

A MINIMAL-DATA TOOLKIT FOR DIAGNOSING LOSS OF FLOW RESILIENCE IN INTERIOR FIT-OUT WORK

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ABSTRACT

This paper proposes and empirically tests a minimal flow performance measurement toolkit for construction fit-out works, designed to characterise flow stability, continuity, and vulnerability to schedule disruption using only routinely collected progress observations. The toolkit operates across activity, trade, and location-levels, requiring no detailed plans or bespoke data capture infrastructure. Drawing on lean construction flow theory and empirical evidence linking variability, discontinuity, and performance loss, the framework generates interpretable diagnostics available during project execution. A case study of interior fit-out works across 11 floors, 111 apartments, 21 activities, and 4 trades were selected. Weekly activity progress was captured using visual data analysed with computer vision. Results demonstrate that similar mean outputs can mask radically different flow patterns. Large schedule slippage is associated with extreme flow instability signatures rather than any single metric. The contribution is a standardisable, empirically grounded diagnostic toolkit that lowers the data and tooling barrier for flow-based performance assessment, supporting managerial sensemaking and early intervention rather than prediction.

KEYWORDS

Flow, waste, production variability, Location-Based Management (LBM), Work in Progress/process (WIP).

INTRODUCTION

Construction productivity remains stubbornly flat despite advances in technology, planning methods, and process improvement initiatives (Barbosa et al., 2017). Within the Transformation-Flow-Value (TFV) framework (Koskela et al., 2007), production control requires attention to transformation efficiency, flow stability, and value generation. Yet lean construction metrics predominantly measure plan reliability rather than flow stability, while practice remains weighted toward transformation metrics such as percent complete and

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schedule variance. Flow metrics are applied inconsistently and often retrospectively (Sacks et al., 2017; Asmone et al., 2025).

Interior fit-out and repetitive location-based construction offer conditions conducive to flow-based control: recurring activities, spatial structure, and trade sequencing. Empirical research has demonstrated strong associations between production rate variability, work discontinuity, excess work in progress, and both productivity loss and schedule delay (Arashpour & Arashpour, 2015; Rathnayake et al., 2023). Takt production and flowline approaches provide structured methods to stabilise work across trades and locations, and recent studies propose takt-specific indicators such as flow efficiency and punctuality (Lehtovaara et al., 2021; Riekkilä et al., 2024). However, these approaches often rely on detailed takt plans and bespoke data capture.

Current progress monitoring, whether manual or digitally enhanced, generates temporal sequences of marginal progress observations. Computer vision has proven to be an approach to reconstruct detailed flow information (Asmone et al., 2024). However, these approaches often require bespoke technology solutions, training data for computer vision, and integration infrastructure, limiting transferability to projects without such capabilities. A recent systematic review of IGLC papers (2013 to 2024) found that only a small fraction explicitly measures performance improvement, with dozens of metrics used inconsistently, limiting benchmarking and operational uptake (Asmone et al., 2025).

This paper therefore asks what flow performance diagnostics can be derived from minimal, temporally ordered progress observations to characterise flow stability, continuity, and vulnerability to schedule disruption during fit-out execution; without requiring detailed activity-level plans, cost data, or bespoke data infrastructure? The contribution is a standardisable, empirically grounded diagnostic toolkit, rather than a new flow theory, predictive model, or composite index.

LITERATURE REVIEW

The TFBV theory of production conceptualises construction as a system requiring simultaneous attention to transformation efficiency, flow stability, and value generation. Flow is characterised by the movement of materials and work through space and time, with waste manifesting as waiting, interruptions, variability, and rework (Koskela et al., 2007). Ballard and Howell (1994) argue that production control in construction must move beyond activity-centric scheduling to embrace flow-centric logic, making visible the continuity, rate stability, and handover reliability across trades and locations.

Location-based production and takt planning operationalise flow principles by structuring work around spatial units and standardised work cycles (Frandsen et al., 2013). Studies such as Lehtovaara et al. (2021) provide a theoretical basis for how takt-based approaches can reduce variability and improve predictability. However, takt planning requires upfront design effort, stable scopes, and organisational commitment (Frandsen et al., 2015).

Variability in production rates is strongly associated with productivity loss. Hopp and Spearman (2011) demonstrate that the coefficient of variation (CV) of processing times is a critical determinant of queue lengths, cycle times, and system progress in queueing systems. In construction, empirical research confirms these relationships: Arashpour and Arashpour (2015) show that work discontinuity and rate variability in multi-storey residential construction are associated with reduced productivity and extended project duration. Sacks et al. (2017) propose the Construction Flow Index (CFI), which aggregates work continuity, pace uniformity, and location handover to produce a composite flow score, demonstrating correlation with overall project performance.

Rathnayake et al. (2023) analyse daily progress data from residential projects and find that high variability in daily production rates, combined with idle streaks, predicts schedule delay.

Simulation can help demonstrate how variability propagates through coupled production systems, amplifying disruption. These studies establish that flow instability is not merely a symptom of delay but a structural vulnerability that precedes observable schedule slippage.

Recent work proposes takt-specific flow indicators. Riecki et al. (2024) define takt flow efficiency and takt punctuality as metrics for assessing adherence to takt plans, demonstrating their use in multi-storey residential projects. These indicators require baseline takt plans and assume stable trade sequencing. Barth and Formoso (2024) propose production control dashboards integrating percentage of planned activities completed (PPC), constraint analysis, and flow indicators. However, these dashboards rely on weekly planning commitments and require structured Last Planner System implementation. Binnering et al. (2017) further developed takt time planning concepts, proposing cycle time optimisation and buffer management as key levers for stabilising flow in repetitive construction; approaches that, like takt indicators, presuppose structured scheduling environments.

In their review of the lean construction literature on performance improvement, Asmone et al. (2025) called for standardisable, interpretable, and minimal metrics suitable for routine application. The literature establishes that flow variability, discontinuity, and work-in-progress instability are empirically linked to productivity loss and schedule delay. Yet, there is no empirically tested, generic flow performance toolkit that requires only simple and readily available data, which makes visible the loss of flow robustness during fit-out work execution. Unlike the CFI (Sacks et al., 2017), which aggregates dimensions into a single composite score, or takt-specific indicators (Riecki et al., 2024; Binnering et al., 2017), which require structured takt plans, a gap therefore exists for toolkits to retain disaggregated metrics and operate without baseline plans, enabling use in contexts where such planning infrastructure is absent.

METHODOLOGY

The aim of this paper is to propose and empirically test a minimal flow performance measurement toolkit for construction fit-out works, designed to characterise flow stability, continuity, and vulnerability to schedule disruption using only routinely collected progress observations. The toolkit does not aim to predict delay but to reveal structural flow fragility during execution, reveal robust from recovery-driven flow patterns, and provide interpretable leading diagnostics (see Figure 1 for a graphical representation of the proposed toolkit).

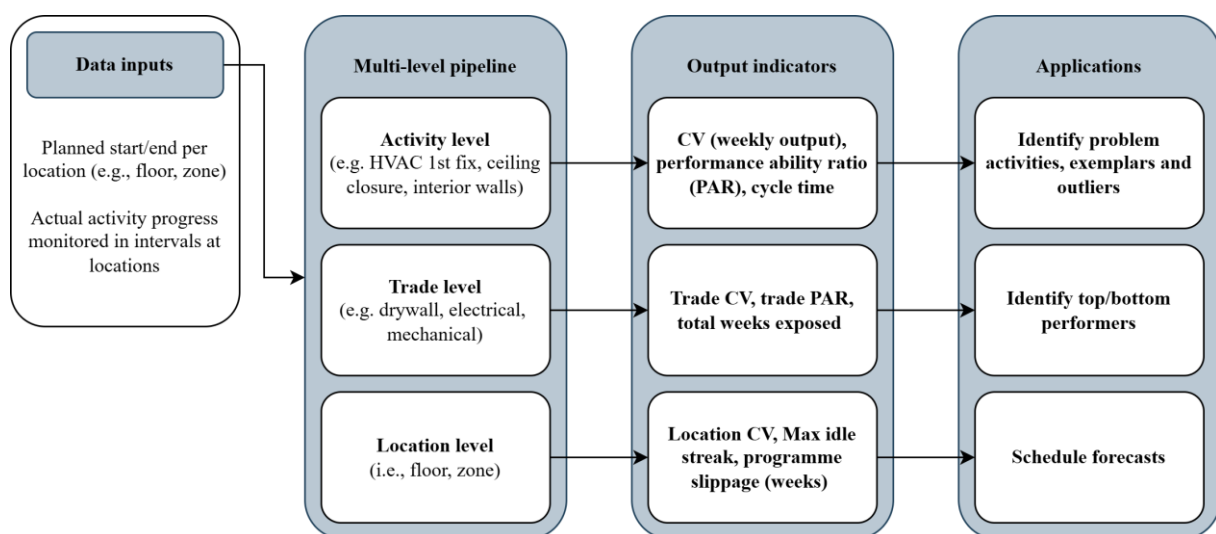


Figure 1: Proposed minimal-data toolkit for diagnosing flow resilience

The case study is the interior fit-out work at a multi-storey residential building in the UK. Weekly observational records captured weekly (extracted from site photographs using

computer vision) are used to compute marginal progress per each activity over time (expanded from the works of Asmone et al. (2024)). Programme data for the fit-out work package per each level was used to derive planned duration per level. No effort weights or cost data were available. Therefore, the current implementation assumes equal weights for all activities. In practice, activities vary in scope, cost, and effort. A 10 percent progress increment on a high-cost, high-effort activity contributes more to overall completion than the same increment on a low-cost, low-effort activity. Effort-weighted aggregation, aligned with earned value concepts, would improve interpretability.

The proposed framework is a multi-level analytical structure that computes flow-based metrics at three nested scales: activity, trade, and location. The framework is an expansion of the framework proposed by Rathnayake et al. (2024). At the activity level, it captures micro-level production stability through week-to-week output variability. Aggregation at the trade level reveals coordination effects by consolidating activity behaviour across trades, highlighting how interdependencies and sequencing influence flow reliability. At the location level, metrics assess delivery performance by comparing planned and observed work progression. Although the same core metrics are used at each scale, they are interpreted according to analytical intent and are employed strictly as descriptive diagnostics, not for prediction or optimisation.

Figure 2 illustrates how activity- and process-level flow are represented within the framework. It shows planned production for demising walls in a single location alongside a line-of-balance plot of actual progress from weekly observations, where deviations reveal interruptions, uneven production, and inactivity underlying high variability. The toolkit quantifies these visually observed disruptions, enabling systematic diagnosis of stability and coordination issues across scales.

The framework was applied to a fit-out scope across 11 floors, and 21 distinct recurring activities carried out by 4 subcontractors (trades). Planned durations for each level ranged from 20 to 35 weeks. Weekly progress observations were extracted from site photographs using a computer vision pipeline trained to detect activity completion states from images captured at fixed intervals; outputs were manually validated before analysis. Results are presented across three levels of analysis: activity, trade, and location.

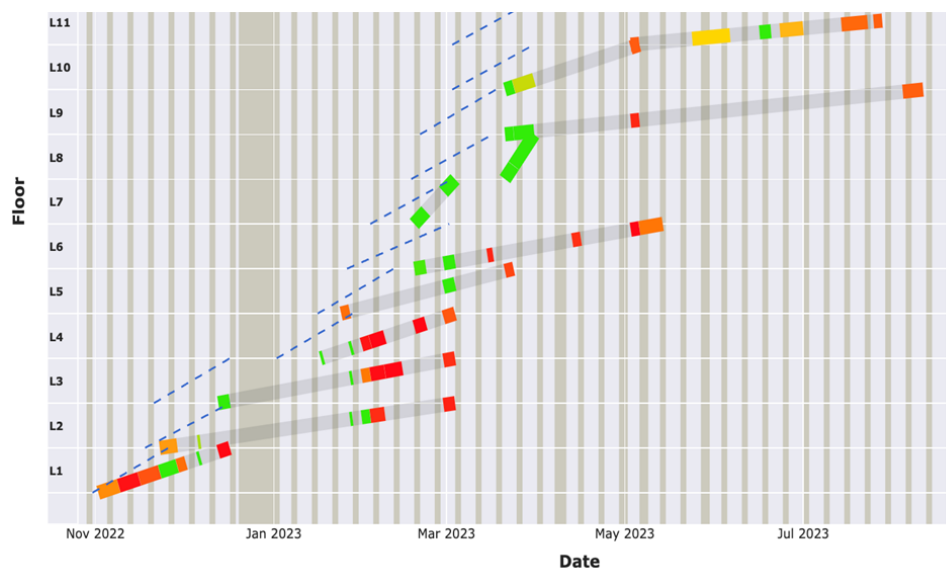


Figure 2: Flowline for a single activity (demising walls) in a single location (line of balances shows actual progress as derived from weekly observations)

Metrics are computed at three nested levels. The unit of analysis at the activity level is a single activity at sub-location (e.g., demising walls at Level 4, Apartment 4); trade-level metrics

aggregate across activities per (level, trade); and location-level metrics aggregate across all trades per level. Table 1 defines the metrics at each level.

Table 1: Flow diagnostic metrics by analytical level

Metric	Definition	Activity	Trade	Location
Mean weekly output	Average marginal progress per week	✓	✓	✓
CV of weekly output	Standard deviation divided by mean	✓	✓	✓
Active weeks ratio	Proportion of weeks with observed progress > 0	✓	—	✓
Observed cycle time / duration	Total weeks from first to last observation	✓	—	✓
Performance Ability Ratio (PAR)	Exemplar median output / current median output (Alfeld, 1988); PAR > 1 indicates below-exemplar performance; exemplar is the best observed median for the same activity/trade elsewhere in the dataset	✓	✓	—
Maximum idle streak	Longest consecutive period without observed progress (weeks)	—	—	✓
Planned duration	Derived from planned start and end dates	—	—	✓
Schedule slippage	Observed duration minus planned duration (weeks)	—	—	✓

At the trade level, weekly progress is aggregated across activities within each (Level, Trade) combination, reflecting coordination effectiveness. At the location level, progress aggregates across all trades. The current implementation uses equal weights for all activities during aggregation. This assumes that all activities contribute equally to overall progress. In practice, activities vary in scope, cost, and effort. Effort-weighted aggregation, aligned with earned value concepts ($EV = \text{percent complete} \times \text{budget}$), would improve interpretability by reflecting true contribution to project completion (Kim & Ballard, 2004). However, effort weights were not available in the case study dataset. This limitation is acknowledged and addressed in the discussion. Analysis focuses on association and differentiation rather than causal inference. Furthermore, the toolkit does not impose control limits or thresholds. Instead, it supports sensemaking by making the structure of flow instability visible. It is noted that the framework draws on location-based aggregation logic; where a takt planning structure exists, the equal weighting assumption becomes more defensible provided work packages are normalised to comparable base units over a large dataset.

RESULTS

ACTIVITY-LEVEL FINDINGS

Activity-level metrics reveal substantial variation in flow stability across work types. Activities associated with enclosure and internal partitioning exhibit severe stop-start behaviour, characterised by high coefficients of variation exceeding 3.0, active weeks ratios below 0.2, and extended observed cycle times. In contrast, finishing activities such as ceiling installation demonstrate more stable flow, with lower CV values between 0.9 and 1.2, active weeks ratios above 0.6, and correspondingly shorter cycle times. Performance Ability Ratio (PAR) values expose large gaps between exemplar and typical performance for certain activities, with some exhibiting PAR values of 2.4 or higher, indicating performance less than half that of best observed practice. Critically, activities with similar mean weekly outputs can exhibit radically different flow characteristics, illustrating that instability is not solely a function of mean production rate but reflects deeper issues of continuity and coordination.

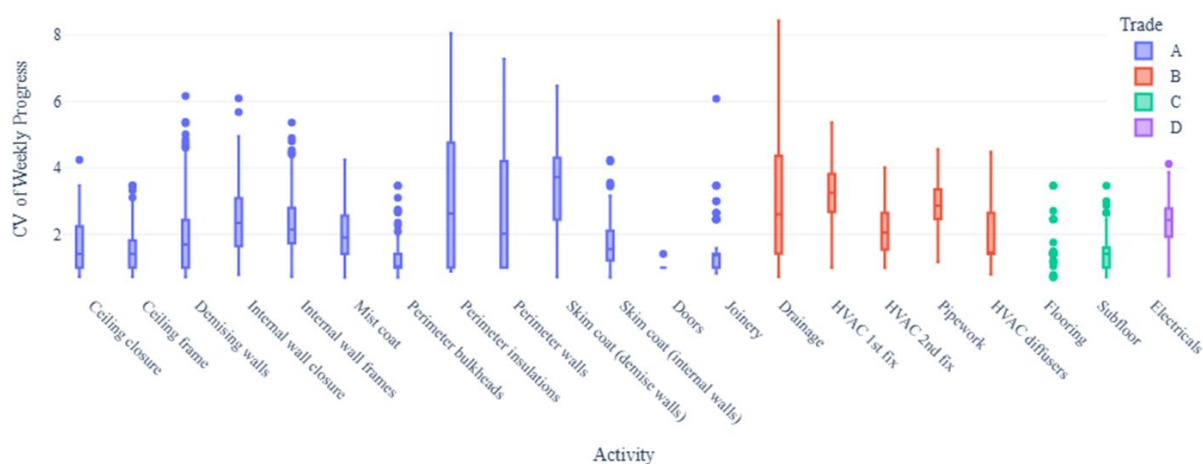


Figure 3: Variability of CV of weekly progress across all activities in all locations

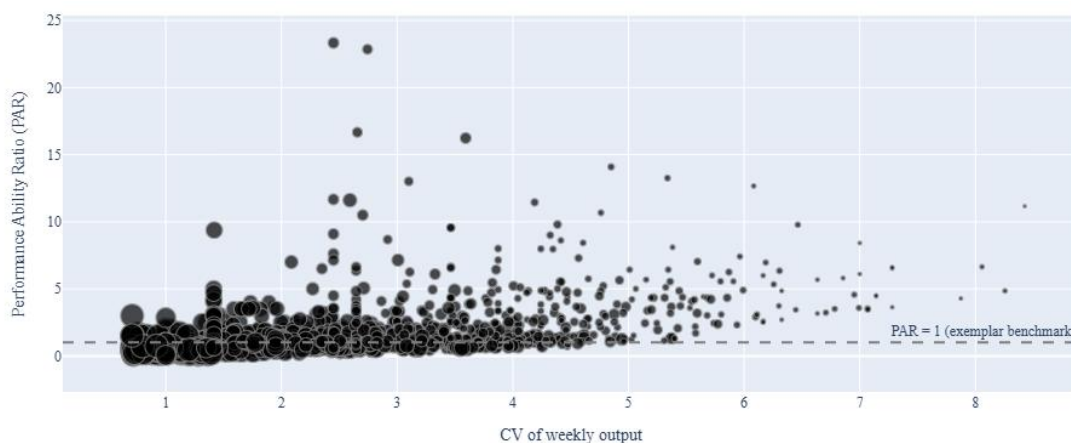


Figure 4: Activity-level flow instability against performance variability (size of dot indicates continuity of work (active weeks ratio)) (for demising walls activity)

Figure 3 presents the distribution of CV values across activities grouped by trade. Trade A activities exhibit a widespread: ceiling-related work clusters at lower CVs, suggesting stable production, while demising walls and internal partitioning show much higher medians and long upper tails, typically pointing to dependency-heavy work with handoffs, inspections, or access constraints. Trade B activities generally sit at moderate to high CVs, especially drainage and

HVAC tasks, likely driven by coordination issues and system-level sequencing. Trades C and D appear more compact, indicating more repeatable work. The distribution suggests that the largest opportunity to improve flow lies in targeting high-CV activities, especially enclosure and MEP interfaces, where removing constraints will yield the largest stability gains. It is noted that the number of observations per trade is unequal, reflecting differences in scope across subcontractors. Figure 4 is another visual representation which demonstrates that similar PAR values can mask fundamentally different production behaviours when viewed alongside CV and active weeks ratio. Activities such as demising walls combine high PAR with high variability and low continuity, indicating bursty, constraint-driven production rather than capacity shortfall. In contrast, comparable PAR with lower variability reflects steadier but subdued output. This highlights that PAR alone is an insufficient diagnostic. Interpreted in isolation, it conflates capacity shortfall with coordination failure. However, jointly with CV and active weeks ratio, PAR enables differentiation between these two distinct causes of performance gap, supporting more targeted managerial response.

TRADE-LEVEL FINDINGS

Trade-level metrics reveal coordination effects and sequencing dynamics. Certain trades operate close to exemplar performance with moderate variability, indicating stable, efficient flow. Others exhibit inflated PAR values alongside high CV, indicating bursty output and sparse activity. This pattern illustrates why PAR must be interpreted alongside variability: a high PAR could reflect either consistently low output or erratic output with long idle periods. Some trades demonstrate that stable flow is achievable even under coordination constraints, provided continuity is maintained, with CV values near 1.1 and PAR close to 1.0 despite operating in a multi-trade environment.

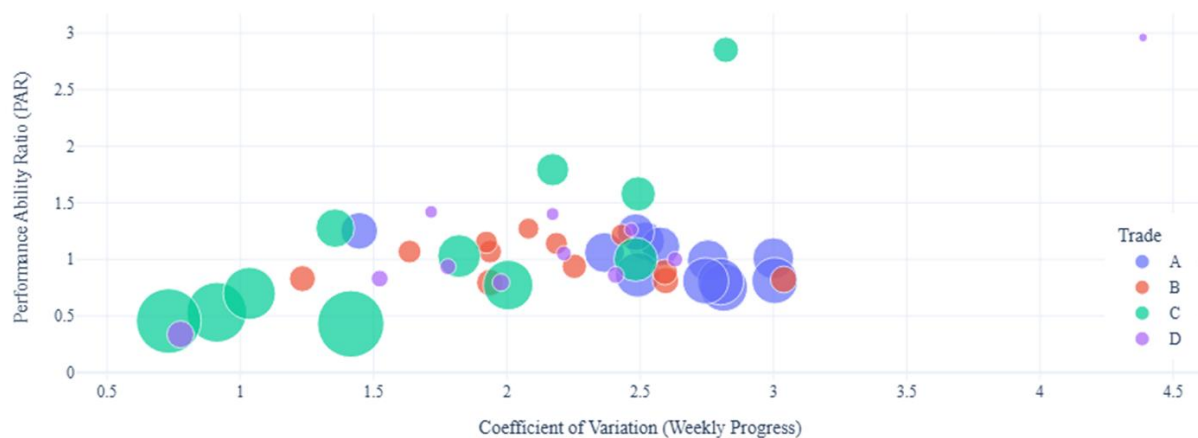


Figure 5: Trade-level productivity variability and performance (size of dot indicates mean weekly progress of each trade)

Figure 5 relates trade-level productivity variability (CV of weekly output) to delivery performance (PAR), with point colour denoting trade and point size reflecting the mean progress over observations. Across all trades, there is no strong positive relationship between variability and performance. Instead, many observations cluster around PAR values of 0.7 to 1.2 across a wide range of CV values, suggesting that higher variability does not reliably translate into better delivery outcomes. Trade A exhibits consistently high CVs of 2.5 to 3.0 paired with PAR values close to or below 1.0, indicating trades that meet plan on average but do so through uneven, bursty production rather than stable flow. Performance is achieved, but at the cost of predictability. Trade B occupies a narrower CV range with PAR values tightly clustered around unity, indicating comparatively better alignment between planned and achieved output with moderate variability. Trade C shows the widest spread in PAR for a given

CV: some observations achieve high PAR at moderate CV levels, while others perform poorly despite low variability, suggesting that performance is more sensitive to local enabling conditions and sequencing than to variability alone. Trade D includes outliers with extremely high CV and high PAR, likely representing recovery behaviour or compressed execution following late access. Overall, the figure demonstrates that flow stability and delivery performance are distinct dimensions. High PAR can be achieved under unstable conditions, but doing so reflects compensatory behaviour rather than system health. The diagnostic value of the framework therefore lies in interpreting CV and PAR jointly, identifying trades that achieve targets while exhibiting high variability, and thus represent hidden coordination risk within the production system.

LOCATION-LEVEL FINDINGS

Location-level metrics aggregate trade-level behaviour to reveal delivery performance across spatial units. Levels with large schedule slippage of 15 to 19 weeks are consistently associated with high CV values of 2.8 to 3.2, low active weeks ratios of 0.38 to 0.42, and long idle streaks of 8 to 9 weeks. In contrast, levels completed on time or with minimal delay of 1 to 4 weeks exhibit moderate to low CV values of 0.8 to 1.3, high active weeks ratios of 0.69 to 0.81, and short idle streaks of 2 to 4 weeks.

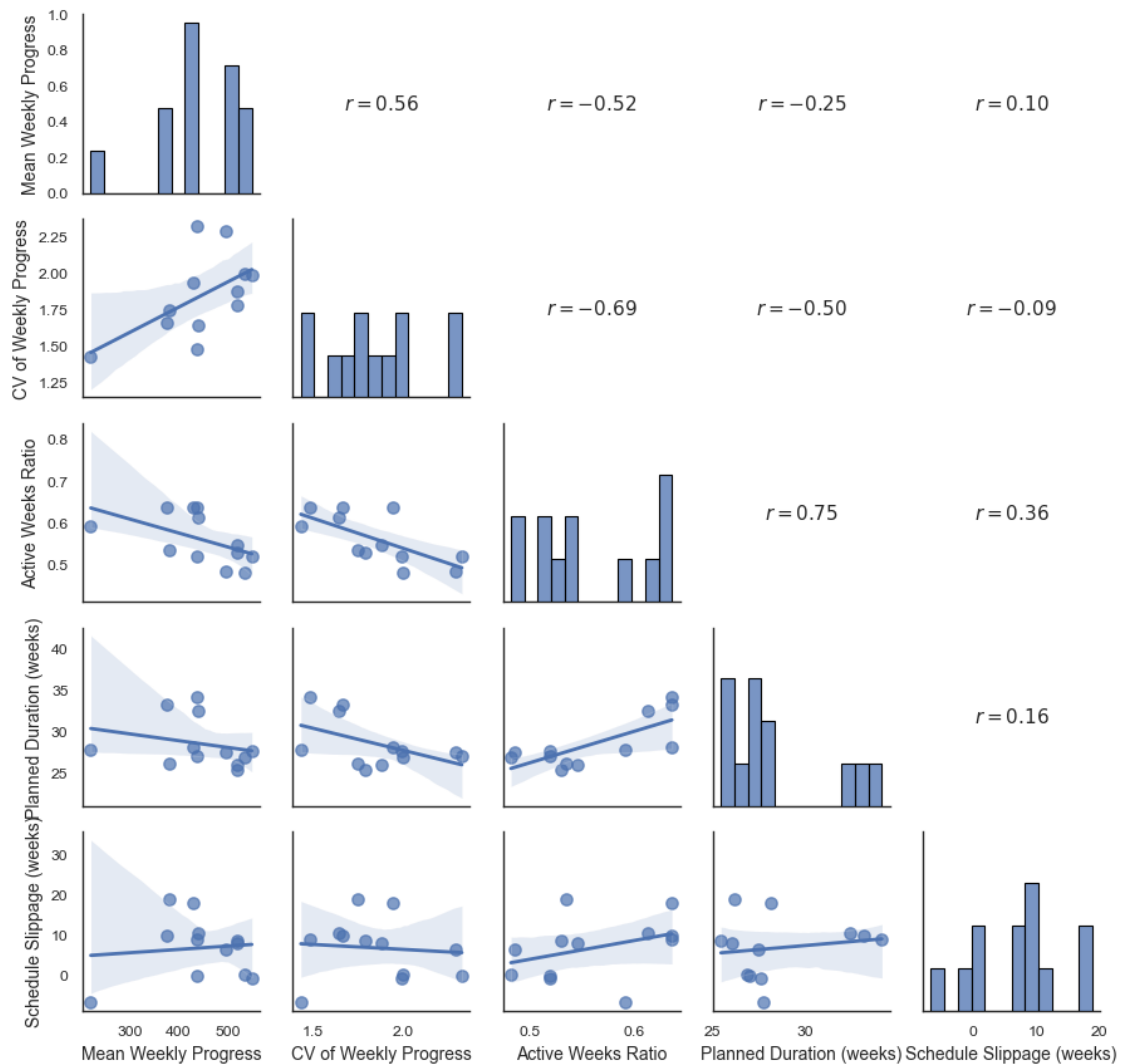


Figure 6: Relationships between the progress, CV, continuity, planned duration and schedule slippage

Critically, mean weekly progress remains relatively consistent across levels, ranging from 45.8 to 54.1, yet schedule slippage varies dramatically from 1 to 19 weeks. This demonstrates that mean output alone is insufficient to characterise delivery performance: flow continuity and stability are critical determinants of schedule adherence. Maximum idle streak appears to be a particularly strong discriminator, with levels experiencing idle streaks exceeding 7 weeks all suffering slippage exceeding 15 weeks.

Figure 6 presents pairwise relationships between mean weekly progress, CV, active weeks ratio, planned duration, and schedule slippage, revealing how these metrics interact to shape delivery outcomes. Mean weekly progress is moderately positively correlated with CV ($r = 0.56$), indicating that higher average progress is associated with more week-to-week fluctuation, and negatively correlated with active weeks ratio ($r = -0.52$), suggesting that faster progress occurs over a smaller fraction of the timeline. Critically, mean weekly progress shows almost no relationship with schedule slippage ($r = 0.10$), reinforcing that average output does not predict delivery performance. CV is strongly negatively correlated with active weeks ratio ($r = -0.69$), indicating that erratic progress is associated with discontinuous work, yet CV alone shows negligible correlation with schedule slippage ($r = -0.09$). The strongest relationship is between active weeks ratio and planned duration ($r = 0.75$), suggesting that longer projects maintain more consistent activity. Active weeks ratio exhibits a modest positive association with schedule slippage ($r = 0.36$), though the effect is not strong.

The CV versus schedule slippage scatterplot within Figure 6, when examined alongside the other pairwise relationships, reveals that levels with extreme slippage exhibit combinations of high CV, low active weeks ratio, and long idle streaks, forming a distinct failure mode characterised by severe flow instability. Levels with minimal slippage occupy regions of moderate CV and high continuity, demonstrating that stable flow, not high average output, underpins schedule adherence. No single metric predicts delivery outcomes reliably: slippage emerges from multi-dimensional flow fragility signatures rather than any isolated factor. This finding supports the core argument that flow diagnostics must be interpreted jointly to distinguish robust delivery from recovery-driven delivery, and to reveal vulnerabilities before they manifest as schedule delay.

DISCUSSION

The results demonstrate that CV, active weeks ratio, and maximum idle streak behave as leading indicators of schedule slippage. Locations exhibiting extreme flow instability (i.e., high CV, low continuity, long idle streaks) experienced slippage of 16 to 19 weeks, while locations with stable flow completed on or near schedule despite similar mean weekly progress. These signatures were observable during execution, not merely in retrospect. This aligns with empirical research linking variability and discontinuity to productivity loss and delay (Arashpour & Arashpour, 2015; Rathnayake et al., 2023), but the contribution here is diagnostic visibility rather than prediction, viz. the toolkit makes visible the structure of flow fragility, enabling managerial intervention during execution.

The case study reveals two distinct flow patterns. Robust delivery is characterised by moderate to low CV, high active weeks ratios, and short idle streaks, with progress accumulating steadily. Recovery-driven delivery exhibits high CV, low active weeks ratios, and long idle streaks, with progress accumulating erratically through bursts following extended idle periods. Mean weekly progress is similar across both flow patterns, yet schedule outcomes differ dramatically, demonstrating that reliance on mean output or percent complete obscures critical vulnerabilities. Flow-based diagnostics reveal whether progress is achieved through stable effort or reactive recovery bursts. High CV indicates erratic output associated with increased cycle time (Hopp and Spearman, 2011). This suggests incomplete handovers, rework, or coordination failures. Low active weeks ratio indicates discontinuous work, reflecting

planning failures, resource unavailability, or dependency blocking. Long idle streaks amplify these effects through mobilisation delays and coordination overhead (Sacks et al., 2017). The toolkit does not diagnose root causes but makes symptoms visible, enabling investigation of constraints, subcontractor availability, material shortages, or design changes. PAR provides a useful relative performance benchmark derived from observed data, contextualising performance without requiring cost data or detailed plans. However, PAR must be interpreted alongside CV and active weeks ratio. $PAR = 2.0$ with $CV = 0.5$ indicates consistent low output, suggesting resource insufficiency. $PAR = 2.0$ with $CV = 4.0$ indicates erratic output, suggesting coordination failures. The activity and trade-level findings demonstrate this empirically: activities with similar PAR values exhibited fundamentally different production structures.

The proposed toolkit diverges from existing approaches by design. Composite indices such as the Construction Flow Index (Sacks et al., 2017) aggregate dimensions into a single score, limiting interpretability. The toolkit retains disaggregated metrics to support diagnosis. Takt-specific indicators (Riekkilä et al., 2024) require detailed takt plans, whereas the toolkit operates without such plans. Earned schedule metrics require cost data and baselines, which were unavailable. While the toolkit includes multiple metrics, calculations can be automated and code could be open-sourced, enabling routine application. The toolkit requires less planning data and fewer assumptions than existing metrics while providing during-execution visibility and high interpretability.

The proposed toolkit aligns with lean control principles by making visible flow stability, continuity, and constraint violations. Weekly planning teams using the Last Planner System (Ballard & Howell, 2003) could integrate these diagnostics to identify flow fragility, investigate root causes, and adjust resource allocation. Digital progress monitoring technologies (Pal et al., 2024; Wang et al., 2024) can automate marginal progress observation, feeding the same framework without changing the logic. This transferability supports operational uptake: projects can start with manual tracking and transition to automated capture without changing the analytical approach. The primary intended user group is site management teams engaged in weekly production control, such as those operating the Last Planner System. Weekly granularity aligns with look-ahead planning cycles rather than daily operational decision-making; for daily interventions, higher-frequency data capture would be required. Asmone et al. (2025) identify fragmentation and lack of standardisation as critical barriers to benchmarking and uptake. This toolkit addresses this by using minimal, routinely available data, operating without detailed plans or cost data, providing interpretable diagnostics, and supporting during-execution visibility. By lowering the data and tooling barrier, the toolkit offers a foundation for standardisable, empirically grounded flow-based performance measurement in construction.

CONCLUSIONS AND FUTURE WORK

This paper proposes and empirically tests a minimal flow performance measurement toolkit for construction fit-out works, designed to characterise flow stability, continuity, and vulnerability to schedule disruption using only routinely collected marginal progress observations. The toolkit operates across activity, trade, and location levels, requiring no detailed activity-level plans, and produces interpretable diagnostics available during project execution. When applied to a case study, the toolkit demonstrated that similar mean outputs can mask radically different flow patterns. Large schedule slippage is associated with extreme flow instability signatures (high CV, low active weeks ratio, long idle streaks) rather than any single metric. Conversely, levels completed on time exhibit stable flow despite moderate variability, highlighting the role of continuity rather than mean output alone. The contribution is an empirically grounded diagnostic toolkit with potential for standardisation, demonstrated here through a single case study requiring validation across multiple project types and contexts that lowers the data and tooling barrier for flow-based performance assessment, supporting managerial sensemaking

and early intervention rather than prediction. The toolkit aligns with lean construction flow theory, is compatible with earned value logic through effort weighting, and is transferable across manual and automated progress monitoring approaches.

The study has several limitations. First, no effort weights were available, so all activities are equally weighted, limiting comparability across activities of varying scope. Second, the toolkit reveals symptoms of flow fragility but does not diagnose root causes. Third, the case study is limited to a single residential fit-out project in the UK; and thus requires future empirical testing towards standardising. Fourth, no prediction model is proposed; the toolkit provides diagnostics, not forecasts. We suggest future research stemming from this study should validate across multiple projects, incorporate effort weighting for different activities leveraging on other available data (e.g., historical cost ratios, activity durations) to align metrics with earned value concepts, and develop predictive models that use flow diagnostics (CV, active weeks ratio, idle streak) as inputs to forecast schedule slippage probability and magnitude. Furthermore, this paper paves the way to demonstrate integration with automated progress capture (computer vision, sensor-based tracking) to enable real-time flow diagnostics. It also facilitates an easier approach to cross-project benchmarking by accumulating flow diagnostic data, supporting evidence-based target setting. The proposed toolkit offers a foundation for standardisable, low-barrier flow-based performance measurement in construction. Its value lies not in prediction or optimisation but in making visible the structure of flow fragility, enabling managers to act before delay becomes inevitable.

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