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## ОПЕРАЦІОНАЛІЗАЦІЯ ОРГАНІЗАЦІЙНОЇ АДАПТАЦІЇ В МОДЕЛІ DEAM: ПОДІЄВИЙ ПРОТОКОЛ ВИМІРЮВАННЯ В УМОВАХ ВИКОРИСТАННЯ ШІ

**Олег Лукутін<sup>1</sup>, Сергій Мічківський<sup>2</sup>**

<sup>1</sup>Старший викладач, Університет економіки та права «КРОК», Київ, Україна, e-mail: oleglv@krok.edu.ua, ORCID: <https://orcid.org/0000-0001-6142-2264>

<sup>2</sup>Канд. екон. наук, доцент, завідувач кафедри комп'ютерних наук, директор Навчально-наукового інституту інформаційних та комунікаційних технологій, Університет економіки та права «КРОК», Київ, Україна, e-mail: michkivskyysm@krok.edu.ua, ORCID <https://orcid.org/0000-0002-9343-2317>

## OPERATIONALIZING ORGANIZATIONAL ADAPTATION IN DEAM: AN EVENT-LEVEL MEASUREMENT PROTOCOL FOR AI-AUGMENTED SOFTWARE DELIVERY

**Oleh Lukutin<sup>1</sup>, Sergiy Michkivskyi<sup>2</sup>**

<sup>1</sup>Senior Lecturer, KROK University, Kyiv, Ukraine, e-mail: oleglv@krok.edu.ua, ORCID: <https://orcid.org/0000-0001-6142-2264>

<sup>2</sup>PhD of Economic Sciences, Associate Professor, Head of the Department of Computer Science, Director of the Educational and Research Institute of Information and Communication Technologies, KROK University, Kyiv, Ukraine, e-mail: michkivskyysm@krok.edu.ua, ORCID <https://orcid.org/0000-0002-9343-2317>

**Анотація.** Інтеграція штучного інтелекту в розробку програмного забезпечення збільшує використання AI-інструментів, кількість операційних сигналів і швидкість зворотного зв'язку, але технологічне впровадження саме по собі не доводить організаційну адаптацію. Попередні дослідження Data-Empirical Agility Model (DEAM) концептуалізували латентність адаптації як часовий розрив між операційним сигналом та узгодженою організаційною реакцією, однак не визначили відтворюваного подієвого протоколу вимірювання. Об'єктом дослідження є організаційна адаптація в багатокмандній розробці програмного забезпечення з використанням ШІ. Мета дослідження — розробити контекстно-специфічний протокол вимірювання інтервалу від кваліфікованого тригера до сталої організаційної реконфігурації та визначити умови його подальшої емпіричної перевірки. Методологія поєднує аналіз конструктів і попередніх досліджень, подієву операціоналізацію, ретроспективне калібрування на лонгitudному кейсі п'яти Scrum-команд і проєктування проспективної валідації. Протокол описує епізод адаптації через  $T_0$ – $T_4$ : кваліфікований тригер, розпізнавання потреби в реакції, зобов'язання щодо відповіді, початок імплементації та сталу організаційну реконфігурацію.  $T_4$  фіксується лише за одночасного виконання п'яти умов: спостережуваної зміни, фактичного застосування, стійкості, простежуваного походження доказів та незалежності від подальших результатів діяльності. На цій основі дослідження операціоналізує часовий показник  $L_{04}=T_4-T_0$  як кандидатну міру, а не як валідований новий конструкт. Для подальшої оцінки визначено вимоги до міжекспертної надійності, стійкості критерію  $T_4$ , дискримінантної, часової та інкрементної валідності. Ретроспективне застосування протоколу до одного епізоду організаційної адаптації у п'ятикомандному кейсі демонструє практичне розмежування початкового тригера, локального пілотування, зобов'язання щодо масштабованої реакції, початку її реалізації та сталої зміни організаційної практики. Для цього епізоду інтервал від приблизно датованого  $T_0$  до  $T_4$  становив близько 184 днів, водночас межа  $T_1$  мала нижчу часову точність через ретроспективний характер доказів. Наведений приклад ілюструє застосування протоколу, але не є емпіричною валідацією  $L_{04}$  і не підтверджує його причинного впливу на результати розробки та постачання програмного забезпечення. Практична цінність запропонованого підходу полягає у створенні структури для проспективного збору даних, яка розділяє AI-експозицію, організаційну реакцію, сталу реконфігурацію та подальші результати. Майбутня емпірична перевірка може підтвердити, уточнити або відхилити запропоновану операціоналізацію.

**Ключові слова:** організаційна адаптація; штучний інтелект; Data-Empirical Agility Model; DEAM; час адаптації; організаційна реконфігурація; динамічні здібності; розробка програмного забезпечення; Agile; вимірювання.

**Формул: 10; Рис.: 1; Табл.: 3; Бібл.: 21**

**Abstract.** *The growing integration of artificial intelligence into software delivery increases AI-tool usage, operational signals, and feedback speed, but technological adoption alone does not establish organizational adaptation. Previous research on the Data-Empirical Agility Model (DEAM) conceptualized adaptation latency as the temporal gap between an operational signal and coordinated organizational response but did not provide a reproducible event-level measurement protocol. The object of the study is organizational adaptation in AI-augmented multi-team software delivery. The study aims to develop a context-specific protocol for measuring the interval from a qualifying trigger to durable organizational reconfiguration and to specify the conditions required for its subsequent empirical evaluation. The methodology combines construct and prior-art analysis, event-level operationalization, retrospective calibration using a longitudinal five-Scrum-team case, and prospective validation design. The protocol represents an adaptation episode through  $T_0$ – $T_4$ : qualifying trigger, recognition of the need for response, response commitment, implementation onset, and durable organizational reconfiguration.  $T_4$  is assigned only when five conditions are jointly satisfied: observable change, operational enactment, persistence, traceable provenance, and independence from subsequent performance outcomes. On this basis, the study operationalizes  $L_{04}=T_4-T_0$  as a candidate temporal measure rather than a validated new construct. Subsequent evaluation requires inter-rater reliability, robustness of the  $T_4$  persistence criterion, discriminant validity, temporal validity, and incremental validity. Retrospective application of the protocol to one organizational adaptation episode within the five-team case demonstrates the practical separation of the initial trigger, local piloting, commitment to a scaled response, implementation onset, and durable change in organizational practice. For this episode, the interval from the approximately dated  $T_0$  to  $T_4$  was about 184 days, while the  $T_1$  boundary had lower temporal precision because of the retrospective nature of the evidence. The example illustrates application of the protocol but does not constitute empirical validation of  $L_{04}$  or establish its causal effect on software delivery outcomes. The practical value of the proposed approach lies in providing a structure for prospective data collection that separates AI exposure, organizational response, durable reconfiguration, and subsequent outcomes. Future empirical evaluation may support, refine, or reject the proposed operationalization.*

**Keywords:** *organizational adaptation; artificial intelligence; Data-Empirical Agility Model; DEAM; adaptation time; organizational reconfiguration; dynamic capabilities; software delivery; Agile; measurement.*

**Formulas: 10; Fig.: 1, Tab.: 3, Bibl.: 21**

**Introduction.** Artificial intelligence (AI) is increasingly embedded in software delivery through coding assistance, analytics, testing, knowledge retrieval, decision support and operational sensing. However, AI use does not itself demonstrate organizational adaptation. Technology use, organizational capability, changes in operating practices, and subsequent delivery performance are related but analytically distinct phenomena.

Previous research progressively established this distinction. An empirical study of 97 Agile practitioners found broad but predominantly shallow AI adoption: 79% reported task-specific or regular AI use, whereas only 3% reported deep integration (Lukutin, 2025). The Data-Empirical Agility Model (DEAM) subsequently conceptualized AI as a sensing and analytical augmentation layer while retaining human responsibility for interpretation, adaptation, and governance; its longitudinal five-team case was explicitly exploratory rather than confirmatory (Lukutin & Michkivskyy, 2026a). Further development of DEAM introduced adaptation capability fragmentation and conceptualized adaptation latency as the temporal gap between

operational signal generation and coordinated organizational response, identifying event-based operationalization and longitudinal validation as subsequent research priorities (Lukutin & Michkivskyy, 2026b).

This creates a measurement problem. Treating AI usage as adaptation conflates technological exposure with organizational response, while using subsequent delivery improvement both to identify adaptation and to evaluate its effect creates circular inference. Moreover, initial implementation does not necessarily constitute durable organizational reconfiguration: an intervention may remain temporary, experimental or locally bounded. A measurement protocol therefore requires observable event boundaries between a qualifying trigger and durable organizational reconfiguration that are independent of subsequent performance.

The research question is: How can trigger-to-durable-organizational-reconfiguration latency be operationalized in AI-augmented multi-team software delivery, and under what conditions can it be empirically distinguished from established

organizational response-speed and reconfiguration constructs?

The study addresses this question by developing an event-level measurement protocol within DEAM and specifying the conditions for evaluating its reliability, discriminant validity, temporal validity, and incremental value. The protocol is retrospectively applied to one adaptation episode within the previously studied five-Scrum-team case to demonstrate event identification and measurement in practice, while retaining the case's exploratory status. This application illustrates the distinction between trigger, organizational response, implementation onset, and durable reconfiguration but does not validate the proposed measure or establish a causal relationship with subsequent delivery outcomes.

**Literature Review.** Organizational adaptation under technological change has established foundations in dynamic capabilities, organizational learning, reconfiguration, and organizational-response research. Dynamic capabilities theory explains how organizations sense change and integrate, build, and reconfigure competences (Teece et al., 1997; Teece, 2007; Eisenhardt & Martin, 2000), while Kump et al. (2019) demonstrate that sensing, seizing, and transforming capacities can be empirically measured. A general organizational capability, however, differs from an observed response to a particular trigger:

adaptation capability  $\neq$  observed adaptation episode (1)

Organizational-learning and reconfiguration research explains how routines, structures, and coordination mechanisms change over time (March, 1991; Zollo & Winter, 2002; Karim, 2006; Girod & Whittington, 2017; Berntzen et al., 2023), but does not independently establish reproducible temporal boundaries for a specific adaptation episode.

AI adds technological and analytical capabilities without removing this distinction.

Organizational AI capability has been conceptualized and measured (Mikalef & Gupta, 2021), while AI adoption and integration depend on heterogeneous technological and organizational conditions (Romeo & Lacko, 2024). AI-enabled capability and adaptive organizational response should therefore remain analytically distinct (Sullivan & Fosso Wamba, 2024), consistent with earlier DEAM evidence that widespread AI use did not correspond to equally deep organizational integration (Lukutin, 2025).

Organizational response speed provides an important boundary for the proposed operationalization. Prior research distinguishes recognition, decision, and implementation stages and examines decision, implementation, and overall response speed (Reykers, 2025; Kolev et al., 2025; Daškevič et al., 2026). Consequently, neither elapsed response time nor its decomposition into intermediate stages can itself constitute DEAM-specific novelty. Longitudinal software-development research further demonstrates that coordination mechanisms and Agile practices evolve over time and that GenAI-augmented teams can be studied using operational and survey data (Berntzen et al., 2023; Vial & Rivard, 2026; Tomaz et al., 2026). Software-delivery outcomes nevertheless remain analytically separate because AI adoption interacts with the underlying organizational and technical system (DORA, 2025).

Previous DEAM research mapped AI usage, organizational adaptation, and delivery measures to different analytical layers and subsequently conceptualized adaptation latency without defining a reproducible endpoint for durable reconfiguration (Lukutin & Michkivskyy, 2026a, 2026b). The resulting distinction can be summarized as:

AI exposure  $\neq$  adaptation capability  $\neq$  adaptation episode  $\neq$  durable reconfiguration  $\neq$  subsequent outcomes (2)

The remaining gap is therefore whether trigger-to-durable-reconfiguration latency can

be operationalized through observable event boundaries and measured reproducibly in a way that provides information distinguishable from established response-speed, reconfiguration, organizational-capability, and engineering constructs.

**Aim and Methodology.** The aim of the study is to develop a context-specific event-level protocol for measuring the interval between a qualifying trigger and durable organizational reconfiguration in AI-augmented multi-team software delivery and to specify the conditions required for its empirical evaluation.

The object of research is organizational adaptation in AI-augmented multi-team software delivery. The subject is event-level measurement of the interval between a qualifying organizational trigger and durable organizational reconfiguration, including event boundaries, classification criteria, and validation requirements.

The study combines construct discrimination, event specification, retrospective calibration, and prospective validation design. Previous DEAM studies provide the cumulative conceptual and empirical foundations for the present operationalization (Lukutin, 2025; Lukutin & Michkivskyy, 2026a, 2026b). Evidence is distinguished as observed, retrospectively calibrated, operationally proposed, or established external measures used for comparison and outcome assessment.

The previously studied longitudinal five-team case is used for retrospective calibration and illustrative application of the protocol. One organizational adaptation episode is reconstructed from available project records to examine whether  $T_0$ – $T_4$  boundaries can be identified and to illustrate calculation of the candidate  $L_{04}$  measure. The reconstruction used available project records, including dated meeting and training records, sprint-level project timelines and Sprint Review evidence. Because the evidence was not collected under

pre-specified event-coding rules, this application cannot validate the proposed measure. It also examines whether AI usage, integration, AI-related activity, organizational intervention, and delivery outcomes can legitimately serve as interchangeable adaptation proxies.

The protocol follows three principles: technological exposure is separated from organizational adaptation; adaptation is classified independently of subsequent delivery outcomes; and the candidate measure is evaluated against established alternatives rather than assumed to constitute a distinct DEAM construct.

**Results.** *Measurement architecture.* The proposed operationalization separates technological exposure, organizational adaptation and subsequent outcomes. AI-tool usage, perceived AI integration, and AI-related delivery work characterize exposure but do not independently establish adaptation; delivery-flow and quality measures describe subsequent system states.

The analytical ordering is:

$$\begin{aligned} &\text{AI exposure/context} \rightarrow \\ &\text{adaptation episode} \rightarrow \text{durable} \\ &\text{reconfiguration} \rightarrow \text{subsequent} \\ &\text{outcomes} \end{aligned} \quad (3)$$

Equation (3) defines analytical and temporal ordering, not an empirically established causal chain. An adaptation episode is represented by five event boundaries:

$$\begin{aligned} &T_0 \rightarrow T_1 \rightarrow T_2 \rightarrow T_3 \rightarrow \\ &T_4 \end{aligned} \quad (4)$$

The sequence is a coding protocol rather than a claim of novel response-stage constructs. The primary unit of analysis is a team-by-trigger adaptation episode; its event boundaries and measurement status are summarized in Table 1.

Table 1

**Operational Measurement Protocol for an Adaptation Episode**

| Element         | Operational criterion                                  | Status                 |
|-----------------|--------------------------------------------------------|------------------------|
| AI exposure     | AI usage, integration, AI-related work                 | Context/exposure       |
| T <sub>0</sub>  | Qualifying bounded trigger                             | Proposed coding rule   |
| T <sub>1</sub>  | First observable recognition                           | Response stage         |
| T <sub>2</sub>  | First observable response commitment                   | Response stage         |
| T <sub>3</sub>  | First operational enactment                            | Response stage         |
| T <sub>4</sub>  | First durable reconfiguration satisfying five criteria | Proposed endpoint rule |
| L <sub>04</sub> | T <sub>4</sub> –T <sub>0</sub>                         | Candidate measure      |
| Outcomes        | Subsequent flow/quality measures                       | External measures      |

Source: developed by the authors

*Durable organizational reconfiguration*

The critical distinction is:

$$T_3 \neq T_4 \quad (5)$$

Initial implementation may be temporary, experimental, abandoned, or locally bounded and therefore does not by itself establish durable organizational reconfiguration. T<sub>4</sub> is the earliest time t at which five conditions are jointly satisfied:

$$T_4 = \min \{ t : C_{\text{change}}(t) \wedge C_{\text{enactment}}(t) \wedge C_{\text{persistence}}(t) \wedge C_{\text{provenance}}(t) \wedge C_{\text{outcome-independence}}(t) \} \quad (6)$$

T<sub>4</sub> therefore requires an observable organizational change (C<sub>change</sub>), actual enactment rather than intention (C<sub>enactment</sub>), persistence beyond initial use (C<sub>persistence</sub>), traceable evidence of the change and its timing (C<sub>provenance</sub>), and classification independent of subsequent performance (C<sub>outcome-independence</sub>).

For prospective testing in sprint-based environments, persistence across two consecutive delivery cycles is proposed as an initial observation threshold rather than a universal theoretical boundary. The observation window should reflect the cadence and nature of the organizational practice; where evidence is insufficient, T<sub>4</sub> should remain indeterminate. The threshold must therefore undergo sensitivity analysis across

alternative persistence windows and organizational cadences.

To prevent circular inference, the protocol requires:

$$T_4 \text{ classification} \rightarrow \text{subsequent outcome observation} \quad (7)$$

rather than identifying adaptation from a favorable outcome and then attributing that outcome to the inferred adaptation.

*Candidate adaptation-latency measure*

Once T<sub>0</sub> and T<sub>4</sub> are independently classified, trigger-to-durable-reconfiguration latency is:

$$L_{04} = T_4 - T_0 \quad (8)$$

For diagnostic purposes, the interval can be decomposed as:

$$L_{01}=T_1-T_0; \quad L_{12}=T_2-T_1; \quad L_{23}=T_3-T_2; \quad L_{34}=T_4-T_3 \quad (9)$$

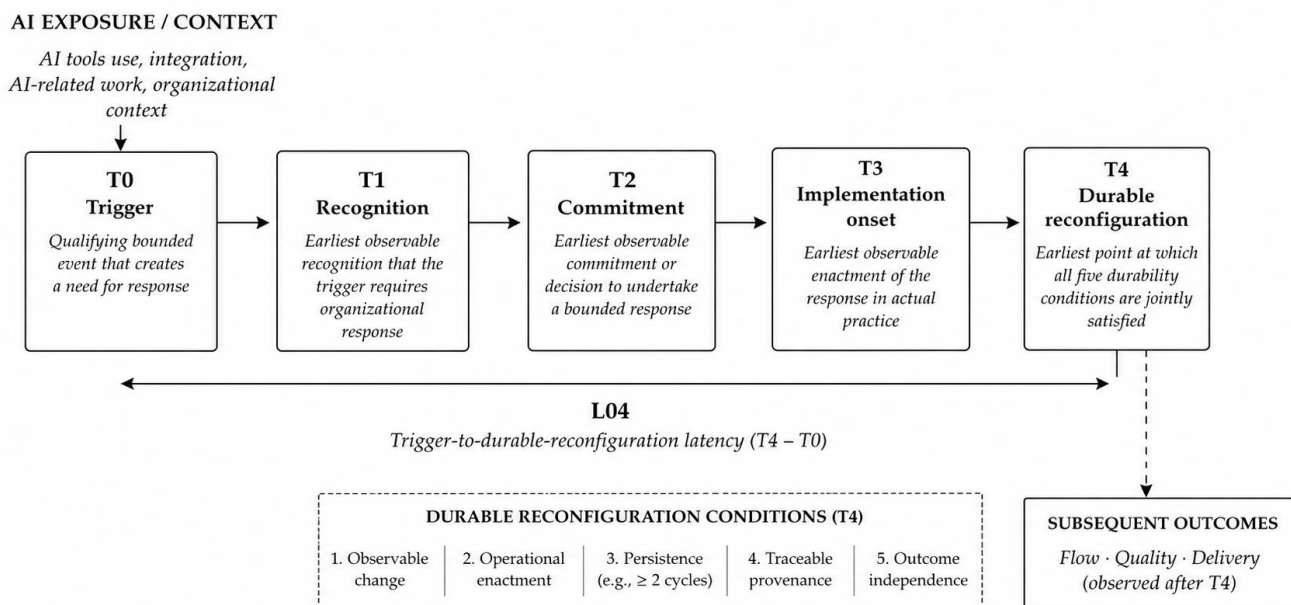
and, for complete episodes:

$$L_{04} = L_{01} + L_{12} + L_{23} + L_{34} \quad (10)$$

The decomposition identifies where delay occurs but is not claimed as DEAM-specific novelty. Because organizational decision, implementation, and response speed are established constructs (Reykers, 2025; Kolev et al., 2025; Daškevič et al., 2026), L<sub>04</sub> remains a candidate measure. If it proves indistinguishable from established response-

or implementation-speed measures, it should be interpreted as their context-specific operationalization rather than as a distinct DEAM construct.

Episodes without observed  $T_4$  remain incomplete and, where appropriate, should be treated as right-censored observations. Figure 1 summarizes the resulting event-level architecture.



**Figure 1. Event-Level Measurement Architecture for Organizational Adaptation**

Source: developed by the authors

Note: The sequence represents a measurement protocol, not novel organizational response stages. Subsequent outcomes are excluded from  $T_4$  classification.

#### Retrospective calibration

The longitudinal five-team case previously used in DEAM research was used to calibrate measurement boundaries and examine retrospective applicability of the protocol (Lukutin & Michkivskyy, 2026a). One AI-related adaptation episode was reconstructed from project records. Because these records were not collected under pre-specified  $T_0$ – $T_4$  coding rules, the reconstruction illustrates application but does not validate the event boundaries or  $L_{04}$ .

Table 2 reconstructs the episode from the initial customer trigger to the incorporation of AI experimentation into a recurring Sprint Review practice.

The episode distinguishes implementation from durable reconfiguration.

Training completion, AI PoC production, and increases in AI-related delivery activity were not used to assign  $T_4$ .  $T_4$  was assigned when AI experimentation results became incorporated into a recurring Sprint Review practice. Subsequent observations across Q3S1–Q3S6FY26 provided persistence evidence, while sprint-level AI PoC activity served only as corroborating evidence of continued enactment.

Using the approximately dated  $T_0$  of 1 April 2025 and  $T_4$  of 2 October 2025, the reconstructed interval was  $L_{04} \approx 184$  days. Temporal precision differed across intermediate boundaries:  $T_1$  was reconstructed at sprint-level resolution, whereas  $T_2$ ,  $T_3$ , and  $T_4$  were associated with dated organizational events. The case therefore illustrates the overall  $L_{04}$  calculation but does not justify artificially precise estimates of all component intervals in Equation (9).

Table 2

### Retrospective Application of the T<sub>0</sub>–T<sub>4</sub> Protocol

| Boundary                       | Observed event                                                                                                                                                                          | Evidence / coding rationale                                                                                                                                |
|--------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|
| T <sub>0</sub> ≈<br>01.04.2025 | Following quarterly planning, the customer redirected product development toward increased AI functionality and greater use of AI tools.                                                | Qualifying external organizational trigger; approximate date reconstructed from the project timeline.                                                      |
| T <sub>1</sub> =<br>Q2S2FY26   | Team A began operating as a pilot for systematic development of AI functionality; an ML engineer joined in Q2S3FY26.                                                                    | Retrospectively reconstructed recognition boundary inferred from the first observable localized organizational response; sprint-level temporal resolution. |
| T <sub>2</sub> =<br>10.06.2025 | At the Project AI L&D Syncup, a decision was made to organize AI/LLM training and engage L&D.                                                                                           | Observable commitment to a bounded capability-building response.                                                                                           |
| T <sub>3</sub> =<br>04.08.2025 | The first LLM Foundation Intensive started for selected senior representatives from the feature teams.                                                                                  | First operational enactment of the coordinated capability-building response.                                                                               |
| T <sub>4</sub> =<br>02.10.2025 | At the Q2S6FY26 Sprint Review, available AI PoCs from the teams were jointly presented to the customer, and AI PoC results were incorporated into the recurring Sprint Review practice. | Observable and enacted change in organizational practice, subsequently retained across later sprint cycles.                                                |

Source: developed by the authors

The reconstruction also shows why AI usage, AI-related activity, organizational interventions, and delivery outcomes cannot be treated as interchangeable adaptation proxies. AI-related product activity preceded durable reconfiguration, while piloting and capability building represented stages of organizational response. Delivery improvement was excluded from event classification because staffing, workload, technical conditions, coordination mechanisms and concurrent interventions remain alternative explanations.

Accordingly, the retrospective application establishes neither measurement reliability nor a causal relationship between adaptation latency and delivery performance. Its purpose is to demonstrate operational applicability, expose differences in event identifiability, and inform prospective validation.

*Validation and falsification requirements.* Operationalization does not constitute validation. Before L<sub>04</sub> can be interpreted as a distinct empirical measure, prospective testing must evaluate the properties summarized in Table 3.

Persistence robustness should be tested across alternative observation windows, while

discriminant and incremental validity should determine whether L<sub>04</sub> provides information beyond established response-speed, organizational, and engineering measures.

The protocol permits three outcomes: SUPPORT, REFINE or REJECT. Support requires reproducible event identification and additional information beyond established alternatives; refinement applies when boundaries or thresholds require modification; rejection applies when T<sub>4</sub> cannot be classified reliably, L<sub>04</sub> is redundant with established measures, or it provides no meaningful additional information.

**Conclusions.** This study develops an event-level DEAM protocol that separates AI exposure, organizational response, durable reconfiguration, and subsequent outcomes. Adaptation is represented through T<sub>0</sub>–T<sub>4</sub>, with T<sub>4</sub> classified independently of subsequent performance only when observable change, operational enactment, persistence, traceable provenance, and outcome independence are jointly satisfied. This enables operationalization of trigger-to-durable-reconfiguration latency as the candidate measure L<sub>04</sub>=T<sub>4</sub>–T<sub>0</sub>.

Table 3

### Validation Requirements for the Candidate L<sub>04</sub> Measure

| Property                | Required empirical test                           | Failure implication                |
|-------------------------|---------------------------------------------------|------------------------------------|
| Event identification    | Independent T <sub>0</sub> /T <sub>4</sub> coding | Revise event definitions           |
| Inter-rater reliability | Agreement between independent coders              | Revise coding protocol             |
| Persistence robustness  | Alternative T <sub>4</sub> thresholds             | Revise endpoint                    |
| Discriminant validity   | Comparison with established speed measures        | Possible redundancy                |
| Incremental validity    | Models with and without L <sub>04</sub>           | Limited added value                |
| Temporal validity       | T <sub>4</sub> classified before outcome window   | Circularity risk                   |
| Context robustness      | Replication across teams/triggers                 | Context dependency                 |
| Outcome relevance       | Subsequent delivery measures                      | Hypothesized mechanism unsupported |

*Source: developed by the authors*

Retrospective application to one episode in the five-team case produced an approximate L<sub>04</sub> of 184 days and demonstrated unequal temporal precision across event boundaries, particularly for T<sub>1</sub>. The application illustrates practical identification of T<sub>0</sub>–T<sub>4</sub> but does not validate L<sub>04</sub> or establish a causal relationship between adaptation latency and delivery performance.

The study has several limitations: T<sub>0</sub>–T<sub>4</sub> coding has not undergone inter-rater reliability testing; the two-cycle persistence threshold remains a proposed observation parameter; L<sub>04</sub> has not demonstrated discriminant or incremental validity; and the retrospective evidence was not collected under pre-specified event-coding rules. Future research should prospectively collect team-by-

trigger episodes, independently code T<sub>0</sub>–T<sub>4</sub>, test alternative persistence thresholds, compare L<sub>04</sub> with established measures, and treat episodes without observed T<sub>4</sub> as incomplete or right-censored where appropriate.

The practical significance of the protocol lies in separating technological adoption from organizational adaptation in prospective data collection, reducing the risk of attributing delivery-performance changes directly to AI adoption when organizational and operational changes provide alternative explanations. The proposed operationalization therefore remains falsifiable: prospective evidence may support, refine, or reject L<sub>04</sub> as a distinct DEAM measure.

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**Author contributions.** Oleh Lukutin: conceptualization, methodology, empirical data curation, analysis, visualization, writing - original draft. Sergiy Michkivskyy: conceptual supervision, methodology review, validation, writing - review and editing. Both authors reviewed and approved the final manuscript.

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