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Enhancing Agile Project Management with Big Data Analytics: A Data-Driven Framework

Mohamed Hagal*, Khairea Altarabolsi

محمد علي حجل
كلية تقنية المعلومات - جامعة بنغازي- قسم هندسة البرمجيات
استاذ مشارك
Mohamed Ali Hagal
University of Benghazi
Faculty of Information Technology
Software Engineering Department

Associate professor
....

خيرية الطرابلسي
Khairea Altarabolsi
كلية تقنية المعلومات . جامعة بنغازي. قسم هندسة البرمجيات.
طالبة

ABSTRACT

In order to improve the Agile project management process, this article offers a data-driven framework that integrates Big Data analytics with the phases of Agile project management. The suggested framework offers an organized method for data-driven decision-making throughout all five essential Agile phases: Envision, Speculate, Explore, Adapt, and Close. This fills a gap in previous research, which frequently lacks ways for integrating Big Data tools into Agile Project management. In order to improve project results and empower Agile teams, it uses Big Data analytics to change project management from intuition-based to evidence-supported decision-making.

A survey of 101 Agile professionals and evaluations from seven project managers were used to assess the usefulness and potential impact of this methodology. The framework's potential to enhance sprint predictability, software quality, team reactivity, and organizational learning was highly valued, according to the survey results. . This study offers a useful guide for incorporating Big Data into Agile project management, promoting continuous optimization and evidence-based decision-making in contemporary software development.

Keywords: Agile Project Management, Big Data Analytics, Data-Driven Decision-Making, Software Development, Project Outcomes, Framework Integration.

الخلاصة

تقدم هذه الورقة إطار عمل قائم على البيانات، مُصمم لتعزيز عملية إدارة المشاريع الرشيقة من خلال دمج تحليلات البيانات الضخمة مع مراحل إدارة المشاريع الرشيقة، ويسد هذا الإطار المقترح ثغرة في الأبحاث الحالية، التي غالبًا ما تفتقر إلى استراتيجيات لدمج أدوات البيانات الضخمة في إدارة المشاريع الرشيقة، وأيضاً يعد إطار العمل هذا نهجًا منظمًا لاتخاذ القرارات القائمة على البيانات عبر جميع مراحل Agileالخمس الأساسية: التصور، والتكهن، والاستكشاف، والتكيف، والإغلاق. ويستفيد من تحليلات البيانات الضخمة لتمكين مدراء المشاريع من اتخاذ قرارات مدعومة بالأدلة بدلاً من اتخاذ القرارات القائمة على الحدس، بهدف تحسين نتائج المشاري، وقد تم تقييم قيمة هذا الإطار وتأثيره المحتمل من خلال استطلاع رأي شمل 101 متخصصين فيAgile ، وتقييم معمق من سبعة مديري مشاريع، وأظهرت نتائج الاستطلاع قيمة مُدركة عالية لقدرة الإطار على تحسين القدرة على التنبؤ بالمخاطر، وجودة البرمجيات، واستجابة الفريق، والتعلم التنظيمي، في حين تم تحديد تحديات مثل نقص الكوادر المؤهلة، وتكلفة أدوات البيانات الضخمة، وتعقيد تكامل البيانات، تم أيضًا تسليط الضوء على عوامل تسهيل رئيسة مثل تحقيق عائد استثمار واضح وضمان رضا أصحاب المصلحة.

يقدم هذا البحث مخططًا عمليًا لدمج البيانات الضخمة في إدارة المشاريع الرشيقة، وتعزيز اتخاذ القرارات القائمة على الأدلة، والتحسين المستمر في تطوير البرمجيات الحديثة.

الكلمات المفتاحية: إدارة المشاريع الرشيقة، تحليلات البيانات الضخمة، اتخاذ القرارات القائمة على البيانات، تطوير البرمجيات، نتائج المشاريع، تكامل إطار العمل.

INTRODUCTION

The field of project management in particular is changing and must take advantage of emerging technologies, such as using the capabilities of Big Data to gain insights from market trends, optimize resources, estimate efforts, and evaluate potential risks, which leads to overall project planning improvement, faster execution, and better project control leading to more informed decisions [1]. In today's data-intensive environment, every transaction involves a massive amount of data. Instead of depending solely on intuition, big data allows project managers to use large and varied datasets in real time, which improves decision-making, increases efficiency, and reduces uncertainty throughout the project lifecycle [2].

The are three dimensions —volume, velocity, and variety— in which big data is commonly characterized by according to the foundational '3Vs' of Big Data [2] big data could present a transformative opportunity to gain valuable insights, improve efficiency, and gain competitive advantages. despite the focus of agile project management on iterative development, incremental delivery, continuous collaboration, and flexibility, However, Agile processes can often depend on intuition or only professional experience rather than on quantitative evidence, limiting their potential in today's data-rich environment [3]. The Integrating of Big Data analytics with Agile project management process could be an opportunity to bridge this gap. Through systematic data analysis, valuable insights can be obtained by project managers and teams which can improve planning accuracy, optimize resource allocation, and continually identify emerging challenges [4].

This study addresses the gap that exists by proposing and evaluating a comprehensive data-driven framework to improve the process of managing projects in an agile way. The Framework aims to integrate big data analytics tools across all five phases of the agile process - envision, speculate, explore, adapt and close - to enable informed and evidence-based decision making at all stages of the project management lifecycle

The structure of this paper is as follows: Section II summarizes relevant literature. The suggested data-driven framework and its phases are presented in Section III. The research findings and framework evaluation are covered in Section IV. The study's impact and future directions are highlighted in Section V.

I. Related work

A. Big Data in Project Management

According to a number of project management research, big data analytics and data mining can improve project management, particularly the management of product development and production, by increasing risk anticipation, optimizing the use of resources, and supporting strategic decision-making [5][6][7].

Several studies have supported data-driven project management a approaches, emphasizing the importance of empirical evidence over intuition as a guiding principle for decision-making. However, these approaches are often theoretical and don not provide comprehensive and comprehensive frameworks illustrating how big data tools can be systematically and thoroughly rigorously integrated into each phase all stages of the Agile project management Project Management process.

B. Software Analytics and Metrics

This development is characterized by the growing use of data-driven methods, which are crucial for evaluating and interpreting the massive amount of data generated throughout the development lifecycle. As businesses strive to improve the quality and functionality of their software products, these analytical techniques are crucial. Throughout the entire development process, from initial planning to deployment and maintenance, they help teams anticipate potential risks and make informed decisions. The development of software analytics has successfully ushered in a new era where data serves as the basis for software engineering's continuous innovation and improvement. This includes mining software repositories and tools such as Githru and Commit Guru, which support release management, identify dangerous commits, and understand the development context by using a specific method of analyzing Git commit history [8].

While these studies demonstrate the power of data for specific aspects of software development, they often lack a framework or structure to integrate these capabilities across all phases of the Agile Project management process, and do not explicitly link them to wider decision-making issues in the project management beyond the technical metrics.

C. Data-Driven Agile Approaches

how Agile processes can benefit from continuous data integration and analysis is discussed by Several researchers, arguing that such practices lead to more adaptive and transparent decision-making [11], [12]. Other studies have examined how Agile principles can be applied within Big Data analytics projects, aiming to make the development of analytical systems itself more iterative and flexible [13].
Existing research in both big data and agile methodologies focuses on the conceptual benefits and lacks a single model or practical integration guidelines explicitly aligning big data techniques with the specific phases of agile project management. Data privacy, security and skill skills gaps are often discussed without offering comprehensive architectural or methodological solutions. The current work lacks a single approach that clearly defines what data to collect, which big data tools to use and how to apply analytical methods at each specific agile stage to provide project managers and teams with actionable insights, which prevents organizations from making full use of big data.

II. The suggested framework

The suggested framework aims to provide a structured approach for data-driven decision-making throughout the entire agile project management phases. It enhances each of the five core Agile phases—Envision, Speculate, Explore, Adapt, and Close which are established by [14]—by injecting specific Big Data tools and analytical methods. In the proposed framework, each phase includes multiple components such as Data source, bigdata injection point, which bigdata tool/s used in the phase, which analysis method utilized by big data and finally what is the expected output from the big data injection, Figure 1 below illustrates the proposed framework and its phases and their components and outputs and how are they connected.

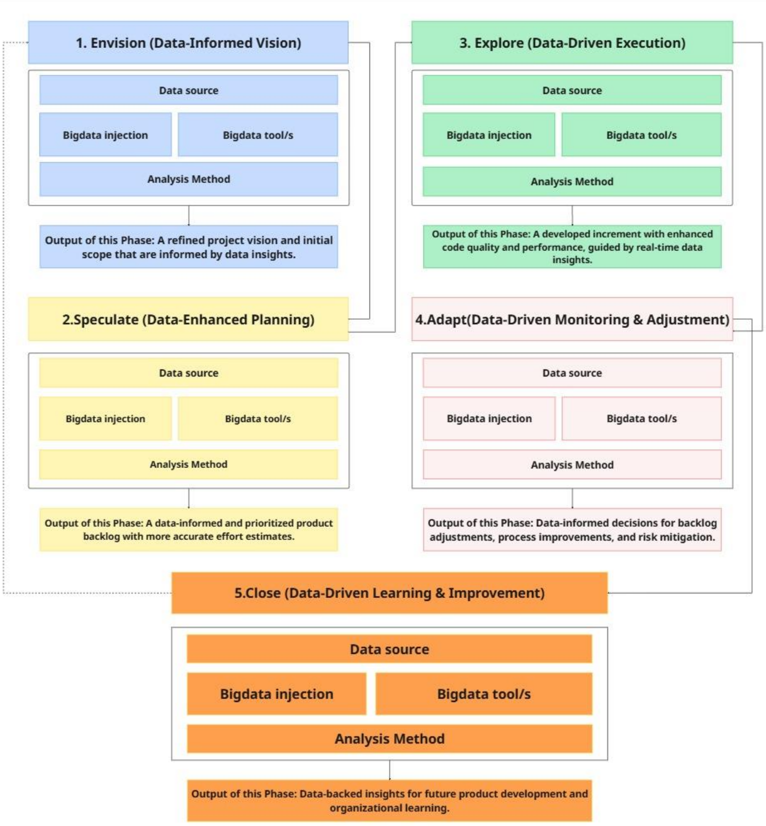

Figure 1: illustrate the proposed framework and its stages

1. Envision (data informed vision)

The envision phase, the first stage in the Agile project management process, involves developing the project vision and high-level documentation such as project charter, thus forming the foundation for Agile management planning. In the proposed framework, the envision phase transforms into a data-driven vision through the strategic injection of big data. Traditional Agile activities: In this foundational phase, Agile teams develop the product vision, define the problem, and establish the high-level project scope. The traditional workflow includes brainstorming, stakeholder interviews, and initial market research. The proposed framework integrates big data tools to generate a more robust, data-driven vision and clarifies the analytical methodologies used, Figure 2 below illustrates the first phase and its components in the proposed framework.

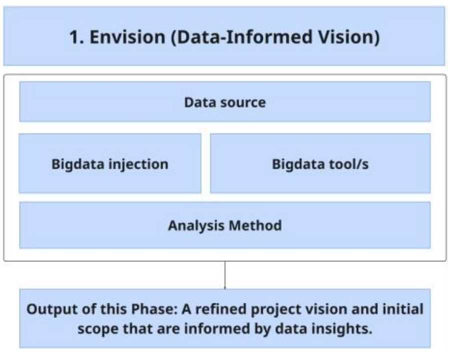

Figure 2: illustrate first phase in the proposed framework

A. Data Sources

Data sources in this phase of the proposed framework includes public web data (e.g., competitor analysis, industry reports), social media posts and conversations to extract sentiments of users concerning apps, online forums, review platforms, and existing customer relationship management (CRM) data or web analytics from previous successful projects.

B. Big Data Injection

The framework proposes leveraging Big Data tools to conduct comprehensive market and user analysis within the process of agile project management. This involves analyzing vast datasets from various sources mentioned in the data sources section to identify opportunities based on bigdata and validate the project's potential to determine if the project is feasible and would have the chance to succeed or restart and redefine the goals and objectives of the project.

C. Big Data Tool(s)

Tools such as Tableau can be employed for visualizing market trends, competitor analysis due to its robust capabilities in interactive data visualization for identifying trend patterns and comparative analysis. Large-scale data collection could make use of Apache Spark's distributed processing power for effective web scraping and natural language processing (e.g. The g. web scraping) and preliminary analysis of unstructured text data from reviews or social media to identify pertinent trends.

D. Analysis Method

The gathered data is subjected to methods such as market benchmarking, sentiment analysis (for social media and reviews), and trend analysis.

E. Output of this Phase

A redefined project vision, well thought initial scope are the output of this phase and are not purely based on assumptions or only the intuition of the project managers or limited qualitative research, instead the results firmly informed and validated by data insights. This data-driven output ensures that the project aligns with the intended market needs and stakeholder expectations from its early stage of development and reduce ambiguity.

2. Speculate (Data-enhanced planning)

The Speculate phase, the second phase in the agile project management process as adapted from Highsmith (2004) where the product backlog is created and prioritized, and efforts are estimated usually relying on project manager’s experience, this phase in the proposed framework, enhanced into a data-enhanced planning by integrating Big Data tools and analytics, phase 2 of the proposed framework and its components shown in figure 3.

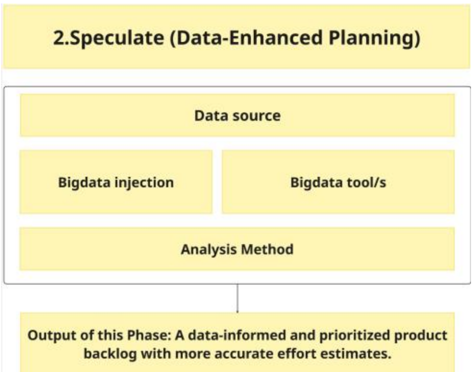

Figure 3: second phase in the proposed framework

A. Data Source

Previous project data, such as sprint velocities, real task completion times, story point accuracy from version control systems (like Git) or project management tools (like Jira), product usage analytics from current systems, and comprehensive customer feedback (e.g. The g. support tickets, answers to surveys)..

B. Big Data Injection

A data-driven method for prioritizing backlog items and enhancing effort estimation accuracy is introduced by the suggested framework.

C. Big Data Tool(s)

Clearer insights could be obtained by using a tool like Tableau to visualize trends in user behavior and A/B test results. For processing massive amounts of project data from the past, Apache Spark is also appropriate at this stage. It can carry out intricate analyses, such as machine learning algorithms, to find relationships between story attributes and real effort or forecast team velocity in the future. Prioritization can be further informed by using Natural Language Processing (NLP) techniques to analyze unstructured customer feedback and extract recurring themes and sentiments. These techniques are typically implemented with Spark or Python libraries.

D. Analysis Method

NLP for sentiment and topic extraction from feedback, A/B test result interpretation, predictive modeling for effort estimation, and user behavior analytics are some of the methods.

E. Output of this Phase

This phase creates a product backlog that is accurately prioritized and informed by data. User needs and business impact are used to validate the ranking of user stories in addition to perceived value. Improved overall project predictability and realistic sprint measurement are the results of a more accurate effort estimation process..

3. Explore (Data-driven execution)

The third phase which is Explore phase, involve the core development activities within sprints, including daily stand-ups and continuous development, by this framework is transformed into a data-driven Execution through real-time Big Data insights, figure 4 illustrates this phase in the framework and its components.

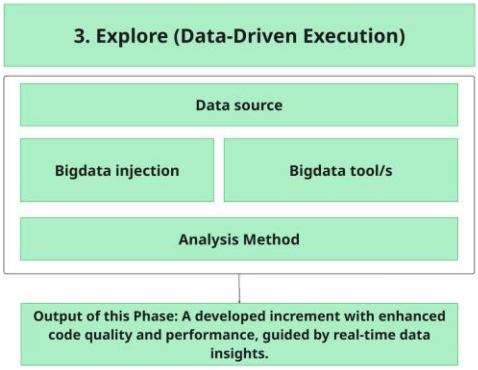

Figure 4: illustrate third phase in the proposed framework

A. Data Sources

data sources could be used in this phase include code repositories (e.g., Git), Continuous Integration/Continuous Delivery (CI/CD) pipeline logs, static code analysis tool outputs, test execution results, and application performance metrics from development environments.

B. Big Data Injection

This framework proposes continuous, real-time monitoring and analysis of development and application performance to identify and address issues in advance.

C. Big Data Tool(s)

Elasticsearch & Kibana form a powerful combination for ingesting, indexing, and visualizing real-time data from logs and metrics from CI/CD pipelines, code analysis tools, and application performance monitors. Flink or Apache Storm are ideal for real-time stream processing, enabling immediate analysis of continuous data flows from development activities (e.g., code commits on git, test runs) to detect anomalies or critical issues as they occur. Tableau can be used for more aggregated, high-level dashboards summarizing quality and performance trends over time.

D. Analysis Method

Real-time anomaly detection, trend analysis, statistical process control, and correlation analysis between code changes and performance/quality metrics.

E. Output of this Phase

The output of this phase is a developed sprint, enhanced code quality and robust performance. The Development process is guided by real-time data insights, allowing teams to identify and resolve issues faster, reducing technical debt and improving the overall stability of the software product.

4. Adapt (Data monitoring and adjustments)

The Adapt phase, traditionally focused on sprint reviews, gathering feedback from stakeholders, and progress monitoring through metrics such as velocity and burndown, in the proposed framework, this phase transformed into a Data Driven Monitoring & Adjustment by integrating Big Data tools and analytics, figure 5 shows the structure of the adapt phase, its component and expected output.

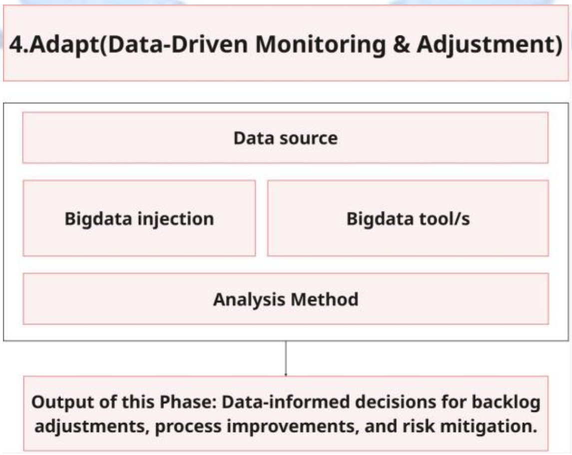

Figure 5: adapt phase in the proposed framework.

A. Data Sources

Data source in this phase includes historical velocity data, burndown charts, defect tracking systems, communication logs (e.g., from collaboration tools like Slack or email) stakeholder feedback (from reviews, surveys, support tickets), and risk registers**.**

B. Big Data Injection

The framework emphasizes using Big Data tools to provide deeper, more objective insights into project performance, stakeholder satisfaction, and potential risks, enabling more informed adjustments and enhancements.

C. Big Data Tool(s)

A tool such as Tableau suitable for creating interactive dashboards that visualize trends in velocity, burndown, and defect rates over multiple sprints. And the visualization can aid managers to take better decisions. Tableau also aggregate and display sentiment analysis results. Elasticsearch & Kibana can be used to analyse large volumes of structured and unstructured feedback data, allowing for quick searching and trend identification. Apache Spark is valuable for more predictive analytics on historical project data, identifying influencing factors on velocity, or predicting potential future risks based on current project parameters.

D. Analysis Method

Analysis method utilized in this phase are Trend analysis, predictive analytics (for velocity and risk), sentiment analysis, and correlation analysis between various project metrics and outcomes.

E. Output of this Phase

This phase results in data-informed decisions for backlog adjustments, strategic process improvements, and proactive risk mitigation. The team gains a clearer, objective understanding of what is working and what needs modifications, leading to continuous optimization of the Agile project management process.

5. Close (Data-driven learning & improvement)

The Close phase, last phase in the proposed framework involves the final product release, data-informed retrospective of the project status and health, and documenting learned lessons. This phase elevated to Data-Driven Learning & Improvement phase through the usage of Big Data, figure 6 below shows the structure of the close phase, its component and expected output.

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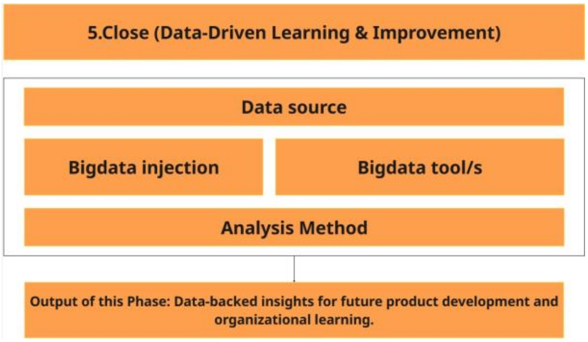

Figure 6: illustrate fifth and last phase in the proposed framework.

A. Data Sources

Key data sources in this phase includes comprehensive product usage analytics (post-release), user behaviour tracking data, customer support interactions, app store reviews, and aggregated project metrics from all previous phases (e.g., total defects, deployment frequency, actual vs. estimated costs).

B. Big Data Injection

The framework proposes leveraging Big Data tools to conduct in-depth post-release analysis and provide objective, data-backed insights for organizational learning.

C. Big Data Tool(s)

Tool such as Tableau is essential for creating dashboards that visualize overall product adoption, feature usage patterns, and long-term customer satisfaction. Elasticsearch & Kibana can be used for production logs and post-release incident data, identifying root causes of issues. Apache Spark is ideal for performing complex, holistic analysis across all collected project data, identifying overarching trends, correlations between development practices and product success, and areas for strategic improvement across the organization.

D. Analysis Method

Analysis methods such as usage analytics, customer journey mapping, root cause analysis of post-release issues, and long-term trend analysis of project performance indicators.

E. Output of this Phase

The output of this phase is a set of insights backed by data help in future product development strategies and contribute to organizational learning. This ensures that probability of success of future projects are high, and failures are reduced, fostering a culture of continuous, data-driven improvement across all subsequent projects.

III. RESULTS AND DISCUSSION

A. Validation of Audience and Survey Profile

Project managers, scrum masters, product owners, and developers are among the 101 Agile professionals who took part in the survey. These positions are critical to the success of Agile projects. In-depth assessments from seven project managers were added to the respondents' varied and experienced backgrounds.

The respondents' demographic profile, which included their years of Agile experience and primary role, verified that the insights collected represent a wide range of actual Agile practice across different organizational sizes and industry sectors.

The roles and experience levels of the survey respondents are broken down in the figures below.

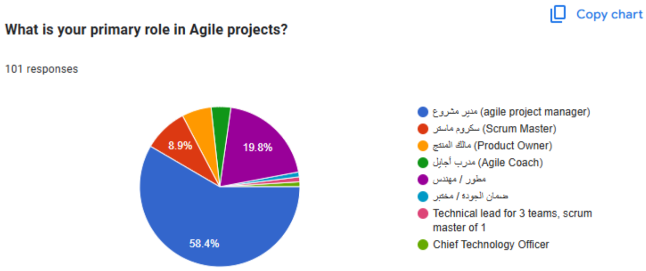

Figure 7: Distribution of Respondent Roles in Agile Projects

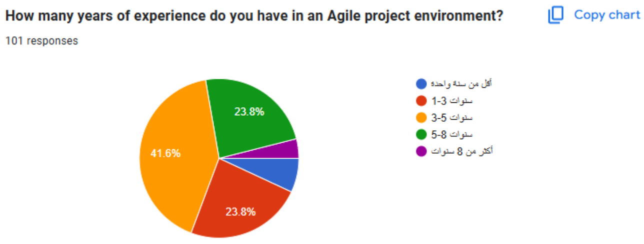

Figure 8: Distribution of Respondent Agile Experience

B. Perceived Value of the Data-Driven Phases

The framework's holistic design was validated by responses that showed a high, consistent perceived value throughout all phases when measured on a Likert scale.

In particular, a high approval rate was given to the Explore (Data-Driven Execution) phase, which focuses on real-time CI/CD and code quality monitoring. This strongly implies that practitioners are aware of an urgent, concrete need for data that improves responsiveness and keeps problem detection going while active development is underway. In a similar vein, the Envision (Data-Informed Vision) phase—which makes use of user and market sentiment analytics—was highly regarded. This shows that Agile leaders are becoming more conscious of the need for project foundations and vision to be based on market big-data rather than just people's presumptions. The survey's results are shown in the figures below.

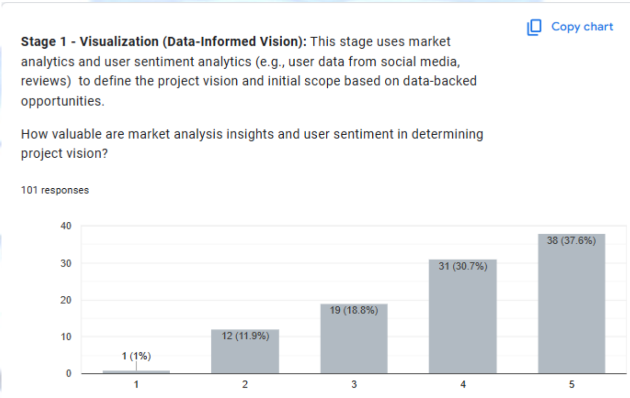

Figure 9: Perceived Value of Envision Phase

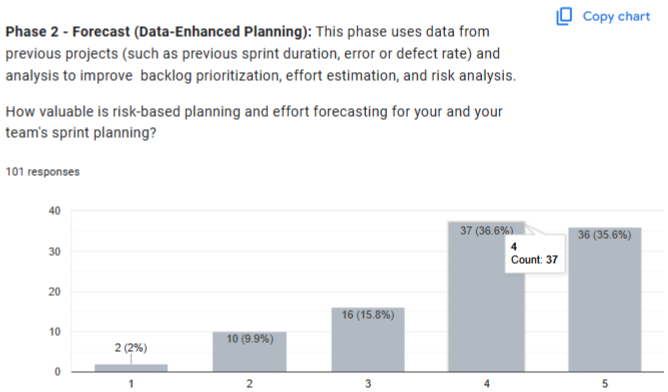

Figure 10: Perceived Value of speculate Phase

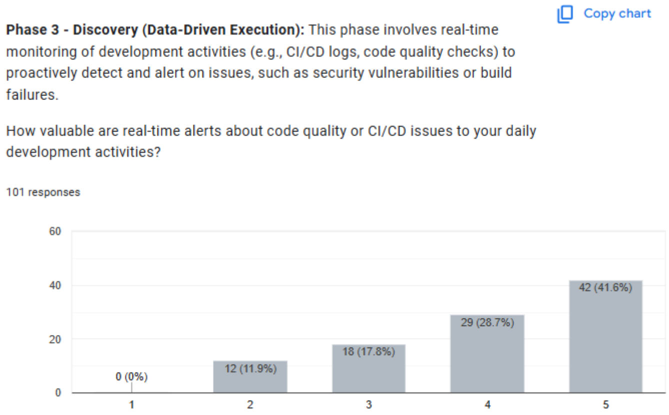

Figure 11: Perceived Value of third Phase explore

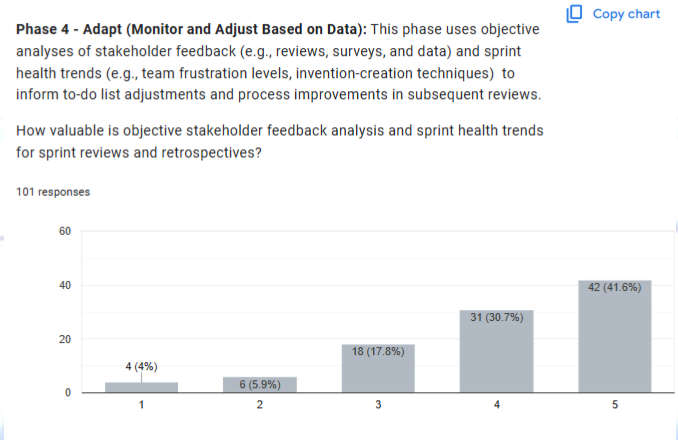

Figure 12: Perceived Value of fourth Phase -adapt

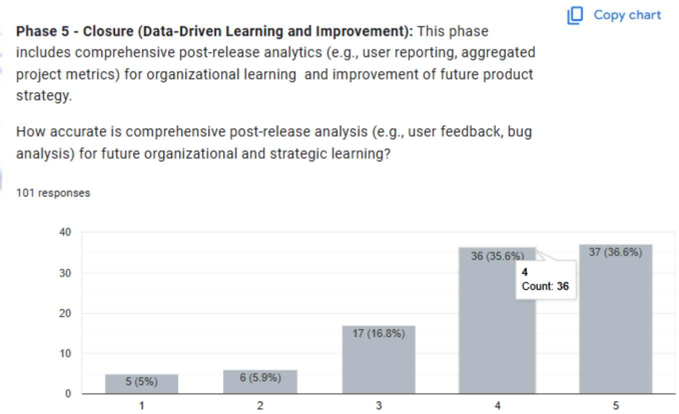

Figure 13: Perceived Value of fifth Phase -close

The high scores in every phase support the practitioners' view that data-driven inputs are an essential evolution for evidence-based decision-making throughout the entire project management process, not just an administrative improvement.

C. Potential Impact on Strategic Agile Outcomes

The survey assessed the perceived influence of the entire framework on Agile project management objectives, going beyond the significance of individual phases. As seen in the figures below, the results indicated a strong consensus that the framework could greatly enhance important project outcomes.

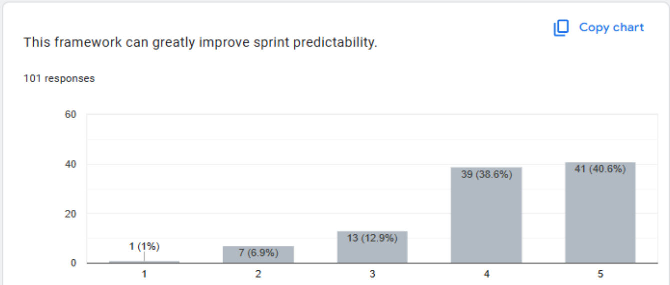

Figure 14: impact of the framework to improve sprint predictability.

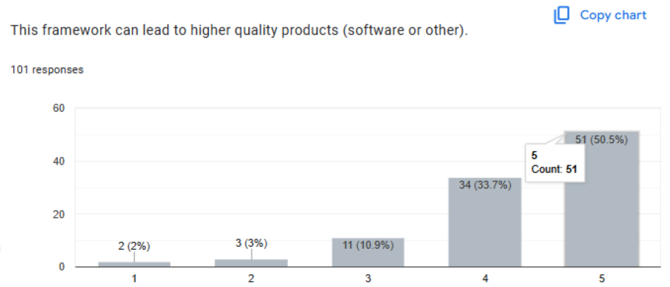

Figure 15: impact of the framework to produce high quality products.

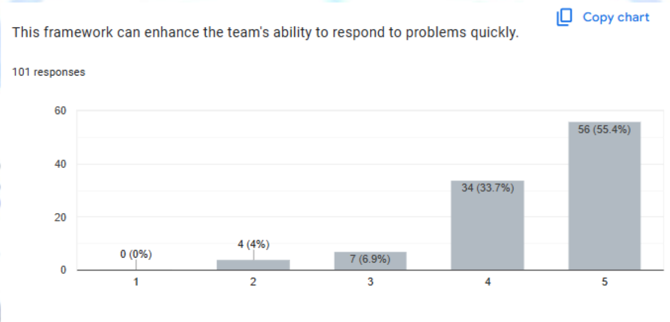

Figure 16: impact of the framework to enhance team's ability to respond to problems quickly.

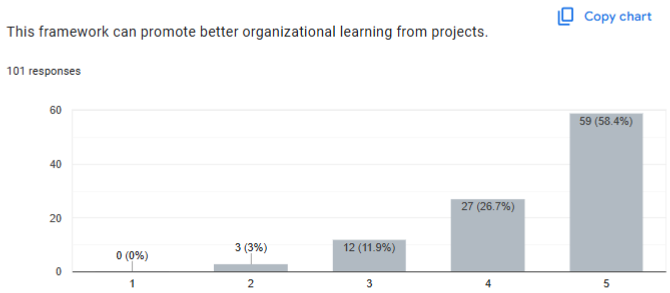

Figure 17: impact of the framework to promote better organizational learning.

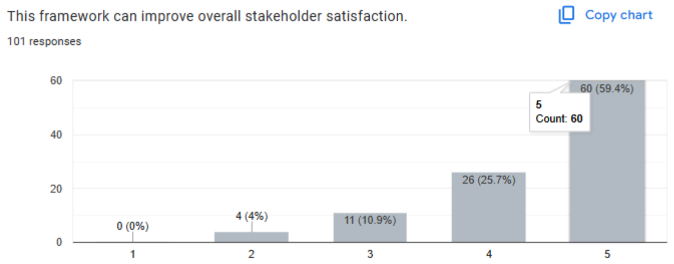

Figure 18: impact of the framework to improve overall stakeholder satisfaction.

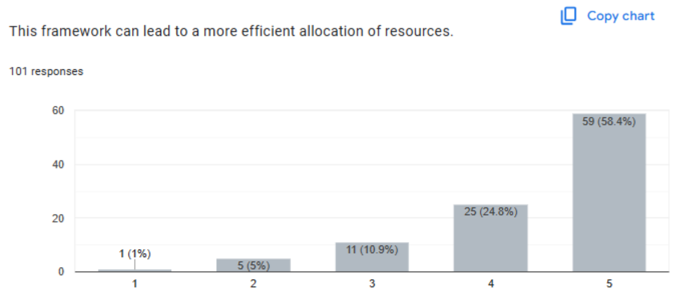

Figure 19: impact of the framework to lead to efficient allocation of resources.

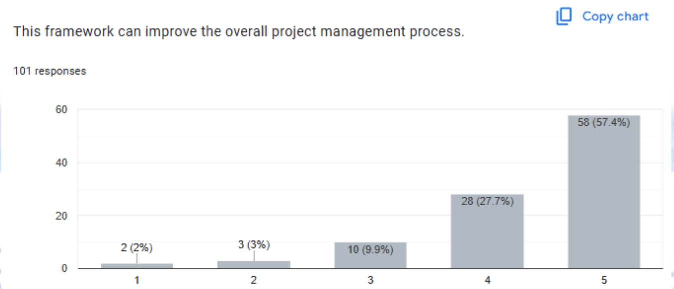

Figure 20: impact of the framework to improve overall Project management process.

- **Improved Sprint Predictability:** 40% of respondents strongly agreed and 39% agreed that the framework's capacity to offer predictive modeling for effort estimation (Speculate phase) and real-time monitoring of roadblocks was extremely helpful for boosting the dependability of sprint commitments.
- **Enhanced Team Responsiveness and Quality:** Real-time alerts and continuous quality analysis would improve the team's capacity to react swiftly to problems, resulting in higher software quality, according to 51% of participants.
- **Fostering Organizational Learning:** The focus of the Framework on objective post-release analysis (closure phase) was recognised as a key mechanism for translating project data into long-term organisational knowledge, ensuring that systemic failures are prevented and successes replicated.

D. Challenges and Facilitators for Real-World Adoption

To offer a useful guide for implementation, the survey also highlighted the key organizational obstacles and supports. This two-sided view is vital for turning a solid theoretical basis into a successful, embraced solution. The spread of answers regarding difficulties and helpers is outlined in the figures below.

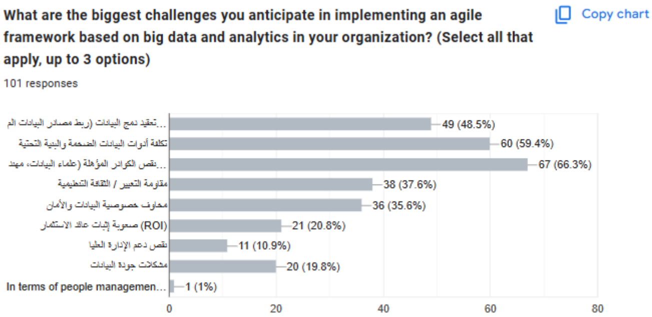

Figure 21: challenges to implement the proposed framework.

Challenges: The top-ranked challenges were intensely centered on organizational capability and fetched:

1. **Lack of Skilled Personnel:** The deficiency of information researchers and engineers able of joining and translating Huge Information devices risen as the foremost noteworthy boundary.
2. **Cost of Big Data Tools and Infrastructure:** Concerns with respect to the beginning speculation required for adaptable analytics frameworks (e.g., Spark) displayed a major budgetary jump.
3. **Data Integration Complexity:** Experts famous the trouble of interfacing different information sources (Git, Jira, CI/CD logs, outside advertise information) into a bound together expository pipeline.

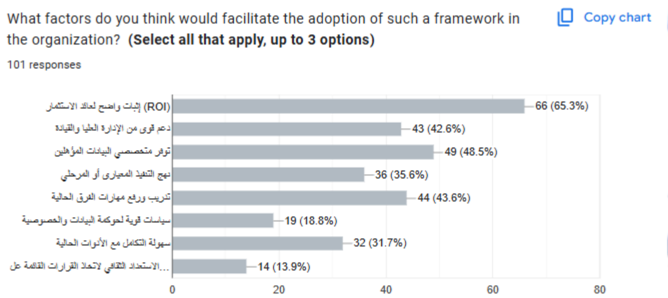

Figure 22: factors facilitating the adoption of the proposed framework.

Facilitators: Importantly, participants also recognized the most evident way ahead, emphasizing the necessity for strategic, people-focused execution:

1. **Clear Demonstration of Return on Investment (ROI):** This has consistently been identified as the most important factor. Project managers have emphasized that without a clear and measurable relationship between data investment and business outcomes (such as reduced time to market or lower defect costs), obtaining management approval (another key factor) would be impossible.
2. **Availability of Skilled Data Professionals / Training:** This indicator points to the use of competent personnel to implement robust programs to enhance the skills of existing Agile teams..

The evaluation from the **7 project managers** Progress has put these challenges into context, emphasizing the need to regulate the acquisition process, since social transformation—that is, getting groups to believe in computerized information rather than intuition—is just as important as specialized engineering.

E. Discussion

In spite of the fact that earlier inquire about [13] has examined challenges in embracing data-driven strategies, there remains restricted observational assessment of the viability of coordinates systems that combine Huge Information and Spry standards. This study's overview and proficient surveys give a significant subjective and quantitative approval of the framework's potential from its target clients. This complements specialized achievability thinks about by illustrating that the proposed system isn't as it were in fact sound but also resonates with the wants and desires of Spry experts, a measurement frequently less investigated in absolutely specialized investigate papers.

challenges and facilitators found by this investigate adjust with and give experimental approval for issues broadly talked about within the writing concerning Enormous Information selection [15] on information complexity; [16] on innovation. Spry experts are particularly overviewed so this inquire about gives a refined point of view on these challenges inside the Spry setting. For occasion, the accentuation on "resistance to alter / organizational culture" (38%) highlights a human component frequently neglected in absolutely specialized Huge Information discourses. The recognized facilitators offer viable methodologies for overcoming these boundaries, giving noteworthy suggestions for future usage that construct upon common Huge Information appropriation counsel.

IV. CONCLUSION

This paper suggested a data-driven comprehensive system planned (framework) to methodicallly coordinated big data analytics into the center stages of agile methodologies. Tending to a hole within the current considers with respect to concrete, integration strategy. This inquire about gives a organized mechanism for leveraging data bits of knowledge over the whole agile lifecycle, from starting Envisioning to final close.

The suggested work addresses all stages of agile management, distinguishing data sources that can be utilized at each arrange, information passage focuses, enormous information tools, and expository strategies over those stages. This orderly integration empowers a move from dependence on individual judgment to evidence-based decision-making, giving the establishment for more precise and versatile venture administration and making a difference pioneers make the proper choices.

The seen utility and potential affect of the framework were observationally approved through a perceptual study of 101professionals. The discoveries demonstrate overpowering proficient bolster, with specialists relegating tall seen esteem to the bits of knowledge produced over all stages. Moreover, the comes about emphatically recommend that the framework has critical potential to upgrade key agile results, counting sprint consistency, computer program quality, group responsiveness, and organizational learning. Whereas viable selection challenges related to ability crevices, foundation fetched, and information integration complexity were recognized. The investigate too clearly highlighted the vital encouraging components, essentially the require for a self evident Return on Venture (ROI) and official bolster..

The proposed work could serve as a basic guide for organizations seeking to develop their skills in leveraging big data for continuous improvement. Future work may focus on real-world pilot use to provide observational validation of the framework's real impact on extended quantitative performance measures and help refine its structural components for widespread use..

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