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ВІД ЕМПІРИЧНОЇ ДО ДАНО-ЕМПІРИЧНОЇ ГНУЧКОСТІ: ПРОЄКТУВАННЯ СИСТЕМ НАВЧАННЯ, ПІДСИЛЕНИХ ШІ, В AGILE-ОРГАНІЗАЦІЯХ

(Представлення моделі Data-Empirical Agility Model — DEAM)

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FROM EMPIRICAL TO DATA-EMPIRICAL AGILITY: DESIGNING AI-AUGMENTED LEARNING SYSTEMS IN AGILE ORGANIZATIONS

(Introducing the Data-Empirical Agility Model — DEAM)

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Анотація. *В епоху штучного інтелекту традиційні Agile-організації стикаються з новими викликами щодо навчання та адаптації. У статті розглянуто перехід Agile-організацій від класичного емпіричного процесного контролю до data-empirical навчання в умовах широкого впровадження інструментів штучного інтелекту. Метою дослідження є обґрунтування та проєктування архітектури організаційного навчання, у якій ШІ виступає безперервним джерелом сигналів (sensing) і рекомендацій, а людина зберігає центральну роль у смислотворенні, прийнятті рішень та етичному врядуванні. Методологічною основою обрано Design Science Research; основним результатом є запропонована модель Data-Empirical Agility Model (DEAM), що структурує організаційне навчання на трьох взаємопов'язаних рівнях: методологічному (врядування та готовність до навчання), фреймворковому (координаційні структури й механізми зворотного зв'язку) та методному (практики адаптації, що реалізуються у циклах постійного поліпшення). Для підсилення практичної релевантності наведено емпіричну ілюстрацію на основі анонімізованих релізних даних п'яти Scrum-команд за 2025 рік, зібраних у фінансовому домені: метрик Velocity, Throughput, Lead Time, CRS, кількості дефектів, а також показників AI Adoption & Engagement і AI Tools Daily Usage. Спостережувані патерни вказують на можливе зниження волатильності навчання та скорочення затримок зворотного зв'язку за умов вищої щільності використання ШІ-інструментів (AI sensing density): у пізніших циклах зменшується варіативність delivery-метрик між релізами, рідше фіксуються виражені сплески CRS та пізно виявлені дефекти, при цьому середні значення продуктивності можуть залишатися стабільними. Отримані результати підтримують внутрішню узгодженість DEAM і уточнюють, що ключовою цінністю ШІ є не прискорення "виходу", а підвищення стабільності навчання та керованості адаптації. Обмеженням дослідження є одноорганізаційний контекст і ілюстративний (не підтверджувальний) характер емпіричного аналізу; подальші дослідження мають включати міжорганізаційні порівняння, кількісну валідацію конструктів та аналіз модераторів (довіра до ШІ, психологічна безпека, політики врядування).*

Ключові слова: *Agile, штучний інтелект, організаційне навчання, системне мислення, Data-Empirical Agility, DEAM, Evidence-Based Management.*

Формули: 0; Рис.: 2; Табл.: 3; Бібл.: 13

***Abstract**. In the age of artificial intelligence, traditional Agile organizations face new challenges in learning and adaptation. This paper examines how Agile organizations transition from traditional empirical process control toward data-empirical learning under the growing adoption of artificial intelligence tools. The study aims to justify and design a learning architecture in which AI provides continuous sensing signals and recommendations, while humans retain the central role in sense-making, decision-making, and ethical governance. Using a Design Science Research approach, the paper's main result is the Data-Empirical Agility Model (DEAM), which conceptualizes AI-augmented organizational learning across three interrelated layers: the methodology layer (learning governance and organizational readiness), the framework layer (coordination structures and feedback mechanisms) and the method layer (adaptive practices enacted through continuous improvement cycles). To strengthen practical relevance, the paper provides an exploratory empirical illustration based on anonymized release-level data from five Scrum teams collected across 2025 in a financial domain, including Velocity, Throughput, Lead Time, CRS, defects (bugs) and complementary AI Adoption & Engagement and AI Tools Daily Usage indicators. The observed patterns suggest reduced learning volatility and shorter feedback delays in contexts with higher AI sensing density: across later release cycles, delivery metrics display lower variance between releases, pronounced CRS spikes occur less frequently and late-discovered defects become rarer, even when average throughput remains relatively stable. These findings support the internal coherence of DEAM and indicate that the primary value of AI in Agile learning systems is not merely output acceleration but improved learning stability and more manageable adaptation. Limitations include a single-organization context and the illustrative (non-confirmatory) nature of the empirical component; future research should extend the study through multi-organizational comparisons, quantitative construct validation and examination of moderators such as AI trust, psychological safety and governance policies.*

***Keywords**: Agile, Artificial Intelligence, Organizational Learning, Systems Thinking, Data-Empirical Agility, DEAM, Evidence-Based Management.*

Formulas: 0; Figures: 2; Tab.: 3; Bibl.: 13

Introduction. The rapid integration of artificial intelligence (AI) technologies into organizational and project management practices has become a defining feature of contemporary digital transformation. In Agile environments, which rely on empirical learning, iterative coordination and continuous adaptation (Schwaber & Sutherland, 2020; Highsmith, 2009), AI adoption introduces an additional layer of data-driven sensing and analytical augmentation that may fundamentally reshape traditional feedback mechanisms. As organizations increasingly embed AI-enabled analytics and generative systems into operational workflows, the classical logic of empirical process control is being reconfigured, creating new theoretical and managerial challenges.

Agile approaches were originally conceptualized as human-centered coordination systems built upon short feedback cycles, inspection, adaptation and collective reflection (Schwaber & Sutherland, 2020). Agile principles are closely aligned with broader theories of organizational learning that emphasize feedback loops, reflection and adaptive behavior (Argyris & Schön, 1996). From a systems-thinking perspective, the effectiveness of such learning depends on the density, quality and interpretability of feedback signals within the organizational structure (Meadows, 2008). The increasing presence of AI technologies introduces automated sensing and analytical mechanisms that may amplify, restructure or stabilize these feedback loops.

Despite widespread AI implementation in project environments, existing research predominantly concentrates on efficiency gains, automation capabilities and decision-support applications. Comparatively less attention has been devoted to examining how AI influences the structural dynamics of organizational learning and adaptive coordination. Prior empirical research in AI-augmented Agile organizations indicates that AI adoption often aligns with existing structural resistance patterns described by Larman's Laws, resulting in incremental improvements rather than deep systemic transformation (Lukutin, 2025). Furthermore, studies of large-scale Agile transformation highlight that technological adoption alone does not guarantee behavioral change due to structural inertia embedded in organizational systems (Larman & Vodde, 2016).

Recent research on managing AI innovation in scaled Agile environments emphasizes the importance of structured governance patterns and coordinated integration mechanisms (Lukutin, 2025a), while other studies conceptualize AI as a catalyst of organizational agility whose impact depends on leadership alignment and learning culture (Lukutin & Michkivskyy, 2025). These findings suggest that AI may amplify existing coordination logics unless supported by redesigned learning architectures.

Despite the growing body of literature on Agile transformation, AI governance and hybrid intelligence systems, there remains a lack of integrative conceptual models that connect AI-driven sensing, empirical process control and systemic learning dynamics within a unified framework. The absence of such models limits the theoretical explanation of how AI modifies feedback density, learning stability and adaptive coordination in project-based environments.

To address the identified research gap, a Design Science Research approach (Hevner & Chatterjee, 2010) is applied to develop and structurally articulate the proposed framework. The detailed methodological design is presented in the subsequent section.

Literature review. Contemporary research on Agile approach emphasizes empirical process control, iterative delivery and adaptive coordination as core mechanisms of organizational responsiveness (Schwaber & Sutherland, 2020; Highsmith, 2009). Scaling frameworks such as LeSS and Nexus extend these principles to complex multi-team environments, yet increasing structural complexity often leads to delays in feedback interpretation and decision-making (Larman & Vodde, 2016). As organizations adopt AI tools within Agile contexts, new forms of data-driven sensing and automated insight generation emerge, potentially reshaping these feedback mechanisms.

Organizational learning theory conceptualizes adaptation through feedback loops and reflective practice (Argyris & Schön, 1996; Senge, 2006). Systems thinking further highlights that learning effectiveness depends on structural feedback density and causal interdependencies (Meadows, 2008). Within Agile environments, retrospectives, sprint reviews and incremental releases function as institutionalized learning cycles. However, the integration of AI introduces additional sensing layers that may increase feedback frequency while simultaneously altering interpretation and governance dynamics.

Existing research on AI in management primarily focuses on automation, predictive analytics and decision support (Dellermann et al., 2019; Krancher et al., 2018). While these studies demonstrate performance-related benefits, they rarely address how AI affects the structural logic of organizational learning in Agile systems. In particular, limited attention has been devoted to understanding whether AI merely accelerates existing coordination patterns or fundamentally transforms learning architectures.

Recent empirical evidence shows that generative AI tools can measurably affect software development performance and work allocation. Controlled experiments report substantial task completion speedups when developers use AI pair-programming support (Peng et al., 2023), while field experiments in real organizational settings indicate that the magnitude of effects varies across contexts and tasks (Cui et al., 2025). Beyond productivity, studies of human–AI collaboration emphasize that GenAI reshapes how developers seek information, coordinate and validate outputs, implying structural changes in feedback interpretation and collaboration routines (Zhang & Venkatesh, 2025).

Recent empirical investigations into AI adoption in Agile environments reveal that high levels of tool usage and positive perception do not necessarily lead to structural transformation (Lukutin, 2025). Findings suggest that AI may reinforce existing coordination patterns unless accompanied by changes in governance structures and role definitions. Complementary research proposes pattern-based approaches for managing AI innovation in scaled Agile environments, emphasizing structured integration and cross-team coordination (Lukutin, 2025a). Furthermore, AI has been conceptualized as a catalyst of organizational agility; however, its transformative impact depends on cultural alignment, leadership commitment and learning maturity (Lukutin & Michkivskyy, 2025).

Despite the growing body of literature on Agile transformation, AI governance and hybrid intelligence systems, there remains a lack of integrative conceptual models that connect AI-driven sensing, empirical process control and systemic learning dynamics within a unified framework. The absence of such models limits the theoretical explanation of how AI modifies feedback density, learning stability and adaptive coordination in project-based environments.

This theoretical gap motivates the development of the Data-Empirical Agility Model (DEAM), which seeks to formalize the transition from human-empirical to data-empirical learning and to provide a structured representation of AI-augmented learning architecture in Agile organizations.

Aim and Objectives of the Study. The identified theoretical gap concerning the structural impact of AI on organizational learning in Agile environments necessitates the development of an integrative conceptual framework. Accordingly, this study aims to design and substantiate the Data-Empirical Agility Model (DEAM) as a structured artifact that explains the transition from human-empirical to data-empirical learning in AI-augmented Agile systems.

The research operationalizes this transition by identifying structural shifts in feedback density, sensing mechanisms, and adaptive coordination patterns. Rather than treating AI as a performance accelerator, the study conceptualizes it as a sensing and amplification layer embedded within existing learning architectures.

To achieve this objective, the research employs a Design Science Research (DSR) methodology (Hevner & Chatterjee, 2010), which is appropriate for developing and evaluating innovative organizational artifacts. Within the DSR paradigm, DEAM is conceptualized as a formal model integrating empirical process control principles with data-driven sensing structures. Particular attention is paid to how increased AI sensing density influences the stability, interpretability and coherence of learning cycles in Agile project systems.

The research design incorporates:

-systematic synthesis of prior research on Agile empiricism and AI integration;

-structural modeling of feedback dynamics through causal-loop analysis;

-iterative conceptual refinement and internal consistency evaluation of the DEAM framework.

In accordance with Design Science Research principles, the study also includes an exploratory empirical illustration to assess the internal coherence and practical relevance of the proposed model. Anonymized longitudinal data from multiple Scrum teams were analyzed at release and quarterly levels to identify observable patterns aligned with the model's learning mechanisms. The empirical component is illustrative rather than confirmatory and does not seek to establish causal relationships; instead, it demonstrates the applicability of the proposed data-empirical architecture in real project contexts.

Research Results.

1.Design Outcomes of the Data-Empirical Agility Model (DEAM) . This section presents the primary design outcomes of the study in the form of the Data-Empirical Agility Model (DEAM), conceptualized as an AI-augmented learning architecture for Agile organizations.

The Data-Empirical Agility Model (DEAM) extends Agile's empirical process control into the era of artificial intelligence. It conceptualizes organizations as *data-empirical learning systems* where AI systems act as learning partners - collecting and processing feedback - while humans interpret, adapt and govern ethically. DEAM consists of three layers interconnected by feedback loops. These layers and their functional roles are summarized in Table 1.

Table 1

Feedback loops of Data-Empirical Agility Model (DEAM)

Layer	Function	AI Role	Human Role
Methodology	Defines learning purpose and governance	Provides insight from global data trends	Sets ethical direction and learning goals
Framework	Structures collaboration and coordination	Observes and visualizes cross-team flow	Interprets and aligns meaning
Method	Executes daily practices and experiments	Automates metrics and feedback collection	Reflects and adapts behavior

Source: developed by the Authors

Each layer operates through a Sense → Interpret → Adapt → Re-learn loop, forming a self-adjusting system that evolves through AI-human interaction.

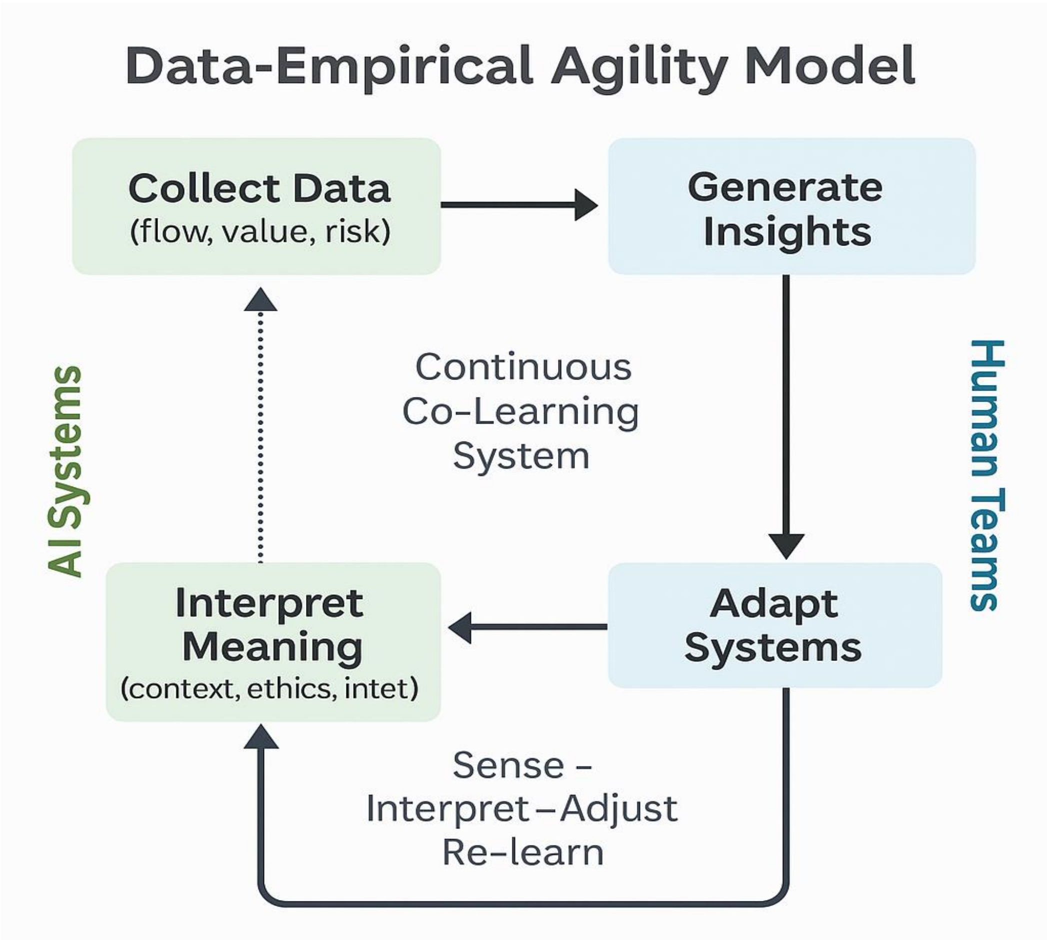

Figure 1. Data-Empirical Agility Model
Source: developed by the authors with the assistance of ChatGPT-5.4

Collectively, these design outcomes redefine agility as a data-empirical learning system rather than a static set of practices. The DEAM framework makes explicit the separation of AI-based sensing and feedback generation from human interpretation, adaptation and ethical governance, thereby addressing the structural mismatch identified in the research problem.

2. Empirical Illustration of the Data-Empirical Agility Model.

2.1. Data Sources and Context. To empirically illustrate the applicability of the Data-Empirical Agility Model (DEAM), anonymized longitudinal data from five Scrum teams were analyzed over the full calendar year 2025. The organizational context represents an AI-enabled Agile environment in which each sprint resulted in a production release, enabling learning dynamics to be observed across successive release-based cycles.

Three complementary data sources were used in this study:

1.Operational team metrics**,** captured at sprint and release levels, including Velocity, Throughput (completed User Stories and Tasks), Lead Time, Change Request Spillover (CRS) and the number of detected defects (Bugs);

2.AI Adoption & Engagement indicators**,** collected via internal surveys and reflecting perceived confidence in AI-generated outputs, level of integration into daily workflows and overall satisfaction with AI-supported practices;

3.AI Tools Daily Usage metrics**,** capturing the frequency of interaction with AI tools such as GitHub Copilot, Confluence AI and Teams Copilot, reported using ordinal usage categories.

All data were fully anonymized and aggregated at team and quarterly levels where appropriate. The empirical illustration is exploratory in nature and does not aim to establish causal relationships, but rather to identify observable patterns aligned with the learning mechanisms proposed by DEAM.

2.2. Interpretation Framework. The empirical data were interpreted through the three-layer structure of the Data-Empirical Agility Model.

At the *Methodology layer*, AI Adoption & Engagement indicators were treated as proxies for organizational learning intent and governance maturity, reflecting the degree to which AI-generated insights are institutionally accepted, trusted and embedded into decision-making processes.

At the *Framework layer*, AI Tools Daily Usage metrics were interpreted as indicators of sensing density, representing the continuity and frequency with which AI-enabled feedback is generated and made available across collaborative and coordination structures.

At the *Method layer*, operational team metrics were analyzed not as direct productivity outcomes, but as indicators of learning stability, predictability and feedback delay between successive releases.

Table 2

Mapping Empirical Metrics to the Layers of the Data-Empirical Agility Model (DEAM)

Metric category	Specific indicators	DEAM layer	Learning interpretation
AI Adoption & Engagement	Confidence in AI outputs, workflow integration, satisfaction	Methodology	Organizational learning intent and governance maturity
AI Tools Daily Usage	Frequency of GitHub Copilot, Confluence AI, Teams Copilot	Framework / Method	Sensing density and continuity of data-empirical feedback
Velocity	Release-to-release variability	Method	Stability of adaptation rather than productivity
Throughput (US, Tasks)	Predictability across releases	Method	Consistency of learning outcomes
Lead Time	Release-to-release variability	Method	Stability of adaptation
CRS	Frequency and magnitude of spillovers	Method	Delayed learning and misalignment signals
Bugs	Timing of defect discovery	Method	Effectiveness of early sensing and interpretation

Source: Developed by the Authors based on empirical data (2025)

2.3. Observed Patterns Across Release Cycles. Analysis across quarterly intervals (Q1–Q4) revealed several consistent patterns.

First, AI Adoption & Engagement indicators increased progressively over the year, suggesting a transition from exploratory or ad hoc AI usage toward more systematic integration into daily Agile practices. This trend aligns with the DEAM assumption that data-empirical agility emerges as AI becomes embedded within learning governance rather than treated as isolated tooling.

Second, higher AI Tools Daily Usage frequency coincided with increased sensing continuity across release cycles. Teams exhibiting higher AI usage intensity demonstrated fewer abrupt fluctuations in operational indicators between consecutive releases, suggesting shorter learning delays and earlier surfacing of actionable signals.

Third, operational team metrics exhibited reduced volatility rather than increased output. While average Velocity and Throughput levels remained relatively stable, their variance between releases decreased in later quarters. At the same time, the frequency of late-discovered defects and pronounced CRS spikes declined, indicating improved alignment and earlier corrective adaptation.

Table 3

Quarterly Dynamics of AI Engagement and Learning Stability Indicators (Aggregated Across Teams)

Quarter	AI Adoption & Engagement	AI Tools Usage Intensity	Delivery volatility	CRS spikes	Late-discovered defects
Q1	Low–Moderate	Low	High	Frequent	Frequent
Q2	Moderate	Moderate	Medium	Occasional	Occasional
Q3	Moderate–High	High	Low–Medium	Rare	Rare
Q4	High	High	Low	Rare	Rare

Note: Indicators represent aggregated trends derived from release-based metrics and survey responses and are used for exploratory illustration rather than statistical inference.

Source: Developed by the Authors based on anonymized operational and AI usage data (2025)

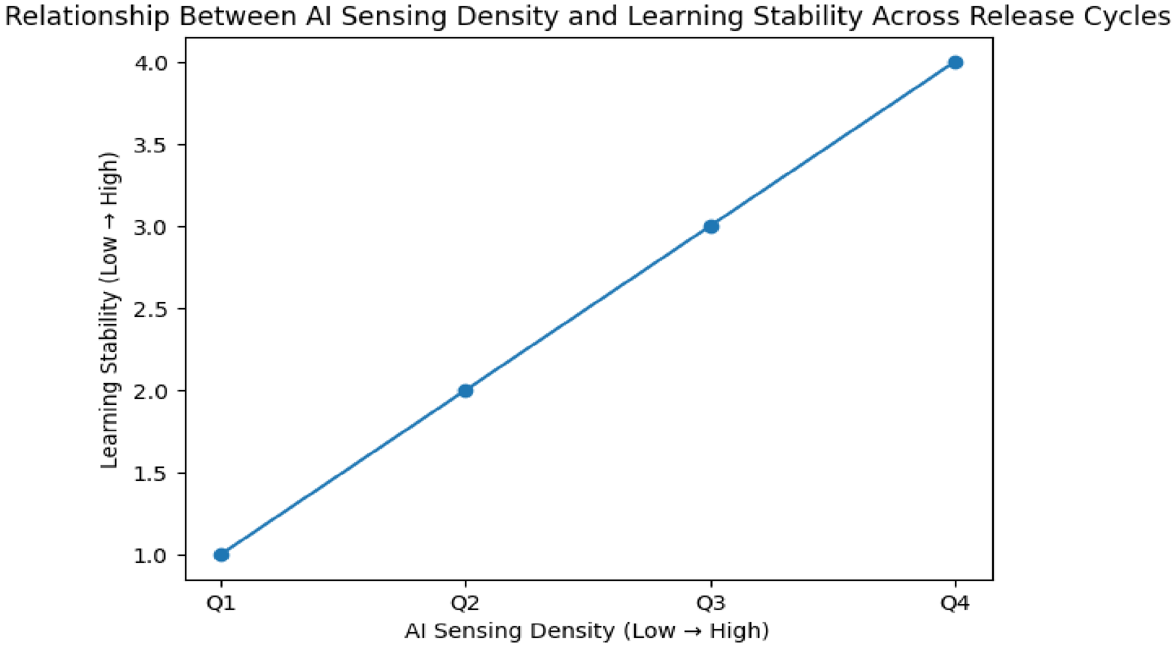

Figure 2. Relationship Between AI Sensing Density and Learning Stability Across Release Cycles

Source: Developed by the Authors based on anonymized release-based data (2025)

The figure illustrates the alignment between increasing AI sensing density and reduced learning volatility across quarterly release cycles (Q1–Q4) without implying causal dependency.

2.4. Implications for Data-Empirical Learning. The observed empirical patterns support the core proposition of the Data-Empirical Agility Model: as AI transitions from a supportive tool to a continuous sensing and feedback partner, Agile learning loops become shorter, more stable and less reactive. Rather than demonstrating productivity acceleration, the data illustrate a shift toward learning stability, characterized by reduced volatility, improved predictability and earlier detection of misalignment. This distinction reinforces the conceptual positioning of DEAM as a framework for data-empirical learning rather than performance optimization.

The combination of increased sensing density at the Framework and Method layers, together with higher adoption maturity at the Methodology layer, appears to enable more coherent interpretation and adaptation between releases, consistent with DEAM’s separation of AI-based sensing from human sense-making and ethical governance.

2.5. Limitations. This empirical illustration is subject to several limitations. The data originate from a single organizational context and are analyzed at an aggregated level, which limits generalizability. AI adoption and usage indicators rely partly on self-reported survey data, and operational metrics were interpreted qualitatively rather than through inferential statistical testing.

Accordingly, the findings should be understood as exploratory and illustrative. Future research should extend this work through comparative multi-organizational studies, controlled empirical designs, and deeper quantitative validation of data-empirical learning mechanisms.

2.6. Interpretation of Findings. The discussion integrates the conceptual design of the Data-Empirical Agility Model with the empirical illustration presented in the previous section. The observed patterns across release cycles provide contextual grounding for the proposed learning mechanisms, allowing the model to be interpreted not only as a theoretical construct but as a practically relevant learning architecture for AI-augmented Agile environments.

DEAM reframes agility as a *co-learning system* where AI provides transparency and pattern recognition, humans ensure sense-making, ethics and contextual adaptation.

This transition from empirical to data-empirical agility implies that feedback originates not only from observation but also from continuous AI analysis. Yet automation without meaning risks *pseudo-learning*; thus, human interpretation remains central.

Practical implications include:

–AI-assisted retrospectives and predictive Evidence-Based Measurement (EBM) metrics;

–AI-supported Scrum Mastering and portfolio visualization;

–governance combining algorithmic insight with ethical oversight.

From a research perspective, the empirical illustration aligns with the study’s research propositions. In particular, the observed reduction in learning volatility under conditions of higher AI sensing density supports the proposition that AI-augmented feedback requires learning architectures beyond traditional empirical process control. At the same time, the findings reinforce existing organizational learning and systems thinking literature by highlighting the continued centrality of human sense-making and ethical governance in AI-enabled learning systems.

Conclusions. The results of the study demonstrate that the proposed Data-Empirical Agility Model (DEAM) provides a coherent structural representation of AI-augmented learning processes in Agile environments. The empirical illustration based on longitudinal data from multiple Scrum teams indicates observable patterns of reduced delivery volatility, increased consistency of throughput and stabilization of coordination dynamics under conditions of increased AI-assisted sensing. These observations do not imply direct causal relationships but support the interpretation of AI as an amplification layer influencing feedback density and learning stability within Agile systems.

The article introduces the Data-Empirical Agility Model (DEAM) - a conceptual framework defining how AI augments Agile learning systems.

In addition to the conceptual contribution, this study provides an exploratory empirical illustration based on anonymized release-level data from multiple Scrum teams. The observed patterns demonstrate alignment between AI sensing density and learning stability across release cycles, reinforcing the internal coherence and practical relevance of the proposed Data-Empirical Agility Model.

The scientific novelty of the study lies in formalizing the transition from human-empirical to data-empirical learning in AI-augmented Agile systems.

The theoretical significance of the research consists in integrating Agile empiricism, systems thinking and organizational learning into a unified data-empirical framework.

The practical value of the study lies in providing design principles and diagnostic guidance for AI-enabled Agile transformations.

While the empirical component does not establish causal relationships, it strengthens the model's grounding by demonstrating how data-empirical learning mechanisms manifest in real Agile environments. This positioning ensures methodological rigor while avoiding overgeneralization of the findings.

Future research directions:

–empirical validation of DEAM via case studies;

–integration of AI-augmented EBM metrics;

–ethical frameworks for human–AI collaboration in adaptive organizations.

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Author contributions. All authors contributed to the study conception, writing, and approval of the final version of the manuscript.

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