ISSN 2395-8618

Comprehensive Analysis of the Contributions of Machine Learning to Efficiency in Agile Project Management

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***Abstract*—Machine learning has driven efficiency in agile project management by increasing planning, risk identification, task assignment, and code quality improvement. These contributions have supported agile teams to work more effectively and meet deadlines, yet there remains untapped potential. Therefore, this paper proposes an analysis of these contributions to identify additional opportunities in this field, aiming to further enhance agile project management.**

***Index Terms*—Sprints, burndown chart, agile approach, machine learning.**

I. Introduction

In recent years, we've witnessed a substantial rise in the utility of agile methods in Project Management (PM). Presently, many software development companies have widely adopted these approaches, particularly highlighting Scrum, which has notably surged in popularity [1]. Furthermore, the collaboration between the Project Management Institute (PMI) [2] and the Agile Alliance [3] has led to the creation of an Agile Practice Guide [4]. All of this underscores the increasing importance of PM and the use of agile methods in project success.

According to the Project Management Body of Knowledge (PMBOK) [2], three primary factors—namely time, cost, and scope—are used to assess the quality of work in a project. However, in a real-world setting, these factors alone are insufficient to determine the success of a project, as other elements significantly contribute to achieving objectives, such as effective collaboration among team members and satisfaction with their roles in the project [4].

Furthermore, prior research has demonstrated that Machine Learning Algorithms (MLA) and methods can play a crucial role in supporting PM. A survey conducted in [5] highlights that implementing Machine Learning (ML) in PM can lead to significant progress by automating routine tasks, task allocation, and other functions, thus freeing up time for innovation and enhancing team productivity. Martínez and Fernández-Rodríguez [6] concluded that Artificial Intelligence (AI) tools outperform traditional tools in terms of accuracy and that AI is valuable for project monitoring and control.

Within the domain of Software Engineering (SE), various prediction approaches supported by ML are employed to estimate aspects such as quality, development effort, cost, and risks, among others. However, challenges and research opportunities persist, particularly concerning Agile Project Management (APM).

The purpose of this paper is to conduct an analysis aimed at examining the contributions of ML to efficiency in APM. In the current field, existing literature indeed tends to focus on systematic reviews dealing with isolated prediction aspects, such as cost or effort in projects following traditional approaches.

However, this limited approach doesn't always translate into a comprehensive view of PM in an agile environment, where dynamics and challenges are different. It's precisely this research gap that drives this work. APM has emerged as a highly effective approach for adapting to rapid changes, improving collaboration, and continuously delivering value to the customer. Yet, the application of ML techniques in this specific context has not been fully explored.

By delving deeper into the use of ML approaches in agile projects, we are opening new perspectives and possibilities to enhance the efficiency and success of these projects. This research not only has the potential to fill a gap in current knowledge but also can provide valuable perceptions into how ML can be a powerful tool in APM. It enables more accurate decision-making, automates repetitive tasks, and optimizes resources.

In summary, the objective of this work is to contribute to a more comprehensive understanding of how ML can enhance APM, thereby benefiting organizations seeking to improve their efficiency and competitiveness in an ever-changing business environment. The relevance of this research lies in its ability to address specific challenges and opportunities that arise in APM, ultimately driving excellence in the delivery of agile projects in today's industry.

The structure of this research is presented as follows: Section 2 describes the research background. Section 3 explains the process of selection and review of works. In Section 4, a review of the contributions of ML in APM is conducted. Section 5 analyzes the results of the review. Finally, in Section 6, conclusions and future directions of work are presented, with a comprehensive focus on how ML contributes to efficiency in APM.

II. Antecedents

Tracking in an agile approach is an essential practice involving continuous review and evaluation of both the developing product and the development process itself. This plays a crucial role in ensuring the product aligns with

Manuscript received on 04/12/2023, accepted for publication on 13/02/2024.
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ISSN 2395-8618

TABLE I
SEARCH KEYWORDS

CLV	Query string
CC01	"Agile Software" AND "Machine Learning"
CC02	"Project Management" AND "Machine Learning"
CC03	"Agile project management" AND "Machine Learning"
CC04	"Agile Development" AND "Machine Learning"

TABLE II
SOURCES CONSULTED

No.	Source	URL
01	Scopus	https://www.scopus.com/
02	IEEE explore	www.ieeeexplore.org
03	ACM digital library	https://dl.acm.org/
04	Science Direct	www.sciencedirect.com
05	Springer	https://link.springer.com/

TABLE III
SEARCH RESULTS

Source Name	CC01	CC02	CC03	CC04	WORK
Scopus	83	356	11	47	**497**
IEEE explore	27	345	3	19	**394**
ACM digital library	139	412	10	142	**703**
Science Direct	176	833	31	126	**1,166**
Springer	89	148	16	55	**308**
Total per search result	**514**	**2,094**	**71**	**389**	**3,068**

requirements and that the project is being managed appropriately. Moreover, it provides a real-time view of the project's status, which is fundamental for all involved parties.

Several techniques and tools support this process of tracking and controlling project progress. However, in current literature, most works have focused on reviewing aspects such as effort, cost, project risks, and defects using ML techniques. Primarily, these studies have concentrated on projects following traditional approaches [7, 8].

Some studies, such as the one conducted in [9], have focused on determining the most common effort estimation techniques in an agile approach. The results indicate that the three most used techniques are ML (37%), expert judgment (26%), and algorithmic methods (21%). Additionally, in works like [10] the use of text mining has been proposed to investigate trends in cost and effort estimation.

In [11], it is highlighted that the use of ML algorithms, particularly supervised learning, is increasing for risk assessment in agile projects. Commonly used ML algorithms include Decision Tree (DT), Naive Bayes classifiers (NB), Neural Networks (NN), and Support Vector Machine (SVM).

Despite these advancements, most agile teams still rely on estimation techniques based on expert judgment, as mentioned in [12, 13]. However, studies like the one conducted in [14], based on the Scrum method, have shown that ML models outperform non-automated methods and traditional estimation techniques.

These advancements and findings indicate that challenges and limitations exist when using ML in agile project tracking. This includes aspects such as effort estimation, cost, risks, and other team characteristics. Furthermore, more research focused on specific tracking techniques, such as the Burndown chart or Kanban board, is needed. Therefore, this work aims to address this opportunity area by conducting a systematized investigation to better understand the current state of ML applications in APM.

III. METHODOLOGY

In the context of this study, four primary research inquiries have been formulated to steer and explore the analysis of ML applications in APM. These questions are made to establish a robust foundation and a structured approach that will direct the research process.

1) **RQ1**: **To what degree can ML contribute to improving APM?** This question focuses on assessing how ML can be an effective tool to improve PM in agile environments.
2) **RQ2: What are the most relevant variables in the context of APM that are considered when applying ML?** It focuses on identifying the most important variables in agile management and how these are considered when using ML.
3) **RQ3: What is the most used MLA in practice to support PM in an agile environment?** It focuses on analyzing which MLA are most employed to support APM and their advantages.
4) **RQ4: What is the predominant prediction approach used in agile management supported by ML?** This question explores the primary prediction approach utilized in agile management and how it integrates with ML.

To begin the literature review on the research topic, specific inclusion and exclusion criteria were established. It was emphasized that the chosen studies must directly correlate with the utilization of ML as a support system for APM. Consequently, studies failing to meet these criteria were excluded from consideration. The selection process will be addressed in the following sections.

A. *The data Source and Study Selection Process*

To identify relevant studies, we will conduct comprehensive searches in academic databases and scientific repositories. Studies will be selected following a peer-review process and considering the predefined inclusion and exclusion criteria. This process will ensure the quality and relevance of the works included as references in this research.

The keywords used as a search strategy to select the data are shown in Table 1, with a predominance of terms such as "*Agile*", "*Project Management*", and "*Machine Learning*". These keywords are considered the closest to the research objective.

Table 2 displays the consulted sources obtained from scientific databases, which were chosen because they are freely accessible within the institution conducting this research.

Table 3 displays the results of the initial search in the databases, considering the search strings established previously. The *'Total'* column shows the sums of the results

ISSN 2395-8618

TABLE IV
FINAL SELECTED PAPERS

#	Work	Description
CVE01	Project Tracking Tool for Scrum Projects with Machine Learning Support for Cost Estimation (2021)	This paper describes the design and implementation of a tool that supports various Scrum project-tracking activities, such as the creation of user stories, sprint tasks, and test cases. In addition, the tool supports Scrum project cost estimation based on your sprint tasks [15]
CVE03	A predictive model to estimate effort in a sprint using Machine Learning techniques (2021).	This paper presents a model to estimate and predict the effort in a Sprint using ML techniques considering several factors that affect a Sprint. The model has been evaluated using several regression algorithms such as linear regression, K- -nearest neighbor, DT, polynomial kernel, radius basis function, and MLP. This model has produced more reliable estimates, with low error values, using the MLP algorithm [16]
CVE04	Predicting effort of agile software projects using linear regression, ridge regression, and logistic regressions (2021).	The paper proposes an approach using different regression techniques for effort prediction [17]
CVE05	Machine Learning-based Estimation of Story Points in Agile Development: Industrial Experience and Lessons Learned (2021).	This paper evaluates a new generation ML technique to estimate user history points in a project developed with agile methods [18]
CVE06	An improved technique for software cost estimations in agile software development using soft computing techniques (2021).	This paper proposes a COCOMO model for software project cost estimation. It is based on ML for its predictions, using historical data from 57 different organizations representing the public and private sectors in Sudan [19]
CVE07	Machine Learning Application in LAPIS Agile Software Development Process (2020).	This paper considers the contributions of work teams to the continuous improvement process, to expand opportunities for improvement, based on data. It also considers information from retrospective meetings to support the proposed ML model, the information is obtained from the LAPIS process, an agile, improvement-oriented product delivery process developed by Logo Yazÿlÿm [20]
CVE08	The Method of Agile Projects Success Evaluation Using Machine Learning (2020).	The purpose of this study is to develop a unified method for measuring and predicting the success of agile IT projects based on the machine learning approach [21]
CVE09	Machine Learning models to predict Agile Methodology adoption (2020).	The main objective of this work is to use ML to develop predictive models for the adoption of the Scrum methodology, identifying a preliminary model with the highest prediction accuracy [22]
CVE10	A predictive model to identify Kanban teams at risk (2019).	In this paper, several models were built to demonstrate that selected variables could help identify teams at risk when the team uses a Kanban framework, resulting in better performance using the KNN algorithm with univariate feature selection [23]

per source query, culminating in a subtotal per query and yielding a total of 3,068 records.

At this stage, only articles meeting the platform-provided selection criteria have been considered, such as *Conference Proceedings*, *Conference Papers*, *Scientific Articles*, or *Books*. Additionally, specific thematic areas and subareas like *Computer Science*, *Social Sciences*, *Agricultural and Biological Sciences*, *Business*, *Administration*, etc., have been considered, all depending on the offerings provided by the platforms. It's worth noting that the research includes documents from 2017 to 2022, aiming to focus on recent advancements in ML directed towards PM.

After gathering data from the databases during the search, the next step involved data cleansing primarily focused on screening articles by their titles. We initiated the process by identifying and eliminating duplicate articles. Furthermore, we filtered out studies that did not align with our objectives, such as research discussing the integration of agile or traditional approaches in ML. Although these topics might be of significant interest based on our search findings, they do not directly contribute to the intended scope of this research article.

IV. RESULTS

After conducting an exhaustive search across various sources and performing the data-cleaning process, a total of 172 papers were obtained for review. Subsequently, a final review was conducted applying the inclusion and exclusion criteria, resulting in the selection of a final set of 10 papers. Table 4 lists the 10 papers chosen in this final stage of selection.

After conducting an in-depth analysis of the identified papers, the research results are described, providing concrete answers to the questions posed at the beginning of the study. Highlighting key findings, identified trends, and the conclusions drawn throughout our research.

ISSN 2395-8618

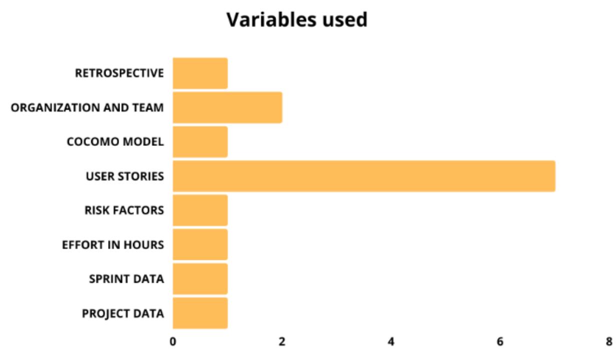

Fig. 1. Results variables considered Result RQ3

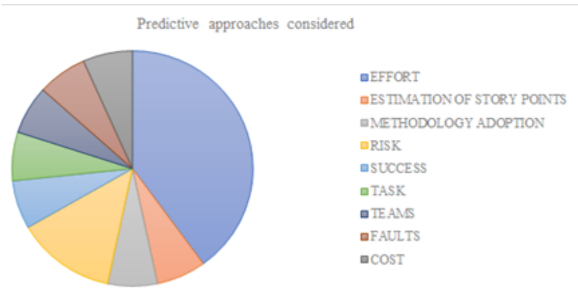

Fig. 2. Results by Prediction Approach

A. *Result RQ1*

During the analysis of the papers, a general perspective was obtained on how ML can contribute to the improvement of agile project management:

1) **Prediction and Planning:** ML can be used to analyze historical data from agile projects and predict delivery times, costs, and other crucial factors. This can assist management teams in planning more effectively and setting realistic expectations for stakeholders.
2) **Early Risk Detection:** MLA can identify patterns and early warning signals in agile projects, enabling managers to take proactive measures to mitigate risks and prevent potential delays or issues.
3) **Resource Optimization:** ML can assist in more efficiently allocating resources in agile projects. For instance, it can optimize personnel assignment based on skills and availability, contributing to more efficient management.
4) **Real-Time Tracking and Metrics:** ML systems can provide real-time insights into project progress, enabling management teams to make informed decisions and adjust their strategies as they progress.
5) **Automation of Repetitive Tasks:** Administrative and repetitive tasks in agile project management can be automated using ML, freeing up time for teams to focus on more strategic activities.
6) **Process Customization:** ML can tailor PM processes to the specific needs of each project, allowing greater flexibility in agile environments.

However, it is important to highlight that the successful implementation of ML in APM| requires a deep understanding of both disciplines, as well as the availability of high-quality data. Additionally, considering ethical and data privacy aspects is fundamental when utilizing ML in such projects.

In summary, ML has the potential to be an effective tool for enhancing APM by providing advanced data analytics capabilities and task automation. Its actual impact will depend on how effectively it's integrated into agile management processes and the quality of data available for its use.

B. *Result RQ2*

The use of user stories as the main predictive variable stands out. Although some other variables are considered, such as COCOMO for cost estimation in conjunction with ML and the agile approach, most studies consider information related to user stories to generate both dependent and independent variables. However, there was a notable absence in the use of other agile project tracking techniques that could serve as predictive variables, such as the Burn Down chart. These techniques allow understanding of work progress by considering parameters like status, and execution times, among others. Please note that, for a better analysis, a classification of variables was conducted, which is observed in Fig. 1. The graph represents the result of the variable classification analysis.

Most selected papers conduct prior comparative studies of certain MLA to choose the most suitable one or validate the proposed one. Among the most frequently used algorithms for comparison are SVM, KNN, ANN, DT, RR, LR, and BN. It's noteworthy that even if a study does not explicitly detail the process of comparative analysis to choose the MLA to use, it still mentions and substantiates its choice.

C. *Result RQ4*

The preference for the predictive approach to risks and effort stands out. Most authors focus on supporting PM in determining project risks and efforts, overlooking some other predictive approaches that could be of great support to the project manager, such as user story analysis. Fig. 2 displays the graph resulting from the analysis by the predictive approach considered.

V. Discussion and Analysis of Results

Throughout this study, it was found that there are still challenges in the field of APM, which provide opportunities for new lines of research. The lack of effective tools presents an opportunity for AI to significantly enhance APM.

The study observed that ML can support APM, enabling project managers to focus on improving project development quality and reducing data analysis time, such as task execution times, development times, etc.

Furthermore, it was observed that the most predominant variables include information related to user stories (US), along with sprint data such as start and end times, and general team data. The primary context in which ML is used to support PM is in risk analysis and development efforts.

Additionally, a wide variety of MLAs were found among the analyzed studies, used to compare new models with previous ones; some of these include RR, KNN, DT, and SVM.

During the development of the current research, it was noted that there are some empirical-type works, as mentioned in [24], showcasing an AI proposal to support PM. While these types of works were not considered in the final selection (only proposals

ISSN 2395-8618

without further development), they could be relevant in the future.

During the analysis, challenges were also identified in the field of APM, opening new research perspectives. The lack of effective tools has created a significant opportunity for AI to enhance APM.

One of the most notable challenges in APM is the need to optimize decision-making and PM in a more agile and effective manner. This often involves constant analysis of data, such as task execution times, development deadlines, resource allocation, and risk estimation. This is where AI and ML can make a difference.

For instance, ML can assist project managers in focusing on improving project development quality by reducing the time needed for data analysis and making informed decisions. Picture a scenario where, through MLA, bottlenecks in an agile project can be predicted before they occur, enabling managers to take preventive measures to avoid delays. Key challenges we identified include:

1) **Accurate Risk Predictions:** Risk management is fundamental in APM, and ML can enhance the ability to predict potential risks and take proactive measures to mitigate them.
2) **Resource Optimization:** Ensuring resources are allocated efficiently and fairly is a constant challenge in APM, and MLA can aid in achieving this.
3) **Realistic Deadline Estimation:** Accurately predicting development deadlines is essential in agile projects, and ML can utilize historical and current data to improve these estimations.
4) **Quality Assessment:** Work quality is a crucial aspect, and ML can analyze metrics and quality data to ensure deliverables meet the required standards.

Additionally, the research findings revealed that certain variables play a predominant role in the application of ML in APM, including information related to US and sprint data such as start and end times, as well as general team data.

Regarding specific examples, let's visualize an agile development team using ML to analyze historical data from their sprints. With this information, the team can more accurately predict the time required to complete tasks and, consequently, plan sprints more efficiently.

On the other hand, another crucial point of relevance in the research was the absence of any dataset specifically related to tracking Sprint work progress within the examined datasets in the gathered works. This omission stands out as a significant gap in the existing literature, signaling an unmet need for a structured dataset encompassing pertinent features and characteristics essential for monitoring and evaluating the evolution of work within Sprint cycles.

The relevance of such a dataset cannot be overstated. It serves as a foundational tool for APM, enabling comprehensive analyses and informed decision-making. Its creation would not only address a crucial void in the current body of literature but also facilitate empirical research, fostering advancements in optimizing agile methodologies, specifically in enhancing the efficiency and effectiveness of Sprint-based work management.

In summary, this study highlights the significant potential of AI and ML to enhance APM by addressing key challenges and optimizing decision-making. However, there's a need to refine and unify prediction approaches in APM, as many works focus on specific aspects like costs or efforts. It would be valuable to move towards a more comprehensive approach, where multiple variables and areas are unified into a single ML model. This approach could serve as a foundation for future research in the field of AI and PM overall.

VI. Conclusions and Future Work

The significant rise in the number of projects following an agile approach has been witnessed not only in the software industry but also in various non-IT domains [5]. Additionally, the success of ML in solving prediction problems has paved the way for its support in new areas, such as SE, for several years now.

Therefore, this study aimed to analyze to understand the current state of ML focused on APM. To conduct this research, the process involved keyword searches, data cleaning, work selection, an initial screening, and ultimately, a final analysis and selection of works. As a result, 10 papers were selected after applying the pre-established selection criteria.

From the analysis of the selected papers, it's noteworthy that one of the primary predictive variables used by the authors was the US, although they also considered others such as Sprint data, team information, and organizational aspects.

There was also a variety of MLA supporting the prediction in specific approaches, some prominent ones being SVM, KNN, and DT, among others. Concerning predominant prediction approaches, they focused on development efforts and project risks.

On the other hand, through this research, it was observed that current literature predominantly focuses on traditional management. Although there are works oriented towards APM, they tend to concentrate on specific prediction aspects, such as costs or risks.

APM, coupled with ML, indeed enhances PM. For instance, it aids in task allocation for geographically distributed teams, provides insights into team dynamics through sentiment analysis, predicts delivery times, forecasts the course of a Sprint based on the US, and assesses project risks, among other functionalities.

Finally, after analyzing this investigation, several research opportunities and areas for future work have been identified, including:

1) Implementing machine learning (ML) models for requirement analysis using an agile approach, given the absence or scarcity of such models within the agile framework. This initiative aims to enhance understanding and management of requirements in agile environments by harnessing the predictive capability of ML models.
2) Conducting a Systematic Literature Review (SLR) and a comparative study of prediction approaches employed in APM, aimed at identifying novel methodologies or approaches within the existing literature. This effort seeks to uncover new trends and promising approaches to improve application performance management.

ISSN 2395-8618

3) Leveraging ML models to support APM, considering diverse prediction approaches to incorporate them into a tool that aids project managers. This integration would enable the utilization of the predictive capacity of ML models to enhance efficiency and decision-making in PM.
4) Creating a dataset with features and attributes enables the evaluation of work progress within a Sprint. The absence of this information in the conducted study underscores the need to develop a dataset containing relevant metrics and characteristics to assess and monitor work progress in agile environments.

These research areas offer significant opportunities to advance the field, addressing identified gaps in the literature and providing new tools and approaches to improve APM.

REFERENCES

[1] K. Schwaber and J. Sutherland, *La Guía Scrum. La Guía Definitiva de Scrum: Las Reglas del Juego*, 2020.

[2] Project Management Institute, *A Guide to the project management body of knowledge (PMBOK® guide)*, 6th ed., Project Management Institute, 2017.

[3] J. Sutherland, *Manifesto for Agile Software Development*, 2022.

[4] Project Management Institute, *Agile Practice Guide*, Project Management Institute, 2017.

[5] Digital.ai, *16th State of Agile Report Agile adoption accelerates across the enterprise*, 2022.

[6] D. Magaña-Martínez and J. C. Fernandez-Rodriguez, "Artificial Intelligence Applied to Project Success: A Literature Review," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 3, no. 5, p. 77, 2015. DOI: 10.9781/ ijimai.2015.3507.

[7] R. A. Santos, D. Vieira, A. Bravo, L. Suzuki, and F. Qudah, "A systematic mapping study on the employment of neural networks on software engineering projects: Where to go next?," *Journal Software Evolution and Process,* vol. 34, no. 3, 2022. DOI: 10.1002/smr.2402.

[8] J. Pachouly, S. Ahirrao, K. Kotecha, G. Selvachandran, A. Abraham, "A systematic literature review on software defect prediction using artificial intelligence: Datasets, Data Validation Methods, Approaches, and Tools," *Engineering Applications of Artificial Intelligence*, vol. 111, pp. 104773, 2022. DOI: 10.1016/J.ENGAPPAI.2022.104773P.

[9] P. Sudarmaningtyas and R. Mohamed, "A Review Article on Software Effort Estimation in Agile Methodology," *Pertanika Journal of Science & Technology*, vol. 29, no. 2, pp. 837–861, 2021. DOI: 10.47836/pjst.29.2.08.

[10] A. Jadhav, M. Kaur and F. Akter, "Evolution of Software Development Effort and Cost Estimation Techniques: Five Decades Study Using Automated Text Mining Approach," *Mathematical Problems in Engineering*, vol. 2022, pp. 1–17, 2022. DOI: 10.1155/2022/5782587.

[11] A. Sousa, J. P. Faria, and J. Mendes-Moreira, "An analysis of the state of the art of machine learning for risk assessment in software projects," in *33rd International Conference on Software Engineering and Knowledge Engineering,* pp. 217–222, 2021. DOI: 10.18293/SEKE2021-097.

[12] M. Fernández-Diego, E. R. Méndez, F. González-Ladrón-De-Guevara, S. Abrahão and E. Insfran, "An update on effort estimation in agile software development: A systematic literature review," *IEEE Access,* vol. 8, pp. 166768–166800, 2020. DOI: 10.1109/ ACCESS.2020.3021664.

[13] P. Srivastava, N. Srivastava, R. Agarwal and P. Singh, "Estimation in Agile Software Development Using Artificial Intelligence," *Lecture Notes in Networks and Systems*, vol. 376, pp. 83–93, 2022. DOI: 10.1007/978-981-16-8826-38.

[14] M. Arora, S. Verma, and K. S. Chopra, "A Systematic Literature Review of Machine Learning Estimation Approaches," *Scrum Projects*, vol. 1040, pp. 573–586, 2020. DOI: 10.1007/978-981-15-1451-759.

[15] K. Periyasamy and J. Chianelli, "A Project Tracking Tool for Scrum Projects with Machine Learning Support for Cost Estimation," in *29th International Conference on Software Engineering and Data Engineering*, vol. 76, pp. 86–76, 2021. DOI: 10.29007/6vwh.

[16] M. A. Ramessur and S. D. Nagowah, "A predictive model to estimate effort in a sprint using machine learning techniques," *International Journal of Information Technology*, vol. 13, pp. 1101–1110, 2021. DOI: 10.1007/s41870-021-00669-z.

[17] M. Vyas and N. Hemrajani, "Predicting effort of agile software projects using linear regression, ridge regression, and logistic regression," in *International Organization on Technical and Physical Problems of Engineering,* vol. 13, pp. 14–19, 2021.

[18] M. Abadeer and M. Sabetzadeh, "Machine Learning-based Estimation of Story Points in Agile Development: Industrial Experience and Lessons Learned," in *IEEE 29th International Requirements Engineering Conference Workshops (REW), USA,* pp. 106–115, 2021. DOI: 10.1109/REW53955.2021.00022.

[19] Q. Bushra and A. Kadam, "An improved technique for software cost estimations in agile software development using soft computing techniques", *Journal of Information Technology in Industry*, vol. 9, 2021.

[20] T. Tekbulut, N. Canbaz, and T.Ö. Kaya, "Machine Learning Application in LAPIS Agile Software Development Process," in *Turkish National Software Engineering Symposium (UYMS)*, pp. 1–6, 2020. DOI: 10.1109/UYMS50627.2020.9247069.

[21] D. Veido, B. Misnevs, and A. Plotkin, "The Method of Agile Projects Success Evaluation Using Machine Learning," in: *Lecture Notes in Networks and Systems*, vol. 117, Springer, pp. 478–487, 2020. DOI: 10.1007/978-3-030-44610-947.

[22] R. Hanslo and M. Tanner, *Machine Learning models to predict Agile Methodology adoption*, Institute of Electrical and Electronics Engineers Inc., pp. 697–704, 2020. DOI: 10.15439/2020F214.

[23] I. Shamshurin and J. S. Saltz, "A predictive model to identify Kanban teams at risk," *Multiagent and Grid Systems*, vol. 14, pp. 321–335, 2019. DOI: 10.3233/MAS-190471.

[24] H. K. Dam, T. Tran, J. Grundy, A. Ghose, and Y. Kamei, "Towards Effective AI-Powered Agile Project Management," in *Proceedings of the IEEE/ACM International Conference on Software Engineering ICSE) - New Ideas and Emerging Results (NIER*), pp. 41–44, 2019. DOI: 10.1109/ICSE-NIER.2019. 00019.