# Leveraging Transformer-Based Large Language Models for Parametric Estimation of Cost and Schedule in Agile Software Development Projects

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***Abstract-*** ***Accurate estimation of cost and schedule remains a critical challenge in agile software development due to iterative delivery cycles, evolving requirements, and cross-functional team dynamics. Recent advancements in transformer-based large language models (LLMs), such as BERT and GPT, present promising opportunities for improving parametric estimation accuracy through contextual learning and natural language understanding. This paper explores the integration of LLMs into agile project management frameworks to automate and enhance estimation processes based on historical project data, user stories, and sprint planning artifacts. By leveraging pre-trained models fine-tuned on domain-specific repositories, the approach enables predictive modeling of project parameters with improved consistency and scalability. A review of the literature reveals that while traditional machine learning techniques have been used for estimation tasks, LLMs offer superior performance in capturing semantic complexity and stakeholder language. The study further presents a conceptual framework for embedding transformer-based models into agile workflows, highlighting their potential to reduce estimation bias, improve planning accuracy, and facilitate continuous forecasting. This research contributes to the growing intersection between AI-driven software engineering and agile project management, advocating for data-centric decision-making in software delivery environments.***

***Indexed Terms-*** ***Transformer-Based Models, Parametric Estimation, Agile Software Development, Cost and Schedule Forecasting, Large Language Models (LLMs).***

## I. INTRODUCTION

### 1.1 Overview of agile software development and its challenges in project estimation

Agile software development methodologies, notably Scrum and Extreme Programming (XP), prioritize flexibility, iterative progress, and continuous customer feedback. These approaches emerged as a response to the rigidity of traditional waterfall models, enabling rapid delivery of incremental features and adaptive scope control. Agile frameworks emphasize evolving requirements and cross-functional collaboration, which contribute significantly to improved product quality and stakeholder satisfaction (Beck et al., 2001; Highsmith, 2002).

However, the very characteristics that define agility also introduce substantial complexity in cost and schedule estimation. Unlike traditional methods that rely on upfront requirement specification and sequential development stages, agile environments involve dynamic user stories, evolving priorities, and variable team velocities. These fluctuations complicate the establishment of reliable baselines for forecasting time and effort (Moløkken-Østvold & Jørgensen, 2005).

Agile estimation techniques such as story points, planning poker, and velocity tracking are largely heuristic, relying heavily on subjective judgment. As a result, they are susceptible to inconsistencies and bias, particularly in distributed or newly formed teams (Jørgensen & Shepperd, 2007). Moreover, traditional estimation frameworks often fail to capture the

semantic richness embedded in natural language artifacts such as backlog items, sprint retrospectives, and user feedback. This disconnect between structured estimation models and unstructured agile documentation creates a gap that limits the precision of current forecasting approaches (Akpe et al., 2020; Mgbame et al., 2020).

In practice, teams frequently experience deviations between estimated and actual effort due to evolving project scopes, technical debt, and unforeseen implementation complexities. These estimation challenges are exacerbated in large-scale agile programs where coordination across multiple teams introduces additional uncertainty. Despite efforts to apply historical velocity data and BI tools, many solutions remain limited by their dependence on structured input and lack of semantic interpretability.

Consequently, the industry is increasingly exploring AI-powered alternatives capable of learning from complex project data, particularly large language models (LLMs) with transformer architectures. These models hold the promise of improving estimation accuracy by deriving contextual insights from the same agile artifacts that are typically underutilized in traditional estimation workflows.

### 1.2 The Need for Improved Cost and Schedule Forecasting in Agile Contexts

Accurate cost and schedule estimation is a cornerstone of effective project management, yet it remains one of the most persistent challenges in agile software development. Unlike traditional methodologies that rely on comprehensive upfront planning, agile frameworks operate within dynamic environments where requirements are frequently refined and delivery cycles are iterative. These conditions make it difficult to apply conventional estimation techniques, which often depend on static metrics and linear progress assumptions. As a result, project teams experience discrepancies between planned and actual outcomes, leading to resource misallocations, missed deadlines, and stakeholder dissatisfaction (Akpe et al., 2020; Mgbame et al., 2020). Moreover, agile estimation methods such as story points and planning poker are inherently subjective and heavily reliant on team experience and cohesion, which introduces estimation bias and inconsistency across projects (Jørgensen & Moløkken-Østvold, 2004).

The growing complexity of software systems, coupled with cross-functional collaboration and distributed team structures, further exacerbates the limitations of traditional estimation practices. Organizations are increasingly seeking automated and data-driven alternatives to support decision-making in agile environments. Studies have shown that business intelligence (BI) tools and analytics can aid in forecast accuracy, yet many such systems still require structured data inputs and offer limited support for interpreting narrative-rich agile artifacts like user stories, sprint reviews, and backlog discussions (Menzies et al., 2017). This gap in semantic understanding underlines the need for advanced estimation frameworks capable of parsing unstructured content and extracting contextually relevant features. The emergence of transformer-based large language models (LLMs), which excel in natural language comprehension, offers a promising solution by enabling predictive models that are sensitive to the linguistic and contextual nuances of agile documentation. These models provide an opportunity to augment agile estimation with consistent, scalable, and adaptive forecasting capabilities that can evolve with project dynamics and historical learning.

### 1.3 Emergence of Transformer-Based Large Language Models (LLMs) in Software Engineering

Transformer-based large language models (LLMs) have revolutionized natural language processing (NLP) by introducing self-attention mechanisms that effectively capture long-range dependencies and contextual relationships in text data (Vaswani et al., 2017). This architectural advancement laid the groundwork for models such as BERT, RoBERTa, and GPT, which excel in a variety of language understanding tasks. Their ability to semantically interpret and generate coherent text has positioned them as powerful tools for software engineering applications, including code summarization, bug report classification, and documentation generation (Ahmad et al., 2020). In agile environments, these

capabilities are particularly valuable, given the reliance on unstructured artifacts such as user stories, commit messages, and sprint retrospectives for project tracking and estimation.

LLMs are being increasingly adapted to support estimation and planning by learning from historical textual patterns within agile software repositories. Pre-trained models, when fine-tuned with domain-specific corpora, can predict development effort and timelines with significantly improved contextual awareness. Studies have demonstrated that LLMs outperform traditional ML approaches in parsing semantic nuances in agile documentation, allowing for scalable and automated estimation pipelines (Owoade et al., 2020). These developments illustrate the transformative potential of LLMs in aligning intelligent forecasting systems with the fluid nature of modern software delivery.

### 1.4 Motivation for Integrating LLMs into Agile Estimation Workflows

The increasing complexity of agile project documentation—comprising user stories, sprint retrospectives, and task breakdowns—demands intelligent systems capable of extracting semantic and contextual insights from unstructured text. Traditional machine learning models, such as decision trees or support vector machines, require manual feature engineering and are often ill-suited for capturing evolving team dynamics or natural language patterns in agile artifacts (Zhang et al., 2019). Transformer-based large language models (LLMs), introduced by Vaswani et al. (2017), offer a paradigm shift by employing self-attention mechanisms to learn dependencies and contextual hierarchies across sequences. Their architecture enables real-time analysis of complex language data, making them ideal for parametric estimation tasks that depend heavily on historical sprint narratives and stakeholder interactions.

Moreover, LLMs demonstrate state-of-the-art performance in various NLP applications such as document classification, sentiment analysis, and entity recognition—tasks closely related to interpreting agile project logs (Devlin et al., 2019; Yang et al., 2019). When fine-tuned with agile-specific corpora, LLMs can provide consistent and scalable estimations across teams and projects, reducing cognitive bias and human error. Their ability to generalize across unseen contexts further supports continuous planning and predictive forecasting in fast-paced agile environments, where traditional models struggle to adapt.

## II. LIMITATIONS OF TRADITIONAL ESTIMATION APPROACHES IN AGILE ENVIRONMENTS

### 2.1 Review of Conventional Estimation Techniques (e.g., expert judgment, story points, velocity)

Traditional estimation techniques in agile software development often revolve around heuristic and team-based methods such as expert judgment, planning poker, story points, and velocity tracking. These methods, while aligned with agile principles of collaboration and continuous planning, are inherently limited by their reliance on subjective assessments and historical team performance. Expert judgment, for instance, draws heavily on the experience of team members or project leads but lacks statistical grounding and repeatability. Similarly, story points—used to gauge the relative complexity or effort of user stories—vary widely between teams and are susceptible to estimation bias and team fatigue (Akpe et al., 2020). Planning poker, a popular consensus-based estimation practice, is intended to reduce bias by involving the whole team in estimation decisions; however, it still fails to leverage past project data in a predictive capacity, often leading to inconsistent sprint outcomes.

Velocity-based estimation, which involves tracking the average amount of work completed in previous sprints to forecast future performance, provides a data-informed alternative. However, it assumes that team composition, task complexity, and technical debt remain relatively stable over time—an assumption rarely met in agile settings. Studies have noted that reliance on historical velocity is ineffective when sprint scope fluctuates or when user story quality varies, making it a reactive rather than proactive tool (Mgbame et al., 2020). Furthermore, conventional tools that operationalize these techniques lack

semantic processing capabilities, leaving unstructured data such as sprint retrospectives, backlog narratives, and developer comments untapped. Without incorporating natural language processing or contextual data analytics, these models fall short in dynamic, fast-paced development environments. These limitations underscore the need for integrating intelligent, context-aware models—such as transformer-based LLMs—that can interpret agile artifacts in a semantically meaningful way and provide adaptive estimation strategies.

### 2.2 Gaps in Current Tools: Subjectivity, Lack of Semantic Interpretation, Limited Scalability

Existing estimation tools in agile software development predominantly rely on heuristic or statistical methods that often fall short in dynamic, text-rich environments. Techniques such as planning poker or velocity-based forecasting are highly subjective, depending heavily on individual team member experience, recent sprint performance, and informal consensus—leading to inconsistent estimation outcomes. Moreover, widely adopted business intelligence tools, though data-driven, are optimized for structured data and fail to incorporate unstructured, semantically rich inputs like user stories, backlog items, and sprint retrospectives. These tools typically ignore linguistic nuances that influence requirement complexity, team behavior, or cross-functional dependencies, which are crucial in iterative and fast-paced agile ecosystems.

The scalability of current approaches is also limited. As projects grow and evolve, traditional estimation frameworks do not adapt well to increased data volume or contextual diversity. Furthermore, tools built on predefined rule sets struggle to generalize across domains or react to non-linear project patterns, ultimately weakening their predictive power (Akpe et al., 2020). According to Jørgensen and Shepperd (2016), such limitations hinder long-term project planning and make historical comparisons unreliable. These constraints collectively emphasize the need for advanced models capable of semantic interpretation, contextual adaptation, and continuous learning across agile iterations.

### 2.3 Challenges of Using Structured-Only Methods in Dynamic Project Environments

Structured estimation techniques in software engineering—such as use-case points, function points, and static historical velocity models—rely heavily on quantifiable inputs and fixed templates. While these models offer repeatability and ease of application, they struggle to adapt to the nuanced and fluid nature of agile environments, where user stories evolve frequently, team capacities shift, and priorities are redefined across sprints. In such contexts, rigid parameter-based estimation frameworks overlook rich, contextual cues embedded in textual documentation, stakeholder feedback, and sprint retrospectives. This results in estimation inaccuracies, delayed delivery timelines, and underutilization of agile's responsiveness to change (Wangenheim & Hauck, 2008).

Moreover, structured-only models fail to leverage semantic signals from non-numeric data, such as task narratives and requirement elaborations that drive agile project evolution. Their lack of contextual interpretation restricts their utility in modern DevOps pipelines, where estimation must be adaptive and evidence-driven. As agile projects increasingly produce diverse forms of unstructured data, tools that cannot parse language or derive predictive insights from it are rendered inadequate. According to Kitchenham et al. (2010), traditional metrics are often misaligned with software process models, leading to underperformance when deployed in dynamic team settings. The inability of structured models to reflect ongoing changes undermines estimation accuracy and compromises stakeholder trust.

### 2.4 Role of BI Tools and Why They Fall Short in Agile Contexts

Business Intelligence (BI) tools have long served as critical enablers of data-driven decision-making by offering dashboards, performance metrics, and historical analytics. In traditional project management environments, these tools provide structured insights for budgeting, resource allocation, and milestone tracking. However, in agile software development—characterized by rapid iterations, decentralized

decision-making, and evolving requirements—BI systems reveal key limitations. Most BI tools are built for structured data environments and are not optimized for the high-frequency, unstructured, and semantically rich textual artifacts such as user stories, retrospectives, and sprint reviews that dominate agile ecosystems (Akpe et al., 2020).

These tools lack the contextual intelligence needed to interpret evolving narratives and team behavior, limiting their capacity to generate dynamic cost or schedule forecasts. As agile workflows demand continuous estimation and adjustment, static dashboards and rigid data schemas often fail to keep pace (Mgbame et al., 2020b). Furthermore, existing BI systems are rarely integrated with agile toolchains such as Jira or GitLab in a way that enables real-time semantic parsing of development artifacts. Without natural language understanding capabilities, BI tools fall short in delivering the predictive precision and adaptability required in agile project environments (Abayomi et al., 2020).

## III. CAPABILITIES OF TRANSFORMER-BASED LANGUAGE MODELS FOR PROJECT ESTIMATION

### 3.1 Overview of Transformer Architecture (e.g., Attention Mechanisms, Sequence Modeling)

Transformer architecture, introduced by Vaswani et al. (2017), represents a major paradigm shift in natural language processing by replacing recurrence and convolutions with self-attention mechanisms. The core innovation of the transformer model is the self-attention mechanism, which allows the model to weigh the relevance of each token in the input sequence relative to others. This enables the model to capture long-range dependencies and contextual relationships more efficiently than traditional models such as RNNs or LSTMs.

The transformer architecture consists of an encoder-decoder structure, where each layer in the encoder applies multi-head self-attention and position-wise feedforward networks. Unlike recurrent models, which process sequences sequentially, transformers process entire sequences in parallel, significantly accelerating training and improving scalability (Vaswani et al., 2017). The use of positional encoding allows the model to retain information about the order of tokens in a sequence—an essential feature when modeling natural language where word order impacts meaning.

In applications related to software engineering, such as project documentation analysis or code summarization, transformers provide a powerful mechanism for understanding semantic relationships. Their ability to model complex, domain-specific textual data makes them particularly suitable for agile environments, where user stories, backlog items, and planning notes are expressed in unstructured formats (Radford et al., 2018). BERT, another influential transformer-based model, applies a bidirectional approach to attention, enabling deep contextual understanding by processing input sequences from both directions (Devlin et al., 2019).

These architectural advantages support the development of intelligent estimation systems that can parse textual artifacts and derive quantitative predictions related to project cost and schedule as seen in Table 1. By capturing semantic nuances, transformers enable more accurate and context-aware parametric estimation in agile workflows.

Table 1: Core Components of Transformer Architecture for Agile Estimation Tasks

| Component | Function | Application in Agile Estimation | Key Advantage |
|---|---|---|---|
| Self-Attention Mechanism | Computes relevance of each word to others in a sequence | Captures dependencies across user stories, backlog items, and sprint summaries | Enables contextual understanding |
| Positional | Adds order information | Preserves the sequence of events in sprint logs | Maintains temporal relationships |

| Component | Function | Application in Agile Estimation | Key Advantage |
|---|---|---|---|
| Encoding | to input tokens | and development histories | |
| Multi-Head Attention | Allows model to focus on different positions simultaneously | Simultaneously evaluates different project parameters (e.g., task type, effort) | Enhances multidimensional representation |
| Feed-Forward Networks | Applies non-linear transformations to encoded information | Translates semantic features into numerical estimations for cost/schedule | Improves expressiveness of model layers |

3.2 Advantages over Classical Machine Learning Models in Understanding Agile Documentation

Classical machine learning (ML) models such as decision trees, support vector machines, and basic regression techniques have been widely applied in software estimation tasks. However, their reliance on structured, pre-engineered features and limited ability to process semantic and contextual nuances render them suboptimal for analyzing the complex, narrative-rich artifacts generated in agile environments. These artifacts—comprising user stories, sprint retrospectives, and team logs—often contain ambiguous, context-dependent language that traditional ML models struggle to interpret.

Transformer-based large language models (LLMs), on the other hand, leverage attention mechanisms and deep contextual embeddings that enable them to learn relationships between words across long sequences. Unlike classical ML models, transformers do not require manual feature engineering and can be fine-tuned directly on domain-specific documentation to capture latent patterns relevant to cost and schedule estimation (Devlin et al., 2019). Their architecture allows them to encode dependencies between backlog items, sprint goals, and technical constraints, making them more effective in agile project understanding.

Studies such as Akpe et al. (2020) highlight the growing application of intelligent frameworks in agile contexts, yet emphasize the limitations of rule-based and metric-driven approaches that dominate current estimation practices. Transformer-based models address these gaps by enabling semantic comprehension and providing scalable solutions for unstructured data interpretation. Furthermore, as demonstrated by Radford et al. (2019), these models are capable of transfer learning, allowing for adaptation across project domains without retraining from scratch.

The ability to automatically extract meaning from agile documentation positions transformer models as superior alternatives to classical ML techniques, especially in domains requiring real-time estimation and continuous learning.

3.3 Examples of LLMs Applied in Contextual and Semantic Analysis of Software Artifacts

Transformer-based large language models (LLMs) have been increasingly adopted to enhance the contextual understanding of software artifacts, providing advanced capabilities in interpreting documentation, source code, and developer communications. Their proficiency in semantic parsing and token-level attention makes them ideal for extracting insights from agile narratives, requirement texts, and issue tracking systems.

One example is the application of BERT and its derivatives in software requirement classification and traceability tasks. Models like RoBERTa and ALBERT have been fine-tuned to detect ambiguous requirement patterns, improve trace link recovery, and cluster semantically similar backlog items (Wang et al., 2020). These LLMs outperform traditional NLP pipelines by modeling bidirectional context, which is essential in detecting nuanced relationships in software project documents.

In addition, LLMs have been employed to automate the classification of GitHub issues and pull request comments, assisting teams in prioritizing refactoring efforts and categorizing technical debt. Using contextual embeddings generated by models like XLNet, researchers have demonstrated improvements in understanding the intent behind developer messages and aligning them with code commits and architectural decisions (Ahmad et al., 2020).

Notably, transformer models have also been deployed in defect prediction and effort estimation by learning from project descriptions, changelogs, and commit messages. This approach enables the correlation of natural language artifacts with development outcomes, a method critical for agile teams that rely on sprint retrospectives and narrative data (Akpe et al., 2020).

Furthermore, recent efforts have utilized LLMs for generating automated code summaries and identifying duplicate bug reports, which streamlines issue tracking and accelerates sprint velocity (Mishra et al., 2019). These applications illustrate the transformative potential of contextual LLMs in agile software environments where textual and conversational data dominate project artifacts.

### 3.4 Literature Support for LLM Adoption in Effort and Resource Estimation

The application of large language models (LLMs) in software engineering has gained momentum due to their superior ability to understand and generate natural language, which is crucial in interpreting agile documentation. Transformer-based architectures have shown promise in automating estimation tasks by learning contextual relationships within project narratives. For instance, Idoko et al. (2020) highlighted the potential of semantic learning models in interpreting technical documents, suggesting that transformer-based approaches could significantly enhance predictive accuracy in resource forecasting. Similarly, Ayoola et al. (2020) demonstrated that AI systems trained on domain-specific language corpora outperform traditional rule-based estimators in agile environments, especially where requirements evolve rapidly.

Azonuche and Enyejo (2020) also emphasized the scalability of LLMs in software lifecycle management, indicating their capability to process historical sprint data for more accurate timeline predictions. Furthermore, Enyejo et al. (2020) noted that transformer models, once fine-tuned, can identify linguistic patterns across user stories and backlogs that correlate with resource constraints and delivery schedules. Supporting these findings, Devlin et al. (2019) and Vaswani et al. (2017) provided foundational insights into the architecture and capabilities of BERT and the Transformer, respectively—technologies now central to NLP-driven effort estimation systems in agile workflows.

## IV. PROPOSED FRAMEWORK FOR INTEGRATING LLMS INTO AGILE ESTIMATION PIPELINES

### 4.1 Conceptual model: inputs (user stories, sprints, logs), model architecture, and outputs (cost/schedule predictions)

The proposed conceptual model for leveraging transformer-based large language models (LLMs) in agile project estimation is structured around three key layers: input processing, model architecture, and output generation. Inputs include unstructured textual artifacts such as user stories, sprint retrospectives, and development logs—data sources rich in semantic context and commonly found in agile tools like Jira or GitHub issues. These inputs are preprocessed into tokenized sequences and passed through transformer encoders that leverage self-attention to capture contextual dependencies (Vaswani et al., 2017).

The model architecture may be based on pre-trained LLMs like BERT or RoBERTa, fine-tuned on historical agile datasets to learn patterns in estimation-relevant phrases, task duration trends, and workload descriptors. This enables contextual mapping of language to quantifiable estimates, such as predicted hours or cost metrics. The outputs are structured as continuous (numerical) values representing cost and time projections, enabling integration with agile dashboards and planning tools.

This approach improves upon traditional estimation methods by offering automated, context-aware predictions adaptable to team dynamics and sprint evolution (Radford et al., 2019; Devlin et al., 2019).

### 4.2 Fine-Tuning Strategies for Domain-Specific Project Data

Fine-tuning large language models (LLMs) on domain-specific project data enhances their predictive accuracy and contextual understanding in agile environments. This process involves adapting pre-trained transformer models such as BERT or RoBERTa to the specific linguistic patterns, terminology, and structural nuances present in software project documentation. To optimize estimation outcomes, fine-tuning datasets often include labeled user stories, sprint summaries, release notes, and historical burn-down charts. These artifacts provide rich semantic content necessary for learning latent relationships between textual input and project effort or duration.

Recent frameworks emphasize the importance of curating high-quality agile corpora with minimal noise and incorporating task-specific objectives such as regression-based output layers for continuous variables like cost and time (Akpe et al., 2020). Techniques such as masked language modeling and next sentence prediction remain foundational, but domain-adaptive pretraining has been shown to significantly improve task performance in estimation contexts (Gururangan et al., 2020). Furthermore, iterative training using feedback loops from project retrospectives can reinforce dynamic adaptation over time, allowing the model to evolve with project complexity and team behavior.

The success of fine-tuning strategies relies on contextual embedding quality, label granularity, and regular updates aligned with sprint cycles to ensure relevance and model generalization in agile software development.

Table 2: Fine-Tuning Strategies for Domain-Specific Transformer Models in Agile Estimation

| Strategy | Description | Application in Agile Context | Expected Outcome |
|---|---|---|---|
| Task-Specific Pretraining | Pretraining LLMs on domain-relevant corpora (e.g., software project documentation) | Enhances understanding of sprint terminology, technical debt, and user stories | Improved semantic accuracy and relevance |
| Transfer Learning | Reusing weights from general models and fine-tuning on agile datasets | Adapts generic models (like BERT) to project-specific language and planning data | Reduces training time and data requirements |
| Few-Shot/Zero-Shot Learning | Utilizing small labeled datasets or prompts to perform estimation tasks | Applies to environments with limited historical project data | Efficient model use in resource-constrained settings |
| Active Learning Loops | Iteratively improving model with human-in-the-loop feedback | Supports continuous refinement from scrum teams or PMs during retrospectives | Increases model adaptability and accuracy |

### 4.3 Example Use Cases in Agile Toolchains (e.g., Jira, Azure DevOps)

Agile toolchains such as Jira and Azure DevOps offer structured repositories of user stories, sprint data, and velocity metrics that can serve as rich inputs for transformer-based large language models (LLMs) in estimation pipelines. For instance, fine-tuned LLMs can be used to analyze historical sprint reports and user narratives within Jira to identify estimation patterns across project cycles. These models enable prediction of task duration and cost range based on semantically similar backlog entries (Akpe et al., 2020). In Azure DevOps, LLMs can be integrated with work item

tracking systems to forecast sprint capacity, identify resource bottlenecks, and detect inconsistencies in planning through anomaly detection mechanisms (Mgbame et al., 2020). Beyond backlog analysis, such models support intelligent recommendation systems by proposing effort-based task clustering and tagging strategies, thereby aiding sprint planning and scope prioritization. This integration advances beyond numeric modeling to contextual interpretation, enabling automated, bias-resistant, and scalable estimation processes that evolve over time.

### 4.4 Implementation Challenges: Training Data, Model Interpretability, Integration Complexity

Implementing transformer-based large language models (LLMs) in agile estimation pipelines introduces several key challenges. One major limitation is the availability and quality of training data. Agile documentation—such as user stories, retrospectives, and sprint plans—is often inconsistent, unstructured, and domain-specific, making model generalization difficult. Moreover, small enterprises may lack the volume of labeled project data required for effective fine-tuning (Akpe et al., 2020).

Model interpretability is another critical concern. While LLMs outperform classical models in language understanding, they operate as black boxes, making it difficult for agile teams to understand how predictions are made. This lack of transparency may hinder trust in automated estimates, especially among non-technical stakeholders (Doshi-Velez & Kim, 2017).

Integration complexity also poses a barrier. Embedding LLMs within agile toolchains such as Jira or GitLab requires API harmonization, real-time data ingestion, and cross-platform compatibility—factors that demand significant engineering overhead and process reconfiguration (Mgbame et al., 2020). Ensuring consistent performance while maintaining low latency further complicates integration in fast-paced agile environments.

## V. IMPLICATIONS, LIMITATIONS, AND FUTURE DIRECTIONS

### 5.1 Strategic Benefits: Improved Accuracy, Continuous Learning, Reduced Bias in Planning

Transformer-based large language models (LLMs) offer transformative benefits for agile project estimation, notably in enhancing accuracy, enabling continuous learning, and mitigating bias. Traditional estimation methods often rely on static models or human intuition, both of which are prone to inconsistency and subjective error. In contrast, LLMs can analyze large volumes of historical project data to identify patterns and correlations that humans may overlook, resulting in more precise and data-driven estimates.

One of the most compelling advantages of LLMs is their ability to learn continuously. As new sprint records, user stories, and planning documents are generated, the model can be updated and refined to reflect current team dynamics and delivery trends. This feedback loop ensures that the estimation system evolves with the project, maintaining its relevance over time.

Additionally, by removing reliance on individual judgment, LLMs reduce cognitive biases such as optimism bias, anchoring, and planning fallacy. This leads to more objective and fair assessments of workload and timelines. Furthermore, by providing standardized estimation across multiple teams and projects, LLMs support organizational consistency and transparency in forecasting. Ultimately, these models enhance the reliability of agile planning and empower teams to make better-informed decisions throughout the software development lifecycle.

### 5.2 Practical Limitations: Data Privacy, Model Drift, Organizational Resistance

Despite the strategic advantages of integrating transformer-based language models into agile estimation processes, several practical limitations must be addressed to ensure successful deployment. One significant concern is data privacy, particularly in environments where sensitive project documentation

and customer information are embedded within user stories, sprint notes, and backlog items. Organizations must ensure that training and inference processes comply with data governance policies, including anonymization protocols and access controls, to mitigate privacy risks.

Model drift presents another critical challenge. Agile project environments are dynamic, with continuous evolution in terminology, business logic, and process workflows. As a result, the performance of a pre-trained or fine-tuned language model can degrade over time if not regularly updated with current data. Without active monitoring and re-training cycles, the model may produce outdated or inaccurate estimates, undermining its reliability.

Finally, organizational resistance can hinder adoption. Many agile teams rely heavily on experiential judgment and collaborative planning rituals. Introducing an AI-based estimator may be met with skepticism or fear of automation displacing human decision-making. Ensuring transparency, involving end-users in model integration, and framing the tool as an assistive rather than authoritative system are essential strategies to overcome this resistance and foster trust in AI-driven estimation frameworks.

### 5.3 Future Research Directions (explainable AI in agile estimation, multi-modal inputs (text, code, metadata)

As transformer-based large language models (LLMs) continue to evolve, future research should focus on enhancing their transparency, adaptability, and integration in agile estimation systems. One promising direction is the incorporation of explainable AI (XAI) frameworks to address the opacity of LLM outputs. By enabling stakeholders to understand why specific estimates were generated, XAI can build trust and facilitate informed decision-making across agile teams.

Another critical area is the development of domain-specific pretraining corpora tailored to software engineering and project management. While general-purpose LLMs like BERT and GPT offer strong linguistic capabilities, models fine-tuned on agile artifacts, engineering logs, and sprint documentation are likely to yield more accurate and context-sensitive predictions. This calls for curated datasets and labeling methodologies that reflect agile workflows.

Additionally, multi-modal integration represents a frontier for advancing estimation models. Combining textual inputs with project metadata, code repositories, version history, and team performance metrics can result in more comprehensive and predictive estimation pipelines. Finally, research should explore continuous learning architectures that adapt in real-time, allowing models to evolve alongside agile project environments without performance degradation. These directions will contribute to building robust, intelligent tools that align seamlessly with the future of agile software development.

### 5.4 Conclusion

The integration of transformer-based large language models into agile software development presents a transformative opportunity for improving the accuracy and efficiency of cost and schedule estimation. Unlike traditional estimation methods that rely on subjective judgment and static metrics, LLMs offer dynamic, data-driven insights by analyzing complex textual artifacts inherent to agile workflows. Their ability to capture semantic nuances and continuously learn from evolving project documentation positions them as powerful tools for enhancing planning precision and reducing estimation bias.

Despite these advantages, successful implementation requires addressing practical limitations such as data privacy concerns, model drift, and organizational resistance. Furthermore, the complexity of integrating LLMs into existing agile toolchains demands thoughtful engineering and stakeholder alignment. As agile environments continue to demand faster, more adaptive planning mechanisms, the use of intelligent systems will likely become a standard practice rather than a competitive advantage.

This paper has highlighted the strategic benefits and technical considerations of embedding LLMs into parametric estimation processes, offering a conceptual framework that aligns with agile principles. Continued

research and innovation in this domain are essential to unlocking the full potential of AI-assisted project management and ensuring sustainable, accurate, and scalable software delivery in a rapidly evolving digital landscape.

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