurs. Similarly, lenders and insurers financing climate-exposed infrastructure are increasingly attentive to how project sponsors monitor and report climate-related delay and cost impacts, both for underwriting purposes and for compliance with emerging climate-risk-disclosure expectations; a metric that separates climate-attributable performance from managerial performance is potentially more informative to these stakeholders than an undifferentiated SPI figure, though this financing-side application has not, to the author's knowledge, been examined empirically in the construction management literature. These contractual and financing-related benefits are therefore presented in this paper as potential applications motivating future empirical and policy research, not as demonstrated outcomes of the framework proposed here.

The feasibility of any climate-aware, digitally mediated performance metric is also bounded by the same adoption barriers documented for BIM and related digital technologies in developing construction markets more broadly. Survey evidence from BIM integration in TETFUND-sponsored tertiary-institution projects in Southwest Nigeria found moderate overall adoption but persistent weaknesses in facility-management use and staff training, with a lack of trained professionals and high implementation cost rated among the most significant barriers (Adeeko & Akinola, 2025). Comparable barriers high upfront cost, restricted access to green financing, limited local technical knowledge, and weak policy support have been documented for carbon-neutral and sustainable construction adoption in Bangladesh specifically (Sani *et al.*, 2025), and specifically for Building Information Modeling adoption in Bangladeshi urban construction (Jany *et al.*, 2026), reinforcing the framework design choice, discussed in Section 3.7, to explicitly penalize incomplete digital-technology adoption through the Digital Maturity Score rather than assuming full adoption as a baseline condition.

Positioning Relative to Existing Approaches

Table 1 summarizes how the framework proposed in Section 3 differs from the principal existing approaches reviewed above, along five capabilities that correspond directly to the paper's design objectives (RQ1–RQ3, Section 1): whether schedule variance is separated by cause, the data source used for Earned Value, whether the approach yields a single composite decision metric, whether it accounts for digital-technology maturity, and its current stage of evaluation. No existing approach reviewed in Sections 2.1–2.3 combines cause-separated schedule variance, UAV-BIM-verified Earned Value, and a maturity-aware composite index in a single framework; each addresses at most one or two of these dimensions. This comparison, rather than an unsupported novelty claim, is the basis for the research gap motivating Section 3.

Table 1: Positioning of the proposed framework relative to existing approaches.

Approach	Cause-separated schedule variance	Earned Value data source	Composite decision metric	Digital-maturity accounted	Evaluation stage
Conventional EVM – SPI/CPI (Fleming & Koppelman, 2016)	No	Manual percent-complete	No (two separate indices)	No	Established practice
Earned Schedule (Lipke, 2003; Lipke *et al.*, 2009)	No	Manual percent-complete	No (time -based SPI(t) only)	No	Empirically validated
Retrospective weather / force-majeure delay analysis (Aziz, 2013)	Yes, but post-hoc, outside routine EVM reporting	Not applicable	No	No	Established practice
UAV-BIM progress monitoring (Ham *et al.*, 2016; Freimuth & König, 2018; Pour Rahimian *et al.*, 2020; Zhang *et al.*, 2024)	No	UAV/point-cloud verified	No (progress metric only)	No	Field-demonstrated (progress only)
BIM-5D–EVM computational tools (Cárdenas *et al.*, 2018)	No	BIM-derived, cost-loaded	No	No	Tool-demonstrated
Proposed framework (CASPI, CACPI, IDCI – Section 3)	Yes, within the EVM index itself and each reporting cycle	UAV-BIM verified (manual fallback tracked via UBVC)	Yes (IDCI)	Yes (DMS)	Conceptual; illustrated on synthetic case

MATERIALS AND METHODS

Design-Science Research Approach

This study follows a design-science research (DSR) approach, in which the research contribution is a novel, purposefully designed artifact here, a metric set and data architecture developed to address an identified practical problem and evaluated through a structured demonstration, consistent with the DSR guidelines articulated by Hevner *et al.* (2004). DSR is an established and appropriate methodology for construction management research that proposes new frameworks, decision-support tools, or performance metrics rather than testing a hypothesis against an existing dataset, and is distinguished from purely conceptual or descriptive review work by its requirement of a working, demonstrable artifact.

The research process comprised three stages. First, the problem was formalized from the literature review in Section 2: conventional SPI conflates climate-excusable and managerially controllable schedule variance, and EV is conventionally derived from subjective rather than geometrically verified progress data. Second, the artifact the UAV–BIM data architecture and the CASPI/CDR metric set was derived formally from classical EVM and Earned Schedule definitions (Section 3.3–3.7), ensuring backward compatibility with existing EVM reporting so that the proposed metrics can be adopted incrementally alongside, rather than in place of, conventional SPI and CPI. Third, the artifact was demonstrated through a worked, fully hypothetical illustrative case (Section 4), constructed to exhibit the framework's behavior under a simulated monsoon and cyclone exposure window representative of, but not drawn from, an actual Bangladeshi high-rise project.

Illustrative Case Design and Data Provenance

The worked example presented in Section 4 uses a fully synthetic, hypothetical dataset constructed by the author to demonstrate the mechanics and behavior of the proposed metrics; it does not represent, and should not be interpreted as, performance data from any specific real project. The dataset was constructed to reflect plausible, realistic parameters for a mid-rise to high-rise reinforced concrete residential building in Dhaka: an 18-month construction duration, a classical S-curve planned-value profile, a monsoon exposure window spanning four months, and one simulated cyclone event causing a severe single-month stoppage, consistent with the seasonal exposure pattern described in Section 2.3. This approach demonstrating a newly proposed metric through an illustrative, clearly labeled synthetic case prior to empirical field validation is consistent with standard practice in design-science and framework-development research and is made explicit throughout this paper to avoid any ambiguity regarding data provenance. Section 5 outlines the empirical validation study required before the framework is applied to real project decision-making.

Data Architecture

The proposed framework connects four data layers. (1) A cost-loaded BIM model in which every model element carries a budgeted cost derived from the project Bill of Quantities (BOQ), so that the model itself constitutes the Planned Value baseline at the element level. (2) Periodic UAV photogrammetric or LiDAR surveys, generating a point cloud of as-built site conditions at defined reporting intervals (e.g., biweekly or monthly). (3) A registration and classification step in which the point cloud is aligned to the BIM model and each element is classified as not started, in progress, or complete, following established point-cloud-to-BIM registration methods (Zhang *et al.*, 2024). (4) An EVM/CASPI computation engine that aggregates element-level completion, weighted by each element's budgeted cost, into bottom-up EV, and cross-references the project's climate-hazard log contractually recognized excusable weather and disaster days against the schedule to compute the climate-adjusted metrics defined below.

Baseline EVM and Earned Schedule Definitions

The framework retains the standard EVM definitions in full, ensuring compatibility with existing project control practice:

$SV = EV - PV \qquad CV = EV - AC \qquad (1)$

$SPI = EV / PV \qquad CPI = EV / AC \qquad (2)$

where PV, EV, and AC are the cumulative planned value, earned value, and actual cost at the reporting date, as defined in Section 3.3. Earned Schedule (ES), following Lipke (2003), is computed as the point on the cumulative PV curve at which PV equals the current EV, providing a time-based schedule performance index SPI(t) = ES / AT, where AT is the actual elapsed time.

Climate-Adjusted Schedule Performance Index (CASPI)

The central contribution of this framework is the decomposition of cumulative Planned Value into a climate-excusable component and a managerially controllable component. For each reporting period t, the framework requires a climate-hazard log recording the number of contractually recognized excusable climate-hazard days (rainfall exceeding a defined threshold, flood inundation, or a declared cyclone shutdown) out of the total scheduled working days in that period. The climate-affected Planned Value for period t is then:

$PVc^{\mathrm{lImaTE}},t = PV_t \times (\text{excusable days}_t \,/\, \text{working days}_t)$ (3)

and the cumulative climate-affected Planned Value at the reporting date is PV_climate = Σ PVc^{lImaTE},t. The Climate-Adjusted Schedule Performance Index is then defined as:

$CASPI = EV / (PV - PVc^{\mathrm{lImaTE}})$ (4)

CASPI measures schedule efficiency against only the managerially controllable portion of the planned schedule, netting out planned value that fell within contractually recognized climate-excusable periods. A CASPI at or near 1.0 during a climate-hazard period, alongside a depressed conventional SPI, indicates that the observed schedule slippage is predominantly climate-driven rather than management-driven; conversely, a CASPI that remains materially below 1.0 during a non-hazard period indicates genuine managerial or contractor-attributable schedule underperformance.

Because PV_climate = PV × CDR (Equations 3 and 5), CASPI can be re-expressed algebraically as CASPI = SPI / (1 − CDR): it is a deterministic transformation of conventional SPI using the climate-exposure ratio CDR, not a statistically independent performance signal. Its practical value is therefore not new numerical information beyond SPI and CDR combined, but three things a project team does not otherwise get from reporting SPI and CDR separately: (i) an auditable governance artifact - the climate-hazard log of Section 3.6 that must exist, be contractually pre-defined, and be cross-checked before the adjustment can be applied at all; (ii) a single validated figure in place of a division that project teams do not reliably and consistently perform under reporting-cycle time pressure, reducing the risk of ad hoc or inconsistent climate adjustment across reporting periods and project teams; and (iii) the standardized input the dashboard, alerting, and excusable-delay-claim workflows of Sections 3.8–3.9 require to remain automated and internally consistent. CASPI is accordingly best understood as a governance and workflow contribution built on top of SPI and CDR, and this paper does not claim that it carries information CDR and SPI do not already jointly contain.

A companion diagnostic, the Climate Delay Ratio (CDR), expresses the proportion of cumulative Planned Value that fell within climate-excusable periods, and is reported alongside CASPI to indicate how much of the schedule baseline was climate-exposed at any given reporting date:

$$\text{CDR} = \text{PVc}^{\text{llmaTE}} / \text{PV} \qquad (5)$$

CDR is a diagnostic weighting term rather than a performance index: a high CDR does not itself indicate poor performance, but signals that a large share of the current schedule baseline should be interpreted through CASPI rather than conventional SPI alone.

Governance: Defining "Climate-Excusable" Days

Because CASPI's validity depends entirely on how excusable climate-hazard days are defined and logged, the framework requires that thresholds be fixed contractually and in advance, following the pattern already used for weather-delay claims in standard construction contracts (e.g., defined rainfall intensity or duration thresholds, flood-inundation depth triggers, or officially declared cyclone warning signals). Excusable-day determinations should be logged by a designated site authority, cross-referenced where possible against independent meteorological or disaster-management agency records, and be auditable in the same way that conventional EVM cost and progress data are auditable. Without this governance discipline, CASPI could be manipulated by over-classifying ordinary delay as climate-excusable; this risk, and the corresponding audit safeguards, is discussed further in Section 4.5. The same governance discipline is required, separately, for the cost-based climate attribution used by CACPI (Section 3.7): climate-related cost codes must be pre-agreed and consistently applied by the site accounting system, not inferred after the fact from the schedule-side excusable-day count, because as Section 4.1 demonstrates numerically the two need not move together.

The Integrated Digital Construction Index (IDCI): A Composite Decision Metric

The framework's central contribution is a single composite index intended for routine project reporting and dashboard display, combining schedule, cost, data-verification, and digital-maturity dimensions that are otherwise reported as separate, uncoordinated figures. Two additional sub-indices are required to construct it.

First, a Climate-Adjusted Cost Performance Index (CACPI) nets climate-attributable actual cost specifically idle labor and equipment standby, weather-protection, remobilization, and site-recovery cost incurred during logged climate-hazard periods, out of the Actual Cost denominator:

$$\text{CACPI} = \text{EV} / (\text{AC} - \text{ACc}^{\text{llmaTE}}) \qquad (6)$$

where AC_climate,t = AC_t × CCR_t, and the Climate Cost Ratio (CCR_t) is the proportion of Actual Cost in period t posted to climate-attributable cost codes (idle labor/equipment standby, weather protection, remobilization, and recovery). CCR_t is determined from the project's cost-accounting system and is deliberately not assumed proportional to the climate-excusable-day fraction (CDR_t) used for CASPI: Section 4.1 shows, using the illustrative case, that CCR and CDR diverge materially period to period, because cost exposure to a climate hazard is not proportional to the number of days it affects. Distinguishing CCR from CDR is a governance and cost-coding requirement (Section 3.6), not a simplifying assumption.

Second, two data-quality and maturity sub-indices reflect how much of the framework's underlying data architecture (Section 3.3) is actually operating on a given project at a given time. The UAV-BIM Verification Confidence (UBVC) score is the proportion of cumulative Earned Value that has been verified through UAV-BIM geometric reconciliation rather than through manual percentage-complete estimation, and ranges from 0 (fully manual) to 1 (fully UAV-BIM verified). The Digital Maturity Score (DMS) is the proportion of the five layers of the companion conceptual framework Data Acquisition, Semantic Modeling (BIM), Integration (Digital Twin), Analytics (AI), and Governance that are actively operational on the project, expressed as a fraction of five.

The Integrated Digital Construction Index is then defined as a weighted combination of the four sub-indices:

$$\text{IDCI} = w_s \cdot \text{CASPI} + w_C \cdot \text{CACPI} + w_v \cdot \text{UBVC} + w_{ɱ} \cdot \text{DMS} \qquad (7)$$

subject to $w_s + w_C + w_v + w_{ɱ} = 1$. In the absence of project- or organization-specific weighting preferences, this paper adopts equal weighting ($w_s = w_C = w_v = w_{ɱ} = 0.25$) for the illustrative demonstration in Section 4; where stakeholders wish to emphasize particular dimensions (for example, weighting schedule performance more heavily on a fast-track project, or weighting digital maturity more heavily where financiers require climate-risk-disclosure evidence), weights can instead be elicited using a structured multi-criteria method such as the Analytic Hierarchy Process (Saaty, 1980). Unlike CASPI or CACPI alone, IDCI is explicitly designed to fall short of 1.0 on projects with only partial digital-technology adoption the UBVC and DMS terms penalize reliance on manual progress estimation and incomplete framework implementation respectively so that the index rewards both good schedule/cost performance and genuine digital-technology maturity, rather than schedule/cost performance alone. This property is deliberately illustrated in the worked example in Section 4, where IDCI remains below 1.0 throughout the hypothetical case despite CASPI and CACPI both approaching or exceeding 1.0 by project end, reflecting the hypothetical project's incomplete adoption of the full five-layer framework.

Because CASPI, CACPI, UBVC, and DMS measure conceptually distinct constructs climate-adjusted schedule efficiency, climate-adjusted cost efficiency, data-verification coverage, and technology-adoption maturity, respectively IDCI is best interpreted not as a single latent "construction performance" score but as a digital-maturity-adjusted decision-support index: it is designed so that strong schedule and cost efficiency alone cannot produce a high headline figure unless that efficiency is also auditable and supported by adequate framework maturity. Under this reading, a project with excellent CASPI and CACPI but low UBVC and DMS is correctly flagged by a moderate IDCI as reporting figures that are not yet fully auditable, and a project's IDCI can rise through genuine digital-technology adoption even where its underlying schedule and cost efficiency are unchanged both intended behaviors of the composite, not defects of it. Because this interpretation depends on the four sub-indices being weighted deliberately rather than by default, Section 4.2 reports IDCI under three illustrative weighting schemes in addition to the equal weighting above.

Proposed Decision Support Dashboard Architecture

To translate the metric set defined above into a practical project-control tool, this paper proposes a decision support dashboard architecture that surfaces the framework's outputs in a single live view for project managers, clients, and financiers. The dashboard is presented here as a conceptual architecture and illustrative mockup rather than a deployed software product; its purpose is to specify the panels, underlying data sources, and refresh logic required for an implementation team to build a working system.

Table 2: Proposed decision support dashboard panels, data sources, and refresh cadence.

Panel	Underlying data source / calculation	Suggested refresh cadence
Performance gauges (SPI, CPI, CASPI, CACPI, IDCI)	Computed each reporting cycle from the EVM/CASPI engine (Sections 3.3–3.5) against the cost-loaded BIM baseline	Biweekly / monthly
EV / PV / AC trend (S-curve)	Cumulative values from the BOQ-derived baseline (PV), UAV-BIM reconciled progress (EV), and site accounting system (AC)	Biweekly / monthly
Drone-verified progress by zone	Percentage completion per building zone/floor derived from the latest UAV photogrammetric survey processed against the BIM model	Per UAV survey (e.g., biweekly)
BIM element status map	Element-level not-started / in-progress / complete classification from point-cloud-to-BIM registration (Section 3.3)	Per UAV survey
Climate alert feed	Rainfall, flood, and cyclone-warning thresholds defined in Section 3.6, ideally cross-fed from national meteorological/disaster-management agency data	Real-time / daily
Delay and completion forecast	CASPI- and Earned-Schedule-based projection of time and cost at completion (EAC/TEAC), updated each reporting cycle	Biweekly / monthly

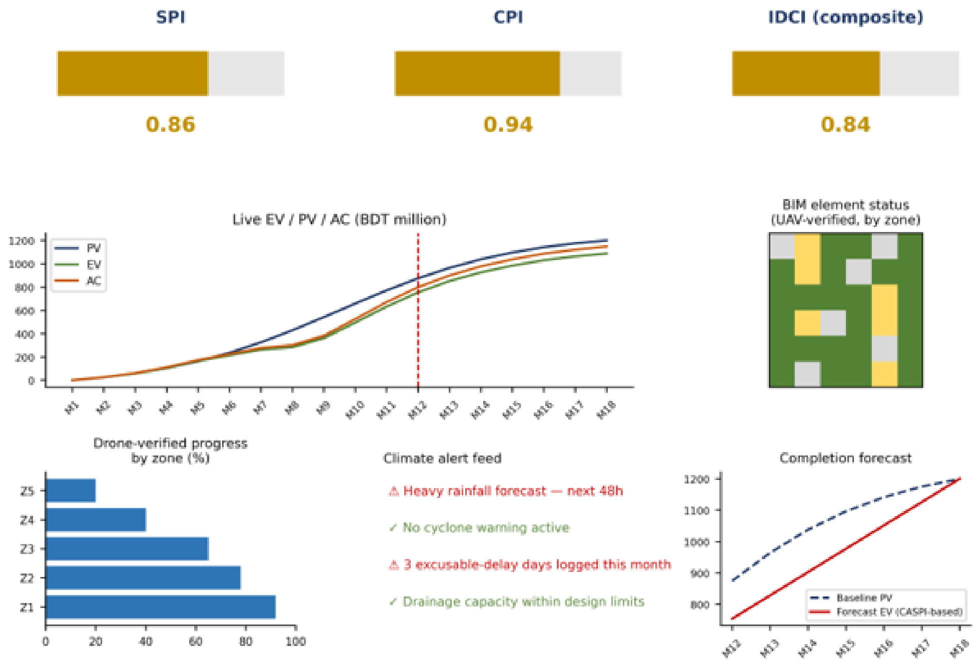

Figure 1: Proposed decision support dashboard architecture - illustrative conceptual mockup shown at a Month 12 snapshot of the hypothetical case in Section 4.

Alerting and Escalation Logic

The climate alert panel is designed to draw directly on the same excusable-day governance thresholds defined in Section 3.6, so that an alert triggering a logged excusable day automatically flows into the next reporting cycle's PV_climate and AC_climate calculations, keeping the dashboard's climate alerts and its CASPI/CACPI/IDCI figures internally consistent rather than reported as separate, disconnected feeds. A simple three-tier escalation logic is proposed: informational alerts (e.g., forecast rainfall below the excusable threshold) require no schedule action; excusable-delay alerts (threshold exceeded) automatically log an excusable day and notify the project manager and client; and critical alerts (e.g., a declared cyclone warning) trigger a predefined site-safety and demobilization protocol in addition to the schedule logging function.

Computational Procedure and Reproducibility

To support independent replication, the following procedure specifies how each metric defined in Sections 3.4–3.7 is computed from raw project data at each reporting date t. Step 1- Baseline: load the cost-loaded BIM model and set PV_t from the BOQ-derived schedule baseline. Step 2 - Progress capture: acquire the UAV photogrammetric/LiDAR survey for period t and register the resulting point cloud to the BIM model (Section 3.3), classifying each element as not started, in progress, or complete. Step 3 - Earned Value: compute EV_t as the cost-weighted sum of completed and partially completed element budgets, and record the fraction of EV_t derived from UAV-BIM verification versus manual estimation to obtain UBVC_t. Step 4 - Actual Cost: import AC_t from the site accounting system, tagged by cost code. Step 5 - Climate-hazard log: from the governance log (Section 3.6), record excusable days_t, working days_t, and the Actual Cost posted to climate-attributable cost codes for period t. Step 6 - Schedule adjustment: compute PV_climate,t (Equation 3), CDR_t (Equation 5), and CASPI_t (Equation 4). Step 7 - Cost adjustment: compute CCR_t as the climate-coded share of AC_t, then AC_climate,t = AC_t × CCR_t and CACPI_t (Equation 6). Step 8 - Digital maturity: score DMS_t as the fraction of the five framework layers (Section 3.7) operational at date t. Step 9 - Composite index: compute IDCI_t (Equation 7) using the agreed weight set, and report all four component values alongside IDCI_t rather than IDCI_t alone (Section 4.2 illustrates why). Step 10 - Forecast and alert: update the dashboard's EAC/TEAC forecast and climate-alert feed (Sections 3.8–3.9) from the same period's inputs. This procedure is deterministic given the underlying data; Section 4.1 reproduces Steps 6–9 numerically for the illustrative case.

RESULTS AND DISCUSSION

Results: Illustrative Worked Example

This section demonstrates the framework using a fully hypothetical 18-month high-rise construction case with a Budget at Completion (BAC) of BDT 1,200 million, constructed specifically to illustrate the framework's mechanics under a simulated monsoon exposure window (Months 6–9) and one simulated cyclone event (Month 8). As stated in Section 3.2, all figures in this section are synthetic and illustrative only.

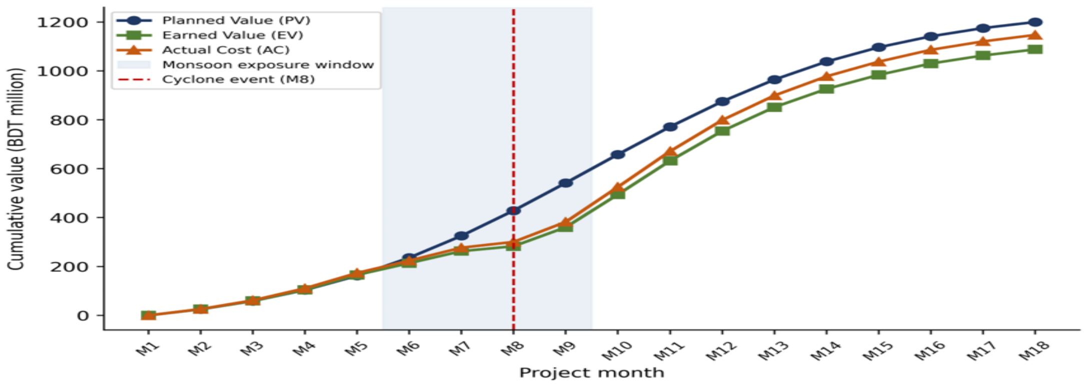

Figure 2 : Illustrative S-curve of cumulative Planned Value (PV), Earned Value (EV), and Actual Cost (AC) for the hypothetical 18-month case, showing the simulated monsoon exposure window and cyclone event.

Table 3: Illustrative cumulative EVM and CASPI values, hypothetical 18-month case (all values synthetic; BDT million except indices).

Month	PV	EV	AC	SPI	CASPI	CDR
M1	0	0	0	1.00	1.00	0.0%
M2	24.9	25.4	26	1.02	1.02	0.0%
M3	58.6	59	61.4	1.01	1.01	0.0%
M4	103.5	104.7	110.7	1.01	1.01	0.0%
M5	162	165.4	173.4	1.02	1.02	0.0%
M6	235.8	213.5	224.1	0.91	0.99	8.4%
M7	325.2	262.7	276.9	0.81	0.96	15.6%
M8	428.5	282.7	300.5	0.66	0.89	25.8%
M9	541.7	360.4	382.2	0.67	0.91	26.8%
M10	658.3	494.6	525.1	0.75	0.96	22.1%
M11	771.5	632.3	671.1	0.82	1.01	18.8%
M12	874.8	754	798.7	0.86	1.03	16.6%
M13	964.2	851.4	899.3	0.88	1.04	15.1%
M14	1038	926.2	977.7	0.89	1.04	14.0%
M15	1096.5	983.7	1037.6	0.90	1.03	13.2%
M16	1141.4	1030.1	1086.3	0.90	1.03	12.7%
M17	1175.1	1063.1	1120.6	0.90	1.03	12.4%
M18	1200	1087.8	1147.1	0.91	1.03	12.1%

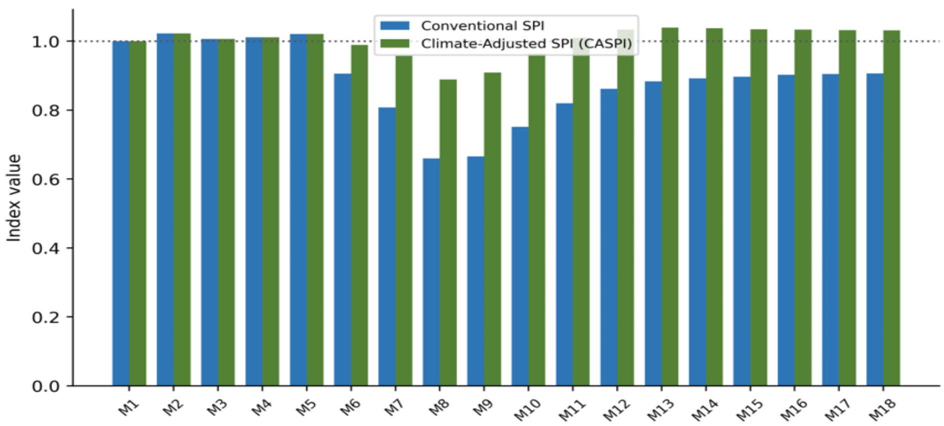

Figure 3: Illustrative comparison of conventional SPI and the proposed Climate-Adjusted SPI (CASPI) across the hypothetical 18-month case.

As shown in Table 3 and Figure 3, conventional SPI falls sharply during the simulated monsoon and cyclone window, reaching a minimum of 0.66 in Month 8, the month of the simulated cyclone event. Under conventional EVM reporting alone, this would appear as a severe schedule underperformance. CASPI for the same month is 0.89 still below 1.0, reflecting some residual managerially attributable slippage, but substantially closer to on-schedule performance once the climate-excusable portion of that month's planned value (reflected in a CDR of 25.8% for Month 8) is netted out. This pattern is consistent with the framework's intended function: distinguishing an unavoidable, contractually excusable climate-driven schedule impact from a genuine management or contractor performance issue, which conventional SPI alone cannot do. By Month 12, after the simulated recovery/acceleration period, CASPI recovers to slightly above 1.0 (1.03), indicating that the project team more than recovered the managerially controllable portion of lost schedule, even though conventional SPI (0.86) still reads as behind schedule because it has not netted out the now-historical climate-excusable delay embedded earlier in the cumulative PV curve.

Worked reproducibility example: recovering CACPI from first principles

To make every CACPI value in Table 4 independently reproducible, Table 3b reports, for each period, the Climate Cost Ratio (CCR_t) implied by the reported AC_climate,t alongside the day-based CDR_t used for CASPI (Section 3.10, Steps 6–7). Taking Month 8 as a worked example: PV_climate = 428.5 × 0.258 = 110.6 (BDT million), so CASPI = 282.7 / (428.5 − 110.6) = 282.7 / 317.9 = 0.89, matching Table 3. On the cost side, AC_climate = 300.5 − (282.7 / 1.11) = 45.8, giving CCR = 45.8 / 300.5 = 15.2%, materially lower than the 25.8% day-based CDR reported for the same month. This divergence between CCR and CDR is a deliberate feature of the illustrative dataset, not an inconsistency: it demonstrates numerically, on the paper's own case, the point raised in Section 3.7 and revisited in Section 4.5 that climate-affected cost share need not equal climate-affected time share and it is precisely why CACPI requires a cost-coding-based CCR rather than reusing the CDR computed for CASPI.

Table 4: Reproducibility check: Climate Cost Ratio (CCR) implied by the reported CACPI values, alongside the day-based CDR used for CASPI, for every period of the illustrative case

Month	CDR (%)	CCR (%)	AC_climate (BDT million)	CACPI
M1	0.0	0.0	0.00	1.00
M2	0.0	0.3	0.08	0.98
M3	0.0	0.0	0.00	0.96
M4	0.0	0.4	0.49	0.95
M5	0.0	0.0	0.00	0.95
M6	8.4	5.7	12.71	1.01
M7	15.6	11.3	31.39	1.07
M8	25.8	15.2	45.82	1.11
M9	26.8	18.7	71.51	1.16
M10	22.1	13.6	71.34	1.09
M11	18.8	10.3	68.91	1.05
M12	16.6	9.2	73.70	1.04
M13	15.1	8.1	72.70	1.03
M14	14.0	7.1	69.66	1.02
M15	13.2	7.1	73.19	1.02
M16	12.7	6.1	66.40	1.01
M17	12.4	6.1	68.03	1.01
M18	12.1	6.1	70.07	1.01

Small non-zero CCR values in pre-monsoon months (e.g., M2, M4) reflect ordinary rounding in the synthetic dataset rather than a climate effect and are within the tolerance expected of illustrative figures.

Table 5: Illustrative IDCI components and composite value, hypothetical 18-month case (equal weighting, w = 0.25 each).

Month	CASPI	CACPI	UBVC	DMS	IDCI
M1	1.00	1.00	0.30	0.40	0.68
M2	1.02	0.98	0.31	0.40	0.68

M3	1.01	0.96	0.33	0.40	0.67
M4	1.01	0.95	0.35	0.40	0.68
M5	1.02	0.95	0.37	0.40	0.69
M6	0.99	1.01	0.41	0.40	0.70
M7	0.96	1.07	0.45	0.60	0.77
M8	0.89	1.11	0.50	0.60	0.77
M9	0.91	1.16	0.55	0.60	0.80
M10	0.96	1.09	0.60	0.60	0.81
M11	1.01	1.05	0.65	0.60	0.83
M12	1.03	1.04	0.70	0.60	0.84
M13	1.04	1.03	0.74	0.80	0.90
M14	1.04	1.02	0.78	0.80	0.91
M15	1.03	1.02	0.80	0.80	0.91
M16	1.03	1.01	0.82	0.80	0.92
M17	1.03	1.01	0.84	0.80	0.92
M18	1.03	1.01	0.85	0.80	0.92

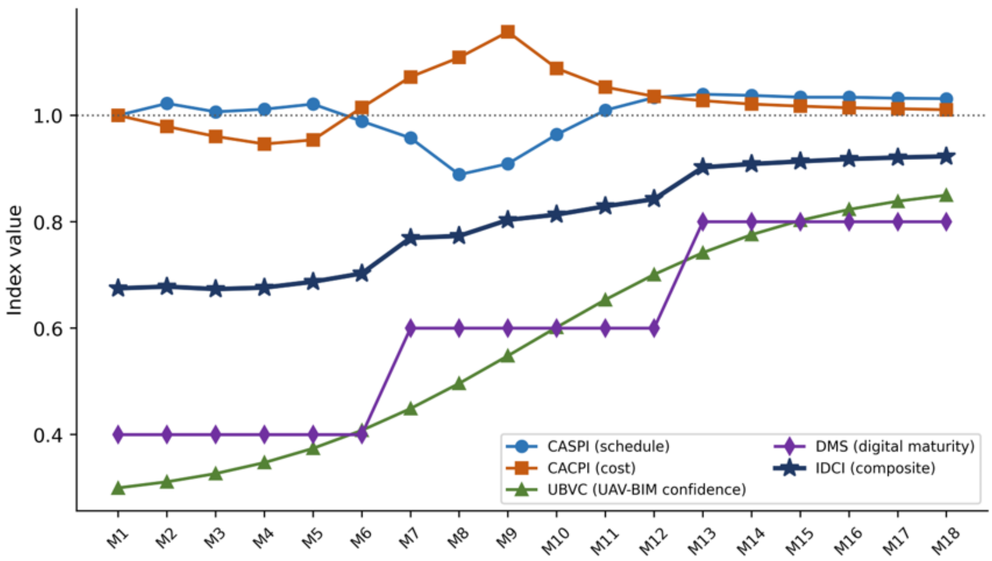

Figure 4: Illustrative Integrated Digital Construction Index (IDCI) and its four component sub-indices across the hypothetical 18-month case.

Composite IDCI Behavior

Table 4 and Figure 4 illustrate the composite index's intended behavior. CASPI and CACPI both approach or exceed 1.0 in the later months, reflecting the project team's recovery of managerially controllable schedule and cost performance once the climate-hazard window has passed. However, IDCI remains between 0.90 and 0.92 even in the final months, well short of the near-1.0 values reached by CASPI and CACPI alone, because UBVC (0.85 at Month 18) and DMS (0.80 at Month 18) never reach full maturity in this hypothetical project: roughly 15% of Earned Value is still derived from manual percentage-complete estimation rather than UAV-BIM verification, and only four of the five conceptual framework layers (Section 3.7) are operational, with the Governance layer never fully implemented. This is a deliberate feature of the composite design: IDCI rewards genuine digital-technology maturity in addition to schedule and cost performance, and a project can therefore show strong conventional EVM performance while still returning a moderate IDCI if its underlying UAV-BIM verification coverage or framework maturity is incomplete precisely the situation described for much of the Bangladeshi construction sector in the author's related survey and review work (Jany, 2026; Jany *et al.*, 2026).

The Month 12 dashboard snapshot shown earlier in Figure 1 corresponds to the values in Tables 3 and 4 at that reporting date (SPI = 0.86, CASPI = 1.03, IDCI = 0.84), illustrating how the dashboard's gauges, S-curve, and forecast panel would present this same underlying data to a project manager in real time.

Because the equal weighting adopted above is a stated default rather than a validated preference, Table 4b illustrates IDCI's sensitivity to weighting choice using the Month 18 component values (CASPI = 1.03, CACPI = 1.01, UBVC = 0.85, DMS = 0.80) under two additional, illustrative weighting schemes: a schedule-emphasis scheme reflecting a fast-track client priority, and a digital-maturity-emphasis scheme reflecting a financier's climate-risk-disclosure priority. (The AHP-elicitation route described in Section 3.7 is noted as the recommended way to derive project-specific weights but is not itself executed in this paper.) IDCI ranges from 0.88 to 0.94 across these illustrative schemes, against 0.92 under equal weighting a meaningful but not dramatic sensitivity, driven mainly by how heavily UBVC and DMS, the two sub-indices furthest from 1.0 in this illustrative case, are weighted. This confirms that weighting choice matters and should be elicited from stakeholders rather than defaulted, as Section 3.7 already recommends, while also showing that the framework's central qualitative finding that IDCI trails CASPI and CACPI while digital-technology adoption remains incomplete is not an artifact of the equal-weighting choice specifically.

Table 6: IDCI weighting sensitivity at Month 18 under three illustrative weighting schemes, holding CASPI, CACPI, UBVC, and DMS fixed at their Month 18 values.

Weighting scheme	w_S (CASPI)	w_C (CACPI)	w_V (UBVC)	w_D (DMS)	IDCI (Month 18)
Equal weighting (default, Section 3.7)	0.25	0.25	0.25	0.25	0.92
Schedule-emphasis (fast-track client)	0.40	0.20	0.20	0.20	0.94
Digital-maturity-emphasis (financier / climate-risk disclosure)	0.15	0.15	0.35	0.35	0.88

Implications for Practice

For practicing project managers in monsoon- and cyclone-exposed construction markets, the CASPI/CDR pair offers a way to report schedule performance to clients, financiers, and contractors that separates "what happened" (conventional SPI) from "what could reasonably have been controlled" (CASPI), potentially reducing disputes over excusable-delay claims and improving the fairness of contractor performance evaluation during and immediately after the monsoon season. The composite IDCI is intended to extend this further by giving executives, clients, and financiers a single top-line figure that captures not only current schedule and cost efficiency but also how much of that efficiency rests on auditable, UAV-BIM-verified data rather than subjective estimation information that is directly relevant to lenders and insurers increasingly interested in the reliability of climate-risk and progress reporting. The dashboard architecture in Section 3.8 is intended to make this composite figure, and its underlying components, visible and actionable on a routine reporting cycle rather than buried in a periodic written report.

Adopting the framework also has organizational implications that project managers should plan for explicitly. Establishing a credible climate-hazard log (Section 3.6) requires designating a responsible site role, agreeing excusable-day thresholds with the client and contractor before construction begins, and, where possible, arranging a data feed from an independent meteorological source rather than relying solely on-site diaries. Introducing UAV-BIM reconciliation as the basis for Earned Value similarly requires an initial investment in survey planning, BIM cost-loading discipline, and staff familiarity with point-cloud outputs, none of which are prerequisites for conventional, manually estimated EVM reporting. Because DMS explicitly penalizes incomplete framework adoption, organizations new to these technologies should expect a lower IDCI in early projects even where CASPI and CACPI are favorable, and should treat this as a diagnostic of digital-maturity gaps to be closed over successive projects rather than as a flaw in the metric itself.

Relationship to the Author's Related Work

The Digital Maturity Score's five-layer structure — Data Acquisition, Semantic Modeling (BIM), Integration (Digital Twin), Analytics (AI), and Governance — is proposed within this paper as part of the IDCI definition in Section 3.7; it is not drawn from a separate publication, and CASPI and CACPI operationalize its Analytics layer while UBVC operationalizes its Data Acquisition and Integration layers, as originally intended. The definition is, however, informed by two related pieces of the author's own work in the same market context: a conceptual review of UAV-integrated monitoring in Bangladeshi high-rise construction, which independently documents regulatory, economic, and organizational barriers to drone- and BIM-based digital adoption (Jany, 2026), and an empirical survey of BIM adoption in Bangladeshi urban construction (Jany *et al.*, 2026). Where that survey work characterizes current digital-technology adoption levels and barriers empirically, the present paper contributes the formal metric definitions, computational procedure (Section 3.10), and dashboard architecture that could translate measured adoption levels into a routine project-control score. Connecting DMS empirically to the adoption barriers documented in Jany (2026) and Jany *et al.* (2026) is identified as a direct next step in Section 5.

Limitations and Threats to Validity

Four limitations should be emphasized. First, and most importantly, the worked example in Section 4.1 is entirely synthetic and has not been validated against real project data; the reported CASPI, CACPI, UBVC, DMS, and IDCI values demonstrate the framework's mechanics, not its real-world accuracy, and should not be cited as evidence of actual project performance. Second, CASPI and CACPI's validity depends on rigorous, auditable governance of what counts as a climate-excusable day and cost (Section 3.6); without contractual pre-definition and independent verification, both metrics and, by extension, IDCI are vulnerable to manipulation. Third, the equal weighting used for IDCI in Section 4.2 is a default rather than a validated preference; different stakeholders may reasonably weight the four components differently, and the sensitivity of IDCI to weighting choices has not been tested empirically. Fourth, the UAV–BIM bottom-up EV derivation and the dashboard architecture in Section 3.8 assume a reasonably mature BIM model, a workable UAV survey cadence, and functioning data integration pipelines, conditions that, as discussed in Jany (2026) and Jany *et al.* (2026), are not yet universal in resource-constrained construction markets and may need to be phased in incrementally, beginning with UAV-based progress verification and a simplified dashboard before full IDCI implementation. Fifth, although Section 4.1.1 demonstrates that CACPI's climate-cost component (CCR) need not equal the day-based CDR used for CASPI, operationalizing CCR on a real project requires climate-attributable cost-coding discipline that is not yet standard practice in the reviewed literature or, to the author's knowledge, in Bangladeshi contracting practice; this is a governance prerequisite that future validation work must establish, not a problem this paper claims to have solved. Sixth, CASPI is algebraically expressible as SPI / (1 − CDR) (Section 3.5); its value lies in operationalizing and auditing this relationship through the governance procedure of Section 3.6 and the dashboard workflow of Section 3.8, not in providing information that is statistically independent of SPI and CDR, and it should be understood and evaluated as a governance and workflow contribution rather than as a new performance signal.

CONCLUSION

This paper has proposed a UAV–BIM-integrated Earned Value Management framework centered on a novel composite metric, the Integrated Digital Construction Index (IDCI), which combines a Climate-Adjusted Schedule Performance Index (CASPI), a Climate-Adjusted Cost Performance Index (CACPI), a UAV-BIM Verification Confidence score (UBVC), and a Digital Maturity Score (DMS) into a single, dashboard-ready decision metric, supported by a bottom-up, geometrically auditable method for deriving Earned Value from UAV–BIM reconciliation and a proposed real-time decision support dashboard architecture. Demonstrated through a fully hypothetical, clearly labeled illustrative case, the framework shows, on its own synthetic case, how conventional SPI can substantially understate managerially controllable schedule performance during climate-hazard periods, and illustrates how CASPI and CACPI are intended to provide a fairer complement to conventional EVM reporting in monsoon- and cyclone-exposed construction markets such as Bangladesh, and how IDCI is intended to surface the maturity gap between a project's raw performance and its underlying digital-technology adoption. These are presented as hypotheses that the illustrative case demonstrates mathematically, not as findings this paper has established empirically; Section 4.5 discusses the conditions, including governance discipline for excusable-day and climate-cost-code determinations, under which each hypothesis would need to hold on a real project.

The priority for future research is empirical validation: applying the proposed data architecture, metric set, and dashboard to one or more real, instrumented construction projects with actual UAV survey data, a cost-loaded BIM model, a verified climate-hazard log, and a working data-integration pipeline, and comparing IDCI-based performance assessment against conventional SPI/CPI and against independent contractor performance evaluations. Further work should also examine appropriate excusable-day thresholds and climate-attributable cost-coding conventions for Bangladeshi contractual practice, extend the weighting sensitivity illustrated in Section 4.2 using Analytic-Hierarchy-Process-elicited, stakeholder-specific weights on real project data, empirically test whether CASPI's governance and workflow benefits over manually computed SPI/(1 − CDR) materialize in practice, pilot the dashboard architecture as a working software prototype, and explore extending the same decomposition logic to additional sub-indices such as a safety- or quality-adjusted performance component, building on the adoption-barrier findings of Jany (2026) and Jany *et al.* (2026).

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Conflict of Interest: The author declares no conflict of interest.

Data Availability: The illustrative dataset used in Section 4.1 is entirely synthetic and was generated by the author for demonstration purposes; it is available from the author on request and does not represent any real project.

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