A Systematic Literature Review on Reasons and Approaches for Accurate Effort Estimations in Agile

JIRAT PASUKSMIT**, The University of Melbourne, Australia
PATANAMON THONGTANUNAM[†], The University of Melbourne, Australia
SHANIKA KARUASEKERA[‡], The University of Melbourne, Australia

Background: Accurate effort estimation is crucial for planning in Agile iterative development. Agile estimation generally relies on consensus-based methods like planning poker, which require less time and information than other formal methods (e.g., COSMIC) but are prone to inaccuracies. Understanding the common reasons for inaccurate estimations and how proposed approaches can assist practitioners is essential. However, prior systematic literature reviews (SLR) only focus on the estimation practices (e.g., [26, 127]) and the effort estimation approaches (e.g., [6]). Aim: We aim to identify themes of reasons for inaccurate estimations and classify approaches to improve effort estimation. Method: We conducted an SLR and identified the key themes and a taxonomy. Results: The reasons for inaccurate estimation are related to information quality, team, estimation practice, project management, and business influences. The effort estimation approaches were the most investigated in the literature, while only a few aim to support the effort estimation process. Yet, few automated approaches are at risk of data leakage and indirect validation scenarios. Recommendations: Practitioners should enhance the quality of information for effort estimation, potentially by adopting an automated approach. Future research should aim to improve the information quality, while avoiding data leakage and indirect validation scenarios.

CCS Concepts: • Software and its engineering → Agile software development.

Additional Key Words and Phrases: effort estimation, agile, software engineering

ACM Reference Format:

1 INTRODUCTION

Effort estimation is an important process in Agile iterative development. When planning an iteration (i.e., a sprint in Scrum), an Agile software development team estimates the effort of a work item (i.e., a task or a story to develop the software). Based on the estimated effort, the team then selects a set of work items to be included in the sprint, while ensuring that the accumulated effort of the selected work items fits within the sprint capacity. The sprint capacity (or team capacity) is the available capacity of the team effort to work in a sprint [107, p.340], which is derived from the estimated effort of the delivered work items in the past sprints.

To achieve reliable sprint planning, the estimated effort should accurately reflect the size (or development time) of the work item. However, prior work pointed out that lightweight methods of Agile effort estimation (e.g., Planning poker)

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^{*}jpasuksmit@student.unimelb.edu.au

[†]patanamon.t@unimelb.edu.au

[‡]karus@unimelb.edu.au

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Table 1. Overview of review studies on effort estimation.

Authors	Year	Agile	Reasons	for	Approaches	Approaches to	Size	Cost	Others
		Con-	Inaccurate	e	to Estimate	Support Effort	Met-	Dri-	
		text	Estimation	ns	the Effort	Estimation	rics	vers	
Jorgensen [59]	2004				✓				
Grimstad et al. [45]	2006								Terminology
Trendowicz [124]	2011								Industrial practices
Wen et al. [131]	2012				\checkmark				
Andrew and Selamat [9]	2012								Data imputation
Dave and Dutta [30]	2014				\checkmark		✓	✓	
Usman et al. [128]	2014	✓			\checkmark		✓	✓	
Idri et al. [57]	2015				\checkmark				
Idri et al. [58]	2016				\checkmark				
Sharma and Singh[116]	2017				✓		✓	✓	
Gautem and Singh [39]	2018				✓				
Dantas et al. [29]	2018	✓			✓		✓	✓	
Hacaloglu and Demirors [49]	2018	✓							Challenges
Fernandez et al. [35]	2020	✓			✓		✓	✓	_
Perkusich et al. [92]	2020	✓			✓				Automated approaches
Alsaadi and Saeedi [6]	2022	✓			\checkmark		✓	✓	
Ours	2024	√	✓		✓	✓			

are prone to be inaccurate [29]. Several studies reported that the team re-estimates the effort after sprint planning is finished (or even during the implementation) to maintain the estimation accuracy [55, 78, 88]. Such late re-estimation may invalidate the original sprint plan and may cost additional effort for re-planning [107].

Many studies were conducted to understand and improve the effort estimation in Agile. While several systematic literature reviews (SLRs) aggregated these Agile studies, the focuses of these SLRs were limited to the estimation practices or effort prediction approaches. Table 1 shows the overview of the existing SLRs in the effort estimation context. While several SLRs were conducted in the Agile context, most of them focused on effort estimation approaches, size metrics, and cost drivers. For example, Usman et al.[128], Dantas et al.[29], and Fernandez et al. [35] reviewed and aggregated the estimation practices in Agile. Hacaloglu and Demirors [49] reviewed the challenges of using estimation units in Agile. However, none has reviewed the reasons for inaccurate estimations. Understanding the common reasons for inaccurate estimations will allow one to address the core common problems in effort estimation, leading to an improvement in the estimation accuracy. Table 1 also shows that many studies reviewed approaches to estimate the effort. For example, Alsaadi et al. [6] focused on reviewing machine learning-based effort prediction approaches. Indeed, there could be other approaches than effort prediction that can support the effort estimation process in Agile. Yet, such approaches to improve effort estimation have not been comprehensively reviewed in the existing literature. These gaps highlight the need for a SLR in these areas, which forms the basis of our research.

Therefore, this paper presents an SLR on the reasons for inaccurate estimations (RQ1) and the approaches to improve effort estimation (RQ2) in the Agile context. We searched for the studies on five digital libraries, i.e., ACM Digital Library, IEEE Xplore, Scopus, Web of Science, and Wiley Online Library. We obtained 578 studies from the search. We conducted the systematic literature review (SLR) following a well-established guideline, i.e., SEGRESS (Software Engineering Guidelines for REporting Secondary Studies) guideline of Kitchenham et al. [69] (see checklists in Table 10). We applied a total of 13 inclusion, exclusion, and quality criteria to select the studies that fit in the scope of our RQs

Table 2. Our PICOC criteria based on our research questions.

Criteria	Description	Our PICOC
P (Population)	The target population of the study.	Academic studies in software engineering
I (intervention)	A methodology, tool, technology, procedure to ad-	Effort estimation
	dress a specific issue or perform a specific task.	
C (Comparison)	The methodology, tool, technology, procedure that	N/A (No comparison between different inter-
	the intervention is being compared.	ventions)
O (Outcome)	The relevant outcomes of the study.	Reasons for inaccurate estimation (RQ1) and
		approaches to improve effort estimation (RQ2)
C (Context)	The context in which the study take place.	Agile Iterative Development

and are of quality. In total, 82 studies passed all the criteria. To answer our RQs, we performed card sorting to derive the themes of the reasons for inaccurate estimations and the taxonomy of the approaches to improve effort estimation.

In RQ1, we identified five categories of the reasons for inaccurate estimations: (1) quality issues of the available information, (2) team-related, (3) estimation practices, (4) project management, and (5) business influence. We found that the quality issues of the available information are the commonly reported reason for inaccurate estimations. In RQ2, we categorized the approaches to improve effort estimation based on their purposes (i.e., to estimate the effort and to support the effort estimation process). We found that 66 out of 75 proposed approaches aimed to estimate the effort. However, only nine approaches were proposed to address the quality issues of the available information, which is the commonly reported reason for inaccurate estimations. While many of these approaches were proposed to be used for sprint planning, we observed that it is unclear whether they used only the information available during sprint planning or used the latest information version (which is considered as using the future data). Our findings suggest that the quality of the available information should be improved for effort estimation. We found that there is a lack of approaches to help the team improve the information quality. In addition, the prior effort prediction approaches may need to be revisited in a realistic usage scenario (i.e., using only the available information in training and validation).

Paper organization. The remainder of this paper is organized as follows. Section 2 motivates for our two research questions. Section 3 presents our research methodology for the systematic literature review and subsequent analyses. Section 4 presents the study results. Section 5 provides broader implications and recommendations based on the results. Section 6 discloses the threats to validity. Section 7 draws the conclusion. Finally, Section 8 (Appendix) lists the SEGRESS checklist and details of the selected studies.

Declaration. This research was conducted without external funding. Jirat Pasuksmit was associated with the University of Melbourne during the research phase of this work and is presently employed by Atlassian Pty Ltd. at the time of revision and publication.

2 RESEARCH QUESTIONS

Similar to Usman et al. [128] and Fernandez et al. [35], we framed our research questions based on the PICOC criteria. As suggested by Petticrew and Roberts [93], PICOC is used to frame a research question for a systematic literature review. Table 2 provides the description of each criterion and our PICOC for this study. Below, we describe the motivation for the two expected outcomes (see Table 2), which framed the two research questions of this study.

Since Agile teams plan the sprint based on the estimated effort [24, 107], inaccurate estimations may cause the sprint plan to become inaccurate. Identifying the common reasons for inaccurate estimations would help the teams

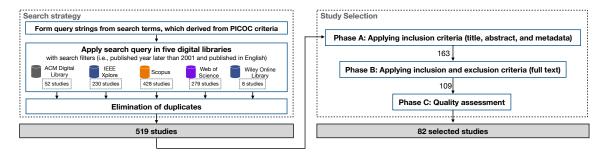


Fig. 1. The search strategy (left) and study selection (part) approaches we used in the systematic literature review.

and researchers pinpoint the possible improvements in the effort estimation process. Yet, to the best of our knowledge, there is no SLR that focuses on the reasons for inaccurate estimations in Agile iterative development. Therefore, we aim to address RQ1:

(RQ1) What are the discovered reasons for inaccurate estimations in Agile iterative development?

Prior SLRs show that many approaches were proposed to improve the effort estimation in Agile [6, 29, 35]. However, these aggregated approaches are limited to effort estimation practices and effort prediction models. On the other hand, there could be other approaches proposed to improve the effort estimation. Therefore, we propose this RQ2:

(RQ2) What are the approaches proposed to improve effort estimation in Agile iterative development?

3 METHODOLOGY: SYSTEMATIC LITERATURE REVIEW

To ensure the quality of our work and to align with other SLRs, we conducted this systematic literature review (SLR) following a well-established guideline, i.e., SEGRESS (Software Engineering Guidelines for REporting Secondary Studies) guideline of Kitchenham et al. [69]. SEGRESS is a revision of the PRISMA 2020 checklist [84] that explains how to apply PRISMA 2020 in the software engineering context. We provided the **SEGRESS checklist** [69] with notes on how we comply with each item in the appendix (Section 8, Table 10). In addition, we also follow the another guideline by Kitchenham and Charter [68] in evidence collection to avoid bias and provide reproducibility. In this section, we describe our search strategy, study selection, and data analysis processes.

3.1 Search Strategy

To search for the studies, we formed the query string based on the PICOC criteria [68] and applied it to five digital libraries in June 2023. Figure 1 (left) outlines the search strategy we used to collect the studies.

3.1.1 Query String. We designed our query string to search for academic studies in software engineering (i.e., P in PICOC) that cover two research areas, i.e., investigating the reasons for inaccurate estimations (RQ1) and proposing the approaches to improve effort estimation (RQ2). To do so, we determined our search terms and aggregated them to form our query string. Table 3 lists our search terms. Aligning with our PICOC, we selected the following main search terms based on each PICOC criteria (see Table 3). For each main search term, we added alternative search terms derived from prior work [29, 35, 128] and their synonyms to broaden our search. Then, we formed our query string

Criteria	Main Search terms	Alternatives or Synonyms
Population	software	code
Intervention (1)	estimat*	predict, forecast, calculat*, assess*, xmeasur*
Intervention (2)	effort	size, story point
Outcome (RQ1)	reason	cause, impact, factor
Outcome (RQ2)	*accura*	*stable, *stabili*, *certain*, *reliab*, error, *precise*
Context	agile	extreme programming, scrum, kanban, scrumban, lean, crystal

Table 3. Keywords used in search queries.

using AND/OR operations as suggested by the guideline [68]. In particular, we first used the OR operator to incorporate all alternatives and synonyms to each main search term to form a set of search terms. After that, we used the AND operator to combine all sets of search terms to form one search query. In conclusion, our query string is:

(software OR code) AND (estimat* OR predict* OR forecast OR calculat* OR assess* OR measur*) AND (effort OR size OR "story point") AND ((reason OR cause OR impact OR factor) OR (*accura* OR *stable OR *stabili* OR *certain* OR *reliab* OR *precise OR error)) AND (agile OR "extreme programming" OR scrum OR kanban OR scrumban OR "agile lean" OR "lean development" OR "lean methodology" OR "crystal method" OR "crystal agile")

3.1.2 **Searching Methodology**. We applied our query string to five academic digital libraries that were used by the prior studies [6, 128], i.e., ACM Digital Library, IEEE Xplore, Scopus, Web of Science, and Wiley Online Library. We applied filters to focus on the studies that were written in English and were published after 2001 (i.e., the year that the Agile Manifesto was published [37]). Then, we downloaded the search results from all digital libraries in Bibtex, combined the results from five digital libraries together, and used a simple Python program to remove duplicate studies based on their title. Figure 1 shows the number of studies in the search results.

3.2 Study selection

To ensure that all studies fit in the scope of our RQs and of the quality, we applied 13 inclusion, exclusion, and quality criteria on the key information manually extracted from the paper in each phase. Similar to prior work [6, 128], we conducted a multiple-phase study selection. Figure 1 (right) outlines our study selection process. We first applied the inclusion criteria to the title, abstract, and metadata of each study (Phase A). Then, we applied the exclusion criteria to the full text (Phase B). Lastly, we applied the quality criteria to the full text (Phase C). Note that the first author performed these processes manually without using any review automation tools. The results along with justifications for the deviant cases were then reviewed by the second author. When disagreement arose, the first and second authors discussed until they reached a consensus then the first author applied the criteria to the whole collection again to ensure consistency. We describe how we applied the criteria below.

3.2.1 Phase A: Applying the inclusion criteria to title, abstract, and metadata. Table 4 lists our inclusion criteria. To only include the studies that fit our scope, we applied the inclusion criteria (IC) to the title, abstract, and metadata of each study in the search results. We applied the IC-1 to IC-3 in order. For each study, we checked the official website of the publication venue to investigate whether a published article needs to be peer-reviewed (IC-1). Then, we examined whether the study context is related to Agile iterative development (IC-2). Lastly, we examined whether the study's objective is to investigate the reasons for inaccurate estimations (IC-3A) or propose an approach to improve effort

Table 4. The study inclusion criteria.

Inclu	sion criteria
IC-1	Must be peer-reviewed and published at a journal, conference,
	or workshop
IC-2	Focusing on any of the Agile Iterative Development
IC-3	Investigating the reasons for inaccurate effort estimation (IC-3A)
	OR proposing an approach to improve the effort estimation accuracy (IC-3B)

Table 5. The study exclusion criteria.

Exclu	Exclusion criteria					
EC-1	EC-1 Provide no access to the full paper					
EC-2	C-2 Is duplicate or continuation of another included study/approach					
EC-3	Is a literature review study					
EC-4	Is an experience report or replication study					
EC-5	Is an evaluation of the existing effort estimation technique					

Table 6. The study quality assessment criteria.

Qualit	y criteria
QC-1	The research objective is described
QC-2	The techniques or methodologies are described
QC-3	The dataset, participants, or case studies of the study are described
QC-4	The evaluation or validation methods are described
QC-5	The results of the study are described

estimation accuracy (IC-3B). For some studies that we could not clearly understand their objective based on their title, abstract, and metadata, we further considered the introduction, background, and conclusion of the study. A study passed phase A only if it satisfied IC-1, IC-2, and either IC-3A or IC-3B.

3.2.2 Phase B: Applying the exclusion criteria on full text. Table 5 lists our exclusion criteria. To fully understand a study in the review, we need to analyze the study based on the full text. First, we attempted to download the published article of each study and excluded the studies that we could not download the full-text articles (EC-1). Then, we collected the data from each study to have a better understanding of the context. After that, we applied other exclusion criteria to each study based on the downloaded full-text article. Since duplication of findings may mislead our review, we excluded the study that is a duplicate (i.e., having similar authors and content) or a continuation (i.e., extended analyses) of another included study (EC-2). Note that we only excluded the older study from a duplicate pair and excluded a newer study from a continuation pair. Finally, we applied EC-3 to EC-5 in order. We excluded literature review studies (EC-3) as they reported their results based on other studies. We then excluded experience reports or replication studies (EC-4) and the studies that only evaluate the performance of the other effort estimation techniques (EC-5) as they conducted their studies based on existing approaches or findings. During this phase, we again applied the inclusion criteria based on the full text to validate the results from Phase A. A study passed phase B only if it was not excluded by any of the exclusion criteria. We provided a list of all included and excluded studies in supplementary material [87].

- 3.2.3 **Phase C: Applying the quality criteria.** Table 6 lists our quality criteria. To ensure the quality of the studies, we first extracted the **objectives**, **techniques**, **approaches**, and **results** of each study. We then excluded the studies that did not describe this information. After that, we applied the quality assessment checklist of Alsaadi et al. [6] to the full-text of the remaining studies. We extracted and determined whether the study describes the important data, i.e., research objective (QC-1), techniques or methodologies (QC-2), dataset, participants, or case studies (QC-3), evaluation or validation methods (QC-4), and results (QC-5). We selected only the studies that satisfy all the quality criteria into our literature review.
- 3.2.4 Phase D: Uncertainty and risk of bias assessment. As suggested by Kitchenham et al. [69], we assessed the uncertainty and risk of bias of our selected studies and reported it along with our results. To do so, we applied GRADE approach [48] (Grading of Recommendations Assessment, Development, and Evaluation) to assess whether there is a high uncertainty (or risk) in any of the five following domains. Risk of bias of individual studies refers to methodological biases reducing the certainty of the finding. In our context, we assessed if a study is relied on a students experiment (high risk), used a weak methodology or lack of detailed explanation (high risk), used an old dataset (high risk), conducted on a small scale (moderate risk), or reported only relative performance metric like MMRE (moderate risk). Imprecision refers to the ambiguity and vagueness in the data or results reported in a study. We assess the imprecision of the selected studies based on the extracted results (e.g., confidence interval). Inconcsistency refers to whether there are strong disagreements among one and other studies in a similar context. We assess the inconsistency among studies of the same category in the taxonomies in Section 3.3. Indirectness refers to when a study is conducted with subjects that are not representative of the target of interest, e.g., conducting Scrum experiment with students or analyzing non-Agile projects. We assess the indirectness based on the extracted datasets or participants. Publication bias in our context refers to the soundness of the search process of our study and whether the majority of the studies we found were conducted on small scales. To avoid publication bias, we clearly explained our search process in Section 3.1 and recheck whether the majority of the studies included in each taxonomy were not conducted on a small scale.

3.3 Data Analysis

In this section, we described the process of discovering the thematic taxonomies of the reasons for inaccurate estimations (RQ1) and the approaches to improve effort estimation (RQ2). Broadly speaking, we extracted the reported reasons for inaccurate estimations with their rankings and the key purpose of the approaches to improve effort estimation with their planning level desired to operate. The extracted data was used for discovering the themes and taxonomy of search results (Section 3.3.1), ranking the reasons for inaccurate estimations (Section 3.3.2), and identifying the planning level of the approaches to improve effort estimation (Section 3.3.3). In general, the first author performed these processes manually without using any automation tools. The second author then reviewed the discovered themes, taxonomies, and other results. When disagreed, the first and the second authors discussed until reached a consensus. Then, the first author conducted another round of analysis again to ensure consistency. To report the results, we used R, Microsoft PowerPoint, and Latex to create charts, diagrams, and tables, respectively.

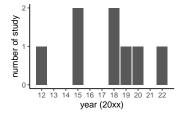
3.3.1 **Discovering the themes and taxonomy**. For both RQ1 and RQ2, we applied an open card sorting technique to categorize and extract the themes and taxonomy. We analyzed the selected studies that passed the three selection phases (see Section 3.2.3). The card sorting was performed in multiple iterations.

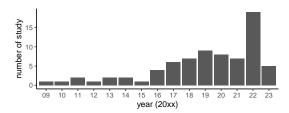
In the first iteration, we classified the studies into groups based on their scope (i.e., whether the scope fits into RQ1, RQ2, or both). After that, we extracted the key information to discover the theme of the reasons for inaccurate

estimations (RQ1) and discover the taxonomy of the approaches to improve effort estimation (RQ2). For the studies that fit RQ1, we extracted the **reasons for inaccurate estimations** from the result section of each study. We then sorted all the reasons into groups based on their thematic similarities and defined a theme for each group. For the studies that fit RQ2, we extracted the **key purpose** based on the key question: "How does the approach aim to help the team in effort estimation?" We sorted the proposed approaches into groups based on their thematic similarities of the purposes and defined a theme for each group. When an approach was sorted into a group, we did not exclude it from the pool to look for the possible heterogeneity among the approaches. In addition, we also mark (if any) the studies with a high risk of bias and describe the impact if we excluded them from our study in the results section. Note that the first author conducted the analyses in the first iteration.

To validate the results, the second author, with different expertise and backgrounds, reviewed and discussed the results with the first author until they reached a consensus. Then, the first author conducted card sorting again to ensure consistency This was to ensure that the themes and taxonomies were not only subjective to the first author.

- 3.3.2 Extracting the ranking of the reasons for inaccurate estimations. In addition to the reasons extracted from the selected studies in RQ1, we further obtained the ranking provided by those studies. This insight will help us understand which reason the practitioners or researchers should pay attention to address in order to improve the estimation accuracy. To extract the ranking, we directly obtained the ranking of each reason (or category of the reasons) as reported in the results section of each study. We found that these rankings were reported based on different methods, i.e., the number of reported participants, the occurrences reported by the participants, and the agreement scores rated by the participants. Therefore, we only presented them as an additional insight into the common reasons for inaccurate estimations.
- 3.3.3 Identifying the planning level of the approaches to improve effort estimation. For RQ2, we further investigated the **planning levels** that the approaches were proposed to be used for. This is because the proposed approaches can be designed to fit their usage scenarios of different planning levels. For example, a prediction model may be designed to predict the total development cost, which will be used for an early planning level (e.g., project bidding). Knowing the planning level would allow us to better understand the applicability of the proposed approach. To achieve this, we categorized the proposed approaches into groups based on their planning levels. We first obtained the list of planning levels that effort estimation is performed from prior studies [35, 125, 127], i.e., daily planning, sprint planning, release planning, project planning, and project bidding. We read the full text to identify the planning level that the proposed approaches were designed to be used for. In this process, we identified the planning level when the paper indicates the planning level to be used (e.g., specified in the abstract, objective, motivation, background, or an example usage scenario). If the planning level was not explicitly indicated in the paper, we used information described in the approach, the outcome of the approach, or the benefit to the practitioners to infer the planning level. For example, Choetiertikul et al. [22] situated their Story Points prediction outcome to be used in Scrum sprint-based development: "Story point sizes are used for [...], planning and scheduling for future iterations and releases, [...]." With sufficient information provided, we categorized this approach as suitable to be used for sprint planning and release planning. Otherwise, we marked the planning level as "not specified" when the planning level is not indicated or the information in the paper is insufficient to infer one of the five planning levels. Lastly, the first author revisited the categorized results of the planning levels. To mitigate the risk that the results are subjective to the first author, the second authors revisited the categorization results and discussed them with the first author until both reached a consensus. Then, the first author conducted another round of categorization to ensure consistency.





- (a) The selected studies that investigated the reasons for inaccurate estimations
- (b) The selected studies that proposed an approach to help the Agile practitioners estimate effort more accurate

Fig. 2. The number of selected studies published in each year.

4 RESULTS

This section presents the search results and describes our findings for each research question.

4.1 Search Results

We retrieved 519 unique studies from the search in five digital libraries and 82 of them passed our three study selection phases. We extracted information from each study, including the purpose of the approach, the desired planning level for operation, the estimating artifact, the technique used, the dataset or participants involved, the study results, the evaluation method, and the outcome of the GRADE uncertainty assessment. We listed all selected studies along with the extracted information in the Appendix (Section 8). Of the 82 selected studies, eight of them investigated the reasons for inaccurate estimations (IC-3A) and 75 of them proposed an approach for effort estimation (IC-3B). Noted that we found one study satisfied both IC-3A and IC-3B. Figure 1 shows the number of studies that passed each study selection phase. The majority of these studies were published in 2016 and thereafter (see Figure 2). Below, we describe the details of the three screening phases. A list of excluded papers with the reasons for exclusions is provided in our supplementary material [87].

In phase A, 163 out of 519 studies satisfied the inclusion criteria based on the title, abstract, and metadata (see Figure 1). We found that no study was excluded due to IC-1 as all of the studies were peer-reviewed, while 58 studies did not satisfy IC-2 as the studies were not conducted in the Agile context. We found that 150 studies did not satisfy IC-3A and IC-3B as they did not investigate the reasons for inaccurate estimations or propose an approach to improve effort estimation. In particular, the objectives of these 150 studies are related to software quality and testing (41 studies), development practices (32 studies), human aspect (18 studies), Agile adoption (17 studies), requirements engineering (13 studies), Agile planning (5 studies), factors or predictors considered during the estimation - not the reasons for inaccurate estimations (4 studies), and others (20 studies). For example, Altaleb et al. [8] investigated the effort estimation predictors and Logue and McDaid [70] proposed an approach to handling uncertainty in release planning. These studies nearly met all criteria but were excluded because the predictors may not cause effort estimation inaccuracies and the approach is not proposed for effort estimation. On the other hand, a study by Vetro et al. [130] satisfied both IC3A and IC3B (heterogeneity case) because it studied the root causes for wrong estimations and proposed a new estimation process to tackle these issues.

In phase B, 109 out of 163 studies passed the exclusion criteria and inclusion criteria based on full text. Particularly, we could not access the full paper of eight studies (EC-1). We sent a direct request to the authors of these studies via

email and retrieved the full-text copies of two studies. After that, we excluded six duplicate or continuation studies (EC-2), 13 literature review studies (EC-3), seven experience report or replication studies (EC-4), and 23 studies that evaluated the existing effort estimation techniques. Noted that all the remaining studies still satisfied the inclusion criteria based on the full text.

In phase C, 82 out of 109 studies passed all the quality criteria. A total of 27 studies were excluded as not satisfy one of the quality criteria. In particular, these studies did not describe techniques (QC-2; 2 studies), datasets, participants, or case studies (QC-3; 12 studies), evaluation or validation methods (QC-4; 11 studies), or results (QC-5; 2 studies). Few approaches nearly met all criteria but were excluded due to insufficient explanation of validation methods (e.g., [83, 96]). We observed that the essential aspects of validation were notably absent, e.g., comparing predicted effort with actual effort, employing cross-validation techniques, or benchmarking against expert estimations.

In phase D, Tables 11, 12, and 13 show the results of our uncertainty assessment. Specifically, we identified 15 out of 82 (18%) studies subjected to high risk [69], i.e., five studies relying only on students or student projects, five studies have unclear characteristics of the datasets or participants, three studies using artificial datasets, one study conducted based on findings from the pre-Agile manifesto, and one study used inconsistent approaches from the literature. Nevertheless, we found that a minority of our selected studies were conducted on a small scale. Thus, the impact of the risks from the selected studies on our findings is minimal.

4.2 RQ1 results: What are the discovered reasons for inaccurate estimations in Agile iterative development?

In this RQ, we aim to better understand the common reasons for inaccurate estimations in Agile. We identified eight studies that investigated the reasons for inaccurate estimations (see Section 3.3.1). Based on our card sorting process, we identified five themes of the reasons for inaccurate estimations, i.e., Quality issues of the available information (R1), Team-related (R2), Estimation Practice (R3), Project Management (R4), and Business Influence (R5), which are described below. Table 7 lists the reasons for inaccurate estimations reported by these eight studies. We also obtained the ranking of each reason from the selected studies (see Section 3.3.2). For each study, we directly obtained the ranking of each reason (or its category) from the result section. We found that the reasons were ranked based on the number of answered participants [17, 127], the mean value of agreement scores provided by the participants [26], and the occurrences reported by the participants [129]. Table 7 also reported the rankings retrieved from these studies. A higher ranking number indicates a higher ranking of a reason compared to the others in the same study, where the following alphabet is used to indicate the ranking methods. In particular, the "n", "a", "o", and "x" indicate that the ranking was based on the "number of answered participants", "agreement scores provided by the participants", "occurrences reported by the participants", and "no ranking", respectively. For example, a rank "1n" indicates that the reason was the most commonly reported based on the "number of answered participants" in the study. Below, we describe each category of the reasons for inaccurate estimations.

4.2.1 Reasons for inaccurate estimations. (R1) Quality issues of the available information: We found that five out of eight studies reported the (R1) quality issues of the available information as the reasons for inaccurate estimations [17, 26, 111, 126, 127]. The reasons in this category are often reported in high ranking, e.g., ranked first and second based on the number of answered participants and the agreement scores provided by the participants. Britto et al. [17] and Conoscenti et al. [26] reported that, with the poor quality of the available information, the team may inaccurately anticipate the effort to implement a desired functionality. They also discussed that the quality

Table 7. Reasons for inaccurate estimations reported in the literature (RQ1). The ranking numbers indicate the rankings of a reason in comparison to the other reasons reported in the same study. The "n", "a", "o", and "x" indicates that the ranking was based on "number of answered participants", "agreement scores provided by the participants", "occurrences reported by the participants", and "no ranking", respectively.

Reasons	Ranks	Studies
R1) Quality issues of the available information		
R1.1) Unclear information	1n, 1n, 2a, 7o, x	[17, 26, 111, 126, 127]
R1.2) Unstable information	1n, 1n, 1a, x	[17, 111, 126, 127]
R1.3) Error in the information	1n, 5o	[17, 26]
R2) Team-related		
R2.1) Lack of experience of team members	10, 2n, 3n, 6a, x	[17, 26, 111, 126, 127]
R2.2) Insufficient stakeholder participation	2n, 2n, 12a	[17, 111, 127]
R2.3) Knowledge sharing problem	3n, 5a, x	[111, 127, 130]
R2.4) Dominant personality	14a	[111]
R3) Estimation Practice		
R3.1) Factors overlooking	1n, 2o, 3a, x	[26, 111, 126, 127]
R3.2) Considering unnecessary work	20, x	[26, 129]
R3.3) Lack of an estimation process	5n, 9a	[111, 127]
R3.4) Inappropirate estimation scale	x, x	[119, 130]
R4) Project Management		
R4.1) Poor change management	2n, 7a	[111, 127]
R4.2) Poor human-resource management	2n, 6o, x, x	[26, 62, 126, 127]
R4.3) Communication overhead in distributed team settings	3n, 16a, x	[17, 111, 126]
R5) Business Influence		
R5.1) Overoptimism due to project bidding pressure	4n, 5a	[111, 127]
R5.2) Pressure of timeline	10a	[111]

issues were late discovered during the implementation. Based on our card sorting process, three sub-themes of the quality issues emerged, i.e., unclear information (R1.1), unstable information (R1.2), or error in the information (R1.3). Unclear information (R1.1) refers to the lack of detail or unclear information during effort estimation (e.g., user stories, acceptance criteria, requirements) [17, 26, 111, 126, 127]. Conoscenti et al. [26] described that the "understandability problems of the story" or "unclear definition of the user acceptance criteria" (i.e., the available information) would lead to inaccurate estimation. Unstable information (R1.2) refers to the available information that keeps changing or changed after the estimation is done, thus may affect the estimation accuracy [17, 111, 126, 127]. Usman et al. [127] reported that "both changing [the existing requirements] and [introducing] new requirements were found to be one of the top reasons for effort overruns". Error in the information (R1.3) refers to the requirements [17] and estimation logging [26] that were mis-documented. Britto et al. [17] noted that "mis-documented requirements affect the accuracy of the effort estimates", which could lead to unpredicted activities during the estimation process.

These quality issues could apply to any level of information. In particular, three studies reported quality issues for requirements. Such a piece of information is considered a high-level abstraction of information [17, 111, 126]. The other three studies reported quality issues for user stories [111, 127] and acceptance criteria [26], which are considered detailed information.

(R2) Team-related: We found that six out of eight studies reported the (R2) team-related issues as the reasons for inaccurate estimations. However, we found that these issues were reported with overall lower ranks than R1. These issues were ranked first, second, third, and fourteenth (or lower) based on the occurrences reported by the

participants, the number of answered participants, and the agreement scores provided by the participants. During our card sorting process, four sub-themes of team-related issues emerged, i.e., lack of experience of team members (R2.1), insufficient stakeholder participation (R2.2), knowledge sharing problem (R2.3), and dominant personality (R2.4). The lack of experience of team members (R2.1) refers to the lack of experience in the technology, domain knowledge, and effort estimation practices of team members [17, 26, 111, 127]. This also includes onboarding novice team members [26, 111, 126, 127] and the team with low cohesion (i.e., the team worked little time together) [17]. Britto et al. [17] and Conoscenti et al. [26] reported that these issues might lead to a wrong assumption of the size of functionality or the team's ability to deliver, which affect the effort estimation accuracy. Conoscenti et al. [26] also reported that the lack of experience occurred the most across all their studied projects, accounting for 26 of 83 over- and under-estimations (31% of the time). Insufficient stakeholder participation (R2.2) refers to the absence of stakeholders (i.e., development team, clients, and scrum master) during the estimation process. Three scenarios of stakeholders' absence were reported in the studies. First, the effort was not estimated by the development team [17]. Second, the clients did not attend the estimation session to provide the details [111, 127]. Third, the effort was estimated considering the active participation of the clients, who in turn they did not participate [17]. Knowledge sharing problem (R2.3) refers to the limited knowledge shared among the team members [111, 127, 130]. For example, Vetro et al. [130] reported that estimating new user stories without an explicit and shared reflection on previous estimations can lead to extreme wrong" estimation." Usman et al. [127] suggested that "knowledge sharing problems in the team and the presence of unskilled members in the team" should be considered in the estimation and managed during the implementation. Lastly, dominant personality (R2.4) refers to a team member with a dominant personality that could influence the team estimations [111].

(R3) Estimation Practices: We found that five out of eight studies reported the (R3) estimation practices issues as the reasons for inaccurate estimations. These issues were ranked first, second, and fifth (or lower) based on the number of answered participants and the occurrences reported by the participants. During our card sorting process, four sub-themes of estimation practices issues emerged, i.e., factors overlooking (R3.1), considering unnecessary work (R3.2), lack of an estimation process (R3.3), and inappropriate estimation scale (R3.4). Factors overlooking (R3.1) refers to the practice where the team did not consider the factors related to the work item during the estimation. For example, in the estimation session, the team overlooked side tasks [26], overlooked non-functional requirements [111, 127], under-estimated the complexity of a developing function [26, 126], ignored test effort [111, 127], ignored code review effort [26], was not aware of technical problems [26], did not considered the usability of a standard function [26], or overlooked hardware problem [111]. Overlooking these factors could lead to an underestimation. On the other hand, some practitioners may consider unnecessary work in the estimation. Considering unnecessary work (R3.2) refers to the practice when the team considers unnecessary work in a work item during the estimation. The reported that unnecessary work is the work that was not required for the work item (i.e., "Gold plating") [26], the duplicate or redundant functions included in the estimation but were implemented as part of other work items [26], or the functions that were over-estimated in terms of complexity [26, 129]. Considering this unnecessary work could lead to an overestimation. Lack of an estimation process (R3.3) refers to the practice where the team did not use any estimation process [111, 127], e.g., Planning Poker. Although the Agile Manifesto prefers interactions among people over processes and tools [37], Usman et al. [127] argued that "this does not mean that agile practices advocate for the estimation process dimension to be completely ignored." Inappropriate estimation scale (R3.4) refers to the practice where the practitioners use an estimation scale that may not reflect the actual effort. Tamrakar et al. [119] found that the use of the Fibonacci scale in the estimation could lead to poor estimation accuracy. On the other hand, Vetro et al. [130] reported that having too many items in the numerical scale or using a misleading numerical scale could lead to wrong estimations.

(R4) Project management: We found that six out of eight studies reported the (R4) project management issues as the reasons for inaccurate estimations. These issues were ranked second and third (or lower) based on the number of answered participants. During our card sorting process, three sub-themes of project management issues emerged, i.e., poor change management (R4.1), poor human-resource management (R4.2), and communication overhead in distributed team settings (R4.3). Poor change management (R4.1) refers to when the scope of work keeps changing due to poor change control (i.e., "scope creep"). Sandeep et al. [111] and Usman et al. [127] reported that these issues may negatively impact the development time and project cost. Poor human resource management (R4.2) refers to delays due to the dependency on external resources [26, 126] and turnover issues [62, 127]. Conoscenti et al. [26] and Usman et al. [126] reported that the dependency on external human resources (e.g., product architects) could delay the implementation process and might also introduce communication overhead. Usman et al. [127] reported that a high employee turnover would affect the estimation accuracy. In addition, Karna et al. [62] reported that not all turnover can have a negative impact on the estimation accuracy, while unplanned turnover can have a significant negative impact on the reliability of the expert estimation. Communication overhead in distributed team settings (R4.3) refers to the management problems when the team is working across multiple sites. Britto et al. [17] and Sandeep et al. [111] reported that distributed teams with different time zones, languages, and cultures may require additional effort for communication between the team members and the clients. Such communication effort should be considered in the estimation. Complementing this finding, Usman et al. [126] reported their analysis based on six product customization that the work being done in multiple sites tends to be largely underestimated.

(R5) Business influence: We found that two out of eight studies reported the (R5) business influence issues as the reasons for inaccurate estimations. These issues were ranked fourth and tenth (or lower) based on the number of answered participants and the agreement scores provided by the participants. During our card sorting process, two sub-themes of business influence issues emerged, i.e., overoptimism due to project bidding pressure (R5.1) and pressure of timeline (R5.2). Overoptimism due to project bidding pressure (R5.1) refers to when the team intentionally underestimates the effort by considering only the best-case scenario to obtain a contract [111, 127]. Usman et al. [127] argued that "purposeful underestimation is an unfair practice and is a clear breach of the code of ethics for software engineers as described in [42]." Pressure of timeline (R5.2) was reported by Sandeep et al. [111] as one of the reasons for the inaccurate estimations. However, no further explanation was provided.

Findings: We identified five main reasons for inaccurate estimations, i.e., quality issues of the available information, team-related, estimation practices, project management, and business influence. The quality issues of the available information are commonly reported and often ranked as the top reasons for inaccurate estimations.

4.3 RQ2 results: What are the approaches proposed to improve effort estimation in Agile iterative development?

In this RQ, we identified 75 studies that proposed the approaches to improve effort estimation in Agile. Based on our card-sorting process, we categorized these approaches into themes based on their purposes (see Figure 3). Section 4.3.1 presents the approaches that aim to estimate the effort, while Section 4.3.2 presents the approaches that aim to support the effort estimation process. In addition, as described in Section 3.3.3, we identified the planning levels for which the approaches were designed to be used. Lastly, Section 4.3.3 discusses the planning levels of these approaches.

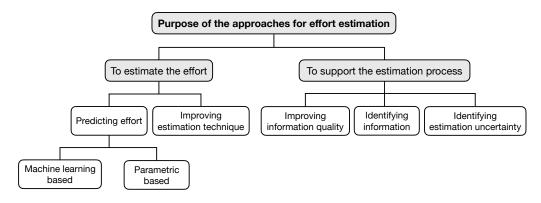


Fig. 3. Categorization of the approaches to improve effort estimation based on the purposes of the approaches.

Table 8. The studies that proposed an approach to estimate the effort at different planning levels (rows), different purposes and techniques (columns), and different estimating artifacts (cells). We summarized these studies in Appendix (Table 12).

		Purposes (and techniques)					
		Predicting the effort	Predicting the effort	Improving estimation			
Planning level	#	(Machine learning-based)	(Parametric-based)	technique (manual)			
Sprint planning	13	work items [4, 22, 28, 38, 75, 113, 122],		work items [5, 7, 72, 103, 130]			
		sprints [100]					
Release planning	4	work items [22, 132]	sprints [60]	work items [105]			
Project planning	9	work items [31, 98], projects [15, 102, 110, 115]	projects [101, 117]	projects [20]			
Project bidding	3		projects [86, 104, 106]				
Maintenance	2	requirement changes [108]	maintenance phases [23]				
Not specified	36	work items [27, 46, 54, 63, 64, 76, 79, 80,	requirement changes [13],	work items [3, 32], projects [82]			
		94, 95, 97, 99], sprints [51, 61], requirement	releases [91], projects [11,				
		changes [109], projects [1, 10, 16, 34, 47, 65-	12, 19, 43]				
		67, 81, 85, 112, 114]					

4.3.1 **Estimate the effort**. We identified 66 studies that proposed an approach to predict the effort (56 studies) and to improve the estimation techniques (10 studies). In addition, we also categorized the approaches to predict the effort based on the techniques used, i.e., machine learning-based and parametric-based. Table 8 lists these 66 studies.

Predicting the effort (Machine Learning-based): We identified 44 approaches aimed to predict the effort using machine learning models. The prediction models were built based on historical data to predict the effort of work items, sprints, releases, projects, requirement changes, and maintenance phases. The "effort" predicted could be in the form of size, time, or cost. These approaches used several techniques, i.e., traditional machine learning models (e.g., Support Vector Machine, Bayesian Network, k-Nearest Neighbors) [1, 28, 34, 46, 54, 61, 80, 81, 97, 99, 100, 102, 108–110, 112–115, 122, 132], artificial neural network [15, 16, 22, 27, 31, 38, 47, 51, 63, 64, 66, 76, 85, 94, 95, 98], Particle Swarm Optimization [10, 67], ensemble-based model [75, 109], fuzzy logic [4, 65], and Monte Carlo simulation [79]. Most of these approaches used a regression technique (e.g., predicting Story Points value). On the other hand, two approaches used a classification technique to predict the effort, e.g., classifying Story Points in the Fibonacci scale (Porru et al. [97]) or classifying the range of man-hours (Dan et al. [27]). Lastly, only one approach used a clustering technique to provide estimations based on the closest work item in the cluster (Tawosi et al. [123]).

Table 9. The studies that proposed approaches to support the effort estimation process. We summarized the context and scope of these studies in Appendix (Table 13).

Purposes	Planning level	Technique
Improving the available information quality		
- applying INVEST criteria to ensure the quality of user stories [18]	Sprint planning	manual
- using developer story to document technical information [2]	Not specified	manual
Identifying additional information		
- proposing a checklist of relevant information for effort estimation [129]	Sprint planning	manual
- helping the team decide to collect data based on the return on investment [118]	Sprint planning	automated
- displaying the possible change impact on the current system [120]	Not specified	automated
Identifying estimation uncertainty		
- collecting and displaying risks of the estimation [44]	Not specified	manual
- proposing a three-points estimation to illustrate the uncertainty [50]	Not specified	manual
- proposing a model to predict the changes of Story Points of a work item [89]	Sprint planning	automated
- proposing a model to predict the changes of work items description [90]	Sprint planning	automated

Predicting the effort (Parametric-based): We identified 13 approaches that used a parametric-based method to predict the effort of sprints, projects, and maintenance phases [11–13, 19, 23, 43, 60, 86, 91, 101, 104, 106, 117]. These approaches defined an equation or calculation method to calculate the effort based on different parameters, e.g., the parameters related to the stories, projects, or developers. For example, effort in person-months = $1.3 \times REQ^{0.512} \times STAFF^{0.478} \times SD^{1.001}$ [106], where REQ is the number of requirements, STAFF is the number of team members available, and SD is the category of application domain (e.g., support=1, engineering=3). These approaches could be used manually or implemented as an automated program.

Improving the estimation technique: We identified 10 studies that proposed new (or improved) effort estimation techniques. Altaleb et al. [7] proposed a pair-estimation technique that requires team members to estimate in pairs to create a deeper communication about the work to be done. Alhamed and Storer [3] proposed a technique that simulates the Planning Poker estimation by recruiting the estimators from the Amazon Mechanical Turk platform. This technique could achieve a similar accuracy as expert estimation with a lower cost. Vetro et al. [130] proposed an expert-based estimation process that uses a shorter non-numerical estimation scale, compares the estimation with past user stories, and reviews past inaccurate estimations. Madya et al. [72] proposed a framework to improve the quality of user stories and to estimate the effort during sprint planning. Butt et al. [20] proposed a web system to collect important information to facilitate the estimation process and to reduce experts' bias in project planning. Nunes and Constantine [82] proposed a method to estimate the size of software projects in the Interactive Use Case Points unit. Rosa and Jardine [105] proposed a method to use two new size measures (i.e., "Functional Story" and "issues") in predicting the effort during release planning.

While these approaches proposed new techniques for individual estimations, other approaches focused on calculating the final estimation (i.e., estimation consensus) for the team. Alsaadi et al. [5] proposed a tool to provide appropriate estimation points and calculate average estimations. Beggar [32] proposed a fuzzy expert judgment method to help practitioners arrive consensus when performing expert judgment estimation. Rola and Kuchta [103] proposed an estimation method using fuzzy numbers and rules to help practitioners form estimation consensus in sprint planning.

4.3.2 **Support the effort estimation process**. We identified nine studies that proposed the approaches to support the effort estimation process. More specifically, these approaches were proposed to support the existing effort estimation processes or techniques by improving the available information quality, identifying additional information, and

identifying estimation uncertainty. majority of these approaches are manual and require the team's effort to operate. Table 9 lists the approaches in this category. Below, we present the approaches based on their purposes.

Improving the available information quality: Two approaches were proposed to improve the quality of the available information that will be used during effort estimation. Buglione and Abran [18] proposed the use of INVEST criteria (i.e., Independent, Negotiable, Valuable, Estimable, Small, Testable) to improve the quality of user stories for effort estimation and sprint planning. The process requires the team and the customers to determine whether a user story meets the INVEST criteria before effort estimation. The authors evaluated the approach in one company case study and reported the lessons learned. Algarni and Magel [2] proposed a documentation form called "developer story" to capture the technical information for effort estimation. Unlike a user story, a developer story typically includes the class design story with a list of methods and the method's contact criteria. The authors evaluated the usefulness of developer stories by applying them as an input parameter to predict the source code size in 30 open-source Java systems.

Identifying additional information: Three approaches were proposed to identify additional information to be used during effort estimation. Usman et al. [129] proposed a checklist to help the team recall relevant factors that should be considered during effort estimation, e.g., the team's skills, team domain knowledge, clarity of the requirements, and team recent productivity. The authors evaluated the checklist with three companies. However, the developers of one company decided to opt out of the checklist as it requires a lot of manual effort to operate. Taibi et al. [118] adapted the concept of Return on Invested Time (ROIT) to help the teams decide whether a metric (e.g., actual time spent, estimation error) should be collected for effort estimation. The ROIT can be calculated as $\frac{TS-TC}{TC}$, where TS is the time saved (i.e., the smaller estimation error) with the help of the collected metric and TC is the time spent to collect the metric. In this concept, a metric should be collected when the ROIT is positive. The authors conducted a multiple-cases study in seven Agile projects and found that the approach could improve the estimation accuracy. Tanveer et al. [120] proposed a framework with a mock-up system that integrates the change impact analysis to provide additional information for effort estimation. Given a user story, the system shows the methods (i.e., functions) that may be impacted by the implementation. For each method, the system also shows its historical changes, dependency graph, and relevant code metrics such as size and complexity. The authors evaluated this framework with six participants from three Agile teams at a company. The authors reported that the framework helps visualize the impact and complexity of a change during effort estimation using Planning Poker.

Identifying estimation uncertainty: Two approaches were proposed to identify the uncertainty in effort estimation. Grapenthin et al. [44] suggested a practice to annotate the risks and effort drivers of user stories for effort estimation. This practice requires the team to manually annotate the risks or effort drivers of user stories before the estimation session. The authors evaluated the approach with a software features dataset from student teams and reported that using this approach could increase the effort estimation accuracy. Hannay et al. [50] proposed a three-points estimation method to illustrate the uncertainty when estimating the effort of Epics (i.e., large and vague work items). In this method, the teams have to provide three estimates, i.e., bad, neutral, and good cases. With the three-points estimation, the authors used Monte-Carlo simulation to illustrate the possible outcome of eight epics. Pasuksmit et al. [89, 90] proposed two machine learning-based approaches to predict the future changes of Story Points [89] and the future changes of descriptions [90] of a work item. The authors stated that, to avoid data leakage, these approaches "use the information available when each work item was assigned to the sprint to align with the realistic usage scenario where the information may be incomplete." They found that the past tendency and the work items description are the most influential prediction factors, and the correctly predicted description changes are related to scope modifications [90].

4.3.3 Planning levels. Table 8 and Table 9 show the planning levels for which the approaches were designed to be used. We identified five planning levels: sprint planning, release planning, project planning, project bidding, and maintenance. Most of the studies proposed the approaches for a single planning level. However, Choetkiertikul et al. [22] proposed a Story Points prediction approach and noted that the predicted Story Points could be utilized for both sprint planning and release planning. Hence, we considered this approach for both planning levels (heterogeneity case). Below, we discuss the approaches based on the associated planning levels. Since effort estimation in Agile is mainly conducted at the sprint planning level [125], our discussion focuses on the approaches proposed for sprint planning. Then, we discuss the approaches designed for other planning levels (i.e., release planning, project planning, project bidding, and maintenance) and the approaches that did not explicitly specify the planning level.

Sprint planning level: Table 8 lists 13 approaches that were proposed to estimate the effort for (or during) sprint planning or iteration planning. To help the teams in sprint planning, seven prediction models were proposed to estimate the effort of a work item [4, 22, 28, 38, 75, 113, 122] or the total effort of a sprint [100]. Five manual estimation techniques were proposed to estimate the effort of work items during sprint planning [5, 7, 72, 103, 130]. These approaches were evaluated using the information extracted from the work items or sprints. The extracted information includes the properties of work items or sprints [4, 75, 113], the textual description of work items [22, 38, 100, 113], the experience and workload of developers [4, 28, 75, 100, 113, 122], or the developing function [28]. For example, Choetkiertikul et al. [22] trained a neural network model to predict the Story Points of work items using the textual description. This model is proposed to be used either as an automated Story Points prediction model or as a decision support system. Malgonde and Chari [75] trained an ensemble-based model to predict the Story Points of work items using priority, size, sprint, subtasks, and developer's experience. The authors noted that these kinds of information were chosen as they assumed that they would be "readily available when a story is created." Nevertheless, as information keeps changing in Agile [55, 78], it is unclear whether the authors of the prior studies used the information available during the sprint planning or used the latest information version (which is considered future data).

Table 9 lists five approaches that were proposed to support the effort estimation process during sprint planning. These approaches were evaluated in Agile settings at the sprint planning level. Buglione and Abran [18] proposed the use of INVEST criteria to ensure the quality of user stories before effort estimation and sprint planning processes. Usman et al. [129] developed a checklist to help the team recall relevant factors during effort estimation at the sprint planning level. Taibi et al. [118] adapted the concept of Return On Invested Time (ROIT) to help the teams decide to collect the metrics for effort estimation at the sprint planning level. Pasuksmit et al. [89, 90] proposed two machine learning-based approaches to predict the changes of Story Points [89] and the changes of work item descriptions [90] that occurred after the sprint had started. The authors trained and evaluated these two prediction approaches using only "the information available when each work item was assigned to the sprint" to avoid data leakage.

Other levels: We identified 18 studies that proposed the approaches to estimate the effort for release planning, project planning, project bidding, or maintenance phase (see Table 8). Four studies proposed the approaches that could be used for release planning. Kang et al. [60] and Winska et al. [132] proposed the approaches to estimate and track the effort. Rosa and Jardine [105] proposed an estimation method based on two new measures, i.e., "Functional Story" and "Issues." Choetkiertikul et al. [22] proposed a Story Points prediction approach and noted that the predicted Story Points can also be used for release planning. Nine studies proposed the approaches to estimate the effort for project planning [15, 20, 31, 98, 101, 102, 110, 115, 117]. Three studies proposed parametric-based approaches for the project bidding phase [86, 104, 106]. Two studies proposed the approaches to predict the effort required for software maintenance phases [23] and functional size of changes [108]. At these levels, the effort is typically estimated in

man-days or monetary cost in order to support business decisions or project planning. Since detailed information usually be absent in these early planning levels [127], these studies used different techniques to overcome the lack of information problem. For example, using the early design factors (e.g., risk resolution, team cohesion) as the model inputs [101] or using an approach that is robust to small inputs [98].

Planning level not specified or insufficient context: There are 36 studies that did not clearly specify the planning level for the approaches to be used (see Table 8 and Table 9). From these studies, 36 of them proposed the approaches to estimate the effort of work items [3, 27, 32, 46, 54, 63, 64, 76, 79, 80, 94, 95, 97, 99], sprints [51, 61], releases [91], requirement changes [13, 109], or projects [1, 10–12, 16, 19, 34, 43, 47, 65–67, 81, 82, 85, 112, 114]. The other four studies proposed the approaches to support the effort estimation process by proposing a developer story form [2], displaying the change impact [120], displaying the estimation risks [44], and proposing a three-point estimation technique [50].

From these approaches, we also identified a few of them that were proposed to "assist" or "replace" the Planning Poker estimation technique but did not clearly specify the planning level. For example, Grapenthin et al. [44] suggested a practice to annotate the risks and effort drivers of user stories for Planning Poker estimation, Tanveer et al. [120] proposed an integration of change impact analysis to provide additional information for Planning Poker estimation, and Alhamed and Storer [3] proposed a crowd-based technique to mimic the Planning Poker estimation performed by the team of experts. Furthermore, four effort prediction approaches were proposed to complement the Planning Poker estimation without clearly specifying the planning level, i.e., Moharreri et al. [80], Phan and Jannesari [94], and Kassem et al. [63, 64]. Nevertheless, Mahnic et al. [73] suggested that Planning Poker can be used for sprint planning or release planning [73, 107]. Thus, we can imply that these proposed approaches might be suitable for sprint planning or release planning levels.

Findings: We identified 75 studies that proposed the approaches for effort estimation in Agile, which can be categorized into two main purposes. We found that 66 approaches aim to estimate the effort, while only 9 approaches aim to support the effort estimation process (i.e., improving the available information quality, identifying additional information, identifying estimation uncertainty). Majority of these approaches were proposed to be used for sprint planning. However, for many of them, we observed that it is unclear whether they have been evaluated based on the information available during the sprint planning or not.

5 DISCUSSIONS

We conducted a systematic literature review on 82 studies where eight studies investigated the reasons for inaccurate estimations in Agile (RQ1) and 75 studies proposed the approaches to improve effort estimation in Agile (RQ2). Note that we found one study included in both RQs. These studies were published from year 2008 to 2023. We now discuss broader implications and provide recommendations for practitioners and researchers based on our findings.

5.1 Implications

Poor information quality is the common reason for inaccurate estimations. In RQ1, we observed that the quality issues of the available information (i.e., whether the information is unclear, unstable, or error) are the common reason for inaccurate estimations that are often reported in high ranking. Some may argue that such quality issues are generally expected since the information in Agile is typically sketched out and changed (refined) over time [33, 52, 56]. However, prior studies reported that information quality issues can be discovered late during the sprint implementation, which could cause the estimation to become inaccurate (RQ1) [17, 26]. Even though the team can re-estimate to

maintain the estimation accuracy [14, 55, 88], doing so after the sprint planning may cause the sprint plan to become unreliable [25]. In response to these issues, the practitioners may become "more conservative in their estimates mainly due to a high level of uncertainty or lack of detail" [126] (i.e., intentionally overestimate the effort). These findings highlight that the available information quality is critical for effort estimation in Agile iterative development.

Little has investigated the approaches to improve the information quality. While our RQ1 found that the quality of the available information is important for the estimation, our RQ2 only identified 9 studies that proposed an approach to support the effort estimation process by improving the available information quality, identifying additional information, and identifying estimation uncertainty. Furthermore, the majority of these approaches require team's manual effort of the developers to operate. As reported by Usman et al. [129], the team may be reluctant to use such approaches due to the additional overhead. These observations suggest that there is a need for an automated approach to support the effort estimation process, especially to improve the quality of the available information.

Challenges related to team and estimation practices could impact effort estimation accuracy. Although in lower ranks, our study identified frequently recurrent themes (see RQ1), particularly the lack of experience of team members (R2.1; reported by five studies) and factors overlooking (R3.1; reported by four studies). More specifically, an inexperienced team member (R2.1) tends to "exhibit the tendency to consider the best case scenario only" (i.e., overoptimism) [127]. Intuitively, considering only best-case scenarios could lead the team to overlook critical information (R3.1), e.g., non-functional requirements [111, 127], test effort [111, 127], or the complexity of a developing function [26, 126]. These findings point out the importance of equipping teams with the necessary skills and knowledge for effort estimation.

The majority of the proposed approaches aimed to estimate the effort. In our RQ2, we observed a significant trend where the majority of the proposed approaches focused on effort estimation (66 studies) rather than support mechanisms for estimation processes (9 studies). A significant observation is the predominance of machine learning-based techniques, including both traditional machine learning and deep learning models (e.g., regression using LSTM + RHWN [22], classification using SVMs [113], Deep Attention Neural network [64]). Some recent studies leveraged recent approaches (in 2022) like FastTexts [94] or GPT-2 [38] that overcome the previous baselines. This highlights an active research trend on the automated approaches for effort estimation. With the emerging advanced AI trends (e.g., GPT-4), we may expect better prediction accuracy while requiring less training data in the near future.

Many effort estimation approaches for sprint planning may not be validated using realistic information. In RQ2, we found that 33 studies specified the planning level for which the approaches to be used, where the majority of them (13 studies) proposed to be used for sprint planning. Intuitively, an effort prediction approach (especially machine learning-based) should be validated using the available information at the specified planning stage. For example, Pasuksmit et al. [89, 90] validated their prediction approaches using the information available during sprint planning. However, it is unclear whether other approaches were validated using only the available information or the future data (i.e., subjected to data leakage). For example, Malgonde and Chari [75] built an effort prediction model using the work item variables (e.g., priority, size, subtasks) while assuming that the variables will be "readily available when a story is created." While their assumption is correct, it is still unclear which version of information they used. On the other hand, using the latest and complete information may not reflect a realistic usage scenario as the information in Agile is typically sketched out and refined over time [14, 55, 78]. Therefore, the performance of these approaches may be sub-optimal in industrial settings.

Validating the approach using artificial datasets or student project data may pose a risk to generalizability. In RQ2, we identified seven studies at high risk of uncertainty due to their reliance on generated datasets [12, 65, 100]

or student project data [5, 44, 82, 91]. These data sources may lack the complexity, scale, and real-world Agile expertise necessary to accurately represent the generalizability of the approach in industrial contexts [69]. Nevertheless, they may be acceptable for primitively validating the performance of an approach, especially when data is scarce.

5.2 Recommendations for Agile Practitioners

Practitioners should prioritize enhancing the quality of the available information used in effort estimations. Particularly, the team should be aware of- and mitigate the common information quality issues (i.e., unclear, unstable, or error information). The reported quality issues are related to user stories [26, 127], user acceptance criteria [26], and requirements [17, 126, 127]. As recommended in the literature [71, 88], the practitioners should perform detail analyses or confirm the information with stakeholders prior to effort estimation, especially to ensure the quality of user stories, user acceptance criteria, requirements, and test plans.

Practitioners should apply the proposed approaches to improve the quality of the available information for effort estimation. The practitioners can consider the approaches for improving the available information quality or identifying additional information (see Section 4.3.2), i.e., applying INVEST criteria on user stories [18], adopting developer story for technical information [2], using an estimation checklist [126], surfacing the change impact [120], or consider the return on investment in data collection [118]. In addition, the practitioners may also consider the approaches to identify the uncertainty (changes) in the information of work items [90]. Although not directly proposed in the Agile estimation context, some approaches might be worth exploring for improving the information quality, e.g., identifying the missing information [21, 134], extracting quality attributes [40], or generating use cases or test cases [36, 41].

Practitioners should equip themselves with relevant domain and technical knowledge for effort estimation. The lack of experience of team members on the technology, domain knowledge, and effort estimation practices might lead to inaccurate estimations [17, 26, 111, 127] (see Section 4.2). This also includes novice team members [26, 111, 126, 127] and the team with low cohesion [17]. In particular, this problem could lead the estimating team to overlook critical information during effort estimations (e.g., non-functional requirements [111, 127], testing effort [111, 127], or function complexity [26, 126]), which eventually causes inaccurate estimations. To address this challenge, Usman et al. [126] recommended that "mature teams should be involved in the effort estimation process as they have architectural knowledge and expertise" [126]. They noted that expert mentoring, especially from product architects, is "critical to achieve technical consistency" in projects with teams of varying maturity levels.

Practitioners should assess the generalizability of the automated approaches prior to implementation. Our SLR points out the potential data leakage issue in the validation process of some automated approaches (see Sections 4.3.3 and 5.1). In particular, these approaches may not have been validated only with the available information. Since information can be changed in Agile [14, 55, 78], relying on final or updated information for validation could result in data leakage, potentially leading to sub-optimal performance in industrial adoption. Hence, practitioners should adopt approaches that effectively mitigate data leakage and are validated in realistic settings.

5.3 Implications for Future Research

Future research should prioritize the development of automated approaches for improving the information quality and identifying the additional information for effort estimation. Our SLR identified only two manual approaches focused on improving information quality, and three approaches (one manual) aimed to assist in identifying additional information for effort estimation. This scarcity highlights the need for automated systems

to identify or improve the quality of the information for effort estimation (e.g., the information elements suggested by Pasuksmit et al. [88]). The future approaches may adopt the existing solutions in other contexts. For example, identifying missing information [21, 134] or generating information [41]. In addition, future work may utilize a large language model to suggest related content (e.g., user stories [77]). These approaches will potentially enrich the quality of information used for effort estimation in Agile.

Future research should focus on validating approaches using realistic scenario information. Our RQ2 highlighted the risk of information leakage in the validation of several approaches. For instance, approaches intended for sprint planning, where information is subject to change [14, 55], may be validated using the latest information (see Section 5.1). This raises concerns about the generalizability and practical relevance of these methods. Hence, future research should validate the approaches using only information available at the intended time of practical use. For example, when proposing a prediction approach for sprint planning at the work items level, such as Jira issues [89, 90], researchers should utilize historical logs to revert issue fields to their state during sprint planning. This approach would provide a more accurate dataset for evaluating the effectiveness of proposed methods.

Future research should validate research findings in industrial contexts. Our RQ2 noted that some studies utilized a generated dataset or student projects to validate the proposed approaches. While useful for initial validations, such datasets may not fully reflect the complexities of industrial scenarios [69]. When it is challenging to find a representative dataset, an effective strategy would be to utilize the crowd-sourcing approach used by Alhamed and Storer [3] or use the open-source project datasets shared by Tawosi et al. [121] or Choetkiertikul et al. [22]). These methods would substantially improve the reliability and relevance of research, bridging the gap between academic findings and practical industry challenges.

6 THREATS TO VALIDITY

This section discusses the potential threats to the validity of this systematic literature review (SLR).

Construct validity is related to the process of identifying the studies of this SLR. There might be a chance that some relevant studies were not retrieved when using our search terms. Changing the search terms (e.g., removing the "Agile" keyword) may impact our search results by including other studies in the literature review. Yet, we designed our search terms to focus our literature review on the studies in a specific context. To mitigate the risk of excluding relevant studies, we strive to extend our search by adding alternatives and synonyms of the main search terms. Table 3 lists our search terms and their synonyms, which we believe that they are sufficient for covering the two research areas.

The five search engines we used may not include every study related to the scope of our RQs. In this study, we opted to use the five common search engines to align with the past SLRs in the related areas (i.e., [6, 29, 53, 128]), which appeared to cover the major software engineering journals and conferences. Nevertheless, some Agile studies may not be included in this paper. For example, a study by Majchrzak and Madeyski [74] on the reasons for inaccurate estimations was not listed on any of the five search engines as they were published in a non-software engineering publication venue. Future work that aims to review Agile studies in other contexts (e.g., management and economics) may need to consider additional search engines.

Internal validity is related to the confounding factors that might impact our study. We assessed the risk of uncertainty and bias assessment using GRADE as suggested by Kitchenham et al. [69] (see Section 3.2.4). A few of our selected studies have a high risk of uncertainty (see Table 11, Table 12, and Table 13). However, even when we excluded these studies with the high risk out, our findings (themes and taxonomies) remained unchanged.

The first author conducted the first iteration of card sorting and manual analyses to discover the thematic taxonomies, other related information, and the risks of uncertainty and bias of individual studies (see Section 3.3). The subjective opinion and personal experience of the first author might influence the analyses. To mitigate this risk, the second author (with a different background and expertise) reviewed the results and discussed the disagreements with the first author. The first author then conducted another round of analyses and reviewed all results until both reached a consensus. Hence, our card sorting process is not subjective only to the first author.

We retrieved the ranks of reasons for inaccurate estimations from the selected studies. These ranks originated from different experimental designs and ranking methods (i.e., the number of participants, occurrences observed, and agreement scores). Comparing these rankings directly may misled our findings. Therefore, we limited the interpretation of the ranking only to support the consensus of the selected studies on the common reasons for inaccurate estimations. We believe that the risk of misinterpretation of the rankings on our findings is minimal.

7 CONCLUSIONS

Effort estimation is an integral part of Agile iterative development. Accurate effort estimations help teams achieve reliable sprint planning, ensuring reliable delivery of software increments. While many studies have investigated the reasons for inaccurate estimations and proposed approaches to improve effort estimation in the Agile context, there was a gap in aggregating and synthesizing evidence regarding these research areas. Our systematic literature review addressed this gap by focusing on two key research questions:

(RQ1) What are the discovered reasons for inaccurate estimations in Agile iterative development? (RQ2) What are the approaches proposed to improve effort estimation in Agile iterative development?

Our RQ1 revealed that the quality of available information is a commonly reported reason for inaccurate estimations impacting estimation accuracy. In addition, team-related, estimation practice, project management, and business influence were also notable reasons. In RQ2, we observed that approaches for estimating the effort were predominantly explored, with fewer studies focusing on supporting the effort estimation process. However, the validation process of some automated approaches was questioned, particularly regarding potential data leakage in validation and the use of indirect validation datasets or participants.

These findings highlight the need for future work to focus on improving the quality of available information for effort estimation with minimal overhead. Practitioners should consider adopting an automated approach to help them improve the information quality that has been carefully evaluated in realistic scenarios. It is crucial for future research to validate the proposed approaches using only the available information, while ensuring the datasets or participants reflect the complexities of industrial Agile environments. Future research should also revisit the previously proposed effort prediction models using only the available information, as it remains uncertain whether they considered this aspect adequately. This will bridge the gap between academic research and industry practice, enhancing the practical application of effort estimation in Agile iterative development.

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8 APPENDIX

The first part of this section provide the SEGRESS Systematic Literature Review checklist [69]. The rest of this section summarize the purpose, approach, scope, and the results of the selected studies. Table 10 listed the SEGRESS (The PRISMA 2020-Inspired Structured Checklist for Reporting SE Secondary Studies), along with our explanation on how this work comply with each checklist item. Table 11 summarize the selected studies that investigated the reasons for inaccurate estimations in Agile. Table 12 summarize the studies that proposed an approach to estimate effort. Table 13 summarize the studies that proposed an approach to support the effort estimation practices.

All the tables are listed on the next page.

Table 10. SEGRESS checklists

Section	Sub-section	PRISMA Item	Summary	Checklist
Full Report	n/a	n/a	Consider referencing material in the protocol, publishing material in supplementary material, and reporting any large-scale model building exercise separately from the SR report.	\checkmark Yes. We stated the use of guideline in the methodology while included this checklist in the supplementary material. 0
Title	Title	1	Identify the type of review and specify the topic being reviewed.	√ Yes. We identified the type of review in the title.
Abstract	Structured ab- stract	2	Provide a structured summary, including Background, Objective, Methods, Results, Limitations, and Conclusion.	\checkmark Yes. We provided the abstract in a structured style.
Introduction	Opening	n/a	Introduce the larger problem the paper is targeting, lay out a broad context for the work, and highlight the importance of the work to a large audience.	\checkmark Yes. We set the context of the study and high lighted the importance of this work in the Introduction section (Section 1).
Introduction	Rationale	3	Describe the rationale of the study and how it contributes to the larger problem.	√ Yes. We explained the rationale of the study and contribution in the Introduction section (Section 1).
Introduction	Objectives	4	Specify the research questions and explain how they contribute to the larger problem.	✓ Yes. We specified and justify the research questions in the Research Questions section (Section 2), next to the Introduction section).
Methods	Eligibility criteria	5	Use the study characteristics to define eligibility criteria based on the intervention or topic of interest. Criteria used to restrict the search must be specified and justified.	✓ Yes. We defined the eligibility criteria based on the past literature reviews in effort estimation. We also constructed the search criteria following the PICOC suggested by Kitchenham and Charters [68]
Methods	Information sources	6	Describe all information sources, databases, primary study references, and others (e.g., researchers) with search end dates	✓ Yes. We described the search end dates of our study in the Search Strategy section (Section 3.1).
Methods	Search Strategy	7	Present full search strategy, e.g., electronic search strings, manual search, method(s) used to assess achieved completeness.	✓ Yes. We described the search strategy in the Search Strategy section (Section 3.1)
Methods	Selection Process	8	State the process for selecting studies, i.e., phases, assessors, handling disagreements, and tools used.	✓ Yes. We described the process for study selection, assessing, and handling disagreements in the Study selection section (Section 3.2).
Methods	Data Collection	9	Specify the method used to collect data from reports, i.e., processes,	\checkmark Yes. We specified the methods used to obtain the data and construct
	Process		reviewers, whether they worked independently, tools used.	the thematic taxonomies in the Data Analysis section (Section 3.3).
Methods	Data items	10a	List, define, and justify all outcomes for which data was sought, explaining their relationship to the research questions.	√ Yes. We presented and justify the extracted data for each research question in the Data Analysis section (Section 3.3).
Methods	Data items	10b	List and define all non-outcome variables (e.g., participant and interven- tion characteristics) and assumptions made about missing or unclear information.	√ Yes. We described the non-outcome variables collected in the Quality criteria and Uncertainty assessment section (Section \ref\sec:\text{litrevphasec\\ and \ref\sec:\text{litrevphased\\)}.
Methods	Study Risk Of Bias Assessment	11	Specify the methods used to assess risk of bias, i.e., tools used, reviewers, and whether they worked independently.	Yes. We specified the process to assess the risk of bias of individual study along with the GRADE assessment in Uncertainty and risk of bias assessment section (Section 3.2.4).
Methods	Effect Measures	12	Specify for each outcome the effect measures used in the synthesis or presentation of results. Not required for qualitative reviews.	\times No. Our qualitative review did not include any calculation of effect measure.
Methods	Analysis and Synthesis	13a	Report the methods used for synthesis of primary study outcomes.	✓ Yes. We reported our Open Card Sorting process to derive the themes and taxonomy of the primary study outcomes (RQ1) in the Discovering the themes and taxonomy section (Section 3.3.1).
Methods	Methods	13b	Describe any methods required to prepare the data for presentation or synthesis. Describe the coding processes adopted.	✓ Yes. We described in details the methods to collect and prepare the data in the Data Analysis section (Section 3.3).
Methods	Methods	13c	Describe any methods used to tabulate or display results.	✓ Yes. We described the tools we used in the Data analysis section (Section 3.3).
Methods	Methods	13d	Describe any methods used to synthesize results with rationale. Qualitative studies should, where necessary, identify constructs analyzed, explain how findings from different studies were compared, and specify how synthesized findings were validated.	\checkmark Yes. We described the validation method of the synthesized findings in the Data Analysis section (Section 3.3).
Methods	Methods	13e	Describe any sensitivity analysis conducted to assess robustness of the synthesized results and, including any impact of deviant cases and exceptions.	✓ Yes. We described that we mark the studies with high risk of bias and describe the impact if we exclude them from our study in the Discovering the theme and taxonomy section (Section 3.3.1).
Methods	Methods	13f	Describe any methods used to explore possible causes of heterogeneity among study results.	✓ Yes. We described that we exploring the heterogeneity among the study results in the Data analysis section (Section 3.3).
Methods	Reporting Bias Assessment	14	Describe any methods used to assess risk of bias due to publication bias.	√ Yes. We described our publication bias assessment using GRADE in Phase D: Uncertainty and risk of bias assessment section (Section 3.2.4).
Methods	Certainty Assess- ment	15	Describe methods used to assess certainty (or confidence) in the body of evidence for an outcome.	✓ Yes. We described the process we applied GRADE certainty assessment to individual study in Phase D: Uncertainty and risk of bias assessment section (Section 3.2.4).
Results	Study selection	16a	Describe the results of the search and selection process, ideally using a flow diagram. Qualitative studies should describe any iteration between selection and synthesis.	\checkmark Yes. We described the results of the search and section processes along with flow diagram in the Search Results section (Section 4.1).

Results	Study selection	16b	Cite studies that met many but not all inclusion criteria ('near-misses') and explain why they were excluded.	✓ Yes. We described the example studies that almost being included in the study along with the supporting reasons in the Search Results section (Section 4.1).
Results	Study characteris- tics	17	Describe the characteristics of each included study, and provide citations.	Yes. We described the characteristics with citation of each included study in the Appendix, i.e., Table 11, Table 12, and Table 13 (Section 8).
Results	Risk of Bias in Studies	18	Present data on the risk assessment for each study.	✓ Yes. We presented the risk of bias assessment of each study in the Appendix, i.e., Table 11, Table 12, and Table 13 (Section 8).
Results	Results of individ- ual studies	19	For qualitative reviews, present the major findings from each study included in the synthesis.	\checkmark Yes. We presented the key findings from individual studies in the Appendix, i.e., Table 11, Table 12, and Table 13 (Section 8).
Results	Results of Analy- ses and Syntheses	20	Describe results of syntheses and analyses.	\checkmark Yes. We presented the derived themes and taxonomies for each research question in the Results section (Section 4).
Results	Results of Analyses and Syntheses	20a	Report each synthesis by briefly summarising the characteristics and risk of bias among contributing studies. For qualitative studies, define any derived themes, and focus on theory building and testing. Provide appropriate quotations with sources.	√ Yes. We shortly summarised the characteristics along with risk of bias when presenting the themes and taxonomies where appropriate. We also provide quotations from studies to help illustrate the characteristics of the themes in the Results section (Section 4).
Results	Results of Analy- ses and Syntheses	20b	Present results of all statistical syntheses conducted. Only required for quantitative reviews.	\times No. Not applicable to our study.
Results	Results of Analy- ses and Syntheses	20c	Present results of robustness assessment of the synthesized results. Qualitative studies should report deviant cases, exceptions, and any additional validation.	\checkmark Yes. We discussed the deviant cases in our results in the Results section (Section 4).
Results	Results of Analy- ses and Syntheses	20d	Present results of all investigations of possible causes of heterogeneity among study results. $ \\$	\checkmark Yes. We reported one study included in both RQs and another study included in two taxonomies in the Search Results section (Section 4).
Results	Reporting Biases	21	Report results of assessing publication bias for each synthesis. Not usually required for qualitative studies.	√ Yes. We presented the risk of bias for the reported themes and tax- onomies in the Results section (Section 4).
Results	Certainty of Evi- dence	22	Present assessment of certainty in the body of evidence for each reported finding.	√ Yes. We presented the assessment of certainty for each finding in the Results section (Section 4).
Discussion	Discussion	23a	Provide a general interpretation of the results in the context of other evidence and compare the findings with other reviews on the same topic.	\checkmark Yes. We discussed interpretation of the results and compare the findings with other work in the Discussion section (Section 5).
Discussion	Discussion	23b	Discuss any limitations of the evidence included in the review.	\checkmark Yes. We discussed the limitations of the evidence included in the review in the Threats to Validity section (Section 6).
Discussion	Discussion	23c	Discuss any limitations of the review process used.	\checkmark Yes. We discussed the limitations of our review process in the Threats to Validity section (Section 6).
Discussion	Discussion	23d	Discuss implications of the results for practice, policy and future research.	√ Yes. We discussed the implications of our results in context of software engineering in practical and the recommendations for practitioners and future research in the Discussion section (Section 5).
Discussion	Registration and Protocol	24a	Provide registration information for the review. Optional for all review types.	\times No. We did not register this study.
Discussion	Registration and Protocol	24b	Indicate where the review protocol can be accessed or state why no protocol is available.	\times No. We did not register this study.
Discussion	Registration and Protocol	24c	Describe and explain any amendments to information provided at registration or in the protocol.	\times No. We did not register this study.
Discussion	Support	25	Describe sources of financial and non-financial support for the review and the role of the funders or sponsors of the review.	\checkmark Yes. We declared that our work has no financial sponsor in the Introduction section (Section 1).
Discussion	Competing Inter- ests	26	Declare competing interests of the review authors.	\checkmark Yes. We declared that the first author is currently working at a public company in the Introduction section (Section 1).
Discussion	Availability Of Data Code and Other Materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review or to produce the review.	\checkmark Yes. We provided all data and results in the supplementary material package.

Table 11. Summary of the selected studies that investigate the reasons for inaccurate estimations in Agile (Section 4.2).

Authors	Title	Purpose and techniques	Dataset used / Participants	Results	GRADE- Individual Study Bias	GRADE- imprecision	GRADE- Inconsistency	GRADE- indirectness
Usman et al. [127]	Effort Estimation in Agile Software Development: A Survey on the State of the Practice	Conducted an online survey on the state of the practice of Agile effort estimation. The reported reasons for inaccurate estimations are grouped into four categories and ranked based on the number of reported respondents.	60 respondents	28 from 60 respondents reported the reasons for inaccurate estimations.	none	none	none	none
Britto et al. [17]	An Empirical Investigation on Effort Estimation in Ag- ile Global Software Devel- opment	Conducted an online survey on the practice of Agile effort estimation in distributed team settings. These challenges were later grouped into seven categories and ranked based on the number of reported respon- dents.	51 respondents	24 from 51 respondents reported the challenges that impact the effort estimation accuracy.	none	none	none	none
Usman et al. [126]	Effort estimation in large-scale software devel- opment: An industrial case study	Conducted an exploratory longitudinal case study based on archival research and semi-structured inter- views on the effort estimation practices in large-scale Agile software development.	Four interview participants	Reported five challenges that led to the inaccuracies in effort estimations.	moderate - small sample size	none	none	none
Conoscenti et al. [26]	Combining data analytics and developers feed- back for identifying rea- sons of inaccurate estima- tions in agile software de- velopment	Employed a tool to ask the developers whether the estimated effort is inaccurate or not along with the supporting reason. The tool provided a checklist of reasons for the developers to check for an inaccurate estimation. The authors also provided an "Other" check-box to collect additional reasons if any. The results were then ranked them based on their occurrences.	70 developers in a medium-sized company with 124 user stories.	Reported 14 reasons for inaccurate estimations that were ranked based on their occurrences.	high - The rea- sons investigated were derived from the paper published before Agile manifesto (before year 2000).	none	none	none
andeep et l. [111]	Effort Estimation in Agile Software Development: A Exploratory Study of Prac- titioners' Perspective	Conducted an online survey that is designed based on a literature review to provide empirical evidence on Agile effort estimation techniques. The reasons were then ranked using the average scores of five-points agreement scales.	53 agile practitioners	Reported 20 reasons for inaccurate estimations in Agile software development.	none	none	none	none
Camrakar nd Jør- gensen [119]	Does the use of Fibonacci numbers in Planning Poker affect effort estimates?	Conducted two empirical studies to estimate effort with and without using Fibonacci scale to understand the effect of the Fibonacci scale adoption in effort estimation.	104 students and 16 professionals	Reported that the use of Fibonacci scale is likely to affect the estimates towards the lower values.	none	none	none	none
arna et l. [62]	The Effects of Turnover on Expert Effort Estimation	Examined the data from a large private software project to determined the effects of the employee turnover on expert effort estimation.	One large Agile project	Reported that only unplanned turnover can have a significant negative impact on the reliability of the estimates.	moderate - only one project dataset	none	none	none
etro et l. [130]	Combining Data Analytics with Team Feedback to Im- prove the Estimation Pro- cess in Agile Software De- velopment	Combined software data analytic and feedback from the teams in a company to identify root causes of the wrong estimates.	Four software development projects	Reported that using estimation scale with 1) too many items in the estimation scale 2) misleading numerical scale and 3) lack of shared reflection on the previous estimations can lead to wrong estimations.	none	none	none	none

Table 12. Summary of the selected studies that proposed an approach to estimate the effort (Section 4.3.1). The "ML" denotes that the purpose of the approach is to predict the effort using machine learning-based technique.

	Authors	Title	Purpose	Planning level	Artifact	Technique	Dataset used	Evaluation method per- formed	GRADE- Individual Study Bias	GRADE- imprecision	GRADE- Inconsistency	GRADE- indirectness	
	Alhamed and Storer [3]	Playing Planning Poker in Crowds: Human Computation of Software Effort Estimates	Improving estimation technique (manual)	Sprint plan- ning	work items	Using the opinions of the crowd recruited from Amazon Turk to estimate the completion time.	5,000 software engineers on Amazon Turks, 39 software tasks	Conducted the crowd estimation for 30 trials with 39 stories. Comparing the prediction accuracy with the experts.	none	none	high - first work using crowd- sourcing	high - crowd estimators may not have sufficient estimation experience	
	Alsaadi et al. [5]	Scrum Poker Estimator: A Planning Poker Tool for Accurate Story Point Estimation.	Improving estimation technique (manual)	Not spec- ified	work items	Proposing a tool to assist the estimation process at work items level in de- termining the estimation method, measure weight of estimation factors, ex- tract questions for the fac- tors, and determine the es- timated fibonacci number.	One undergraduate student senior project, consists of five user stories in four sprints	Applied the proposed approach with four students in their undergraduate senior project.	high - student projects	none	none	none	
32	Altaleb et al. [7]	A Pair Estimation Technique of Effort Estimation in Mobile App Development for Agile Process: Case Study	Improving estimation technique (manual)	Sprint plan- ning	work items	Proposing a pair estima- tion technique based on learnings from a focus group and an observation to enhance a deeper dis- cussion between develop- ers before estimating the effort.	A case study with a company of 150 employees	Examined the prediction accuracy after adopting the approach using a correlation test.	none	none	none	none	
	Madya et al. [72]	PREP: A Post- Requirements Effort Estimation Method in Scrum's Sprint Grooming	Improving estimation technique (manual)	Sprint plan- ning	work items	Proposing a framework that guides the practition- ers to develop high quality user stories, estimate the effort in detailed steps, and evaluate the approach after each iteration.	Seven sprints dataset from one project in one company	Compared the prediction accuracy with the actual effort, and measured the reduction of bugs.	none	none	none	none	
	Omar El Beggar [32]	IFEJM: New Intuition- istic Fuzzy Expert Judgment Method for Effort Estimation in Agile Software Development	Improving estimation technique (manual)	Not spec- ified	work items	Using a non-linear model to adjust the Planning Poker estimations of a work item when a consen- sus is not reached.	One agile project data with two sprints estimated by students and professionals	Compared the prediction accuracy with the actual effort.	none	none	none	none	
	Rola and Kuchta [103]	Application of fuzzy sets to the expert es- timation of Scrum- based projects	Improving estimation technique (manual)	Sprint plan- ning	work items	Proposing a framework for a team to provide an es- timation range, and apply a mathematical formula to calculate the final estima- tion of a work item.	Two case studies of an interna- tional IT project and an R and D project	Following symmetry principles, evaluated and compared the accuracy of the fuzzy approach and compare to the crisp estimate.	none	none	none	none	

	Vetro et al. [130]	Combining Data Analytics with Team Feedback to Improve the Es- timation Process in Agile Software Development	Improving estimation technique (manual)	Sprint plan- ning	work items	Proposing an estimation technique that requires the team to revisit the estima- tions of previous sprints and use a shorter numer- ical scale.	708 user stories from 4 projects in a company	Applied the estimation process on a new project	none	none	none	none
	Adnan et al.	Ontology-Oriented Software Effort Estimation System for E-commerce Applications Based on Extreme Program- ming and Scrum Methodologies	Predict the effort (ML)	Not spec- ified	projects	Using a regression model to predict the project effort based on lesson-learned (textual data) from previ- ous estimations.	20 XP and Scrum projects	Used the model to predicted the project effort in a case study.	moderate - report only relative accuracy units	none	none	none
	Alostad et al. [4]	A Fuzzy based Model for Effort Estimation in Scrum Projects	Predict the effort (ML)	Sprint plan- ning	work items	Using fuzzy-based model to estimate the Story Points.	30 tasks from 3 sprints in a project	Applied the model on three sprints and observed the accuracy in each sprint.	moderate - report only relative accuracy units	none	none	none
3	Ardiansyah et al. [10]	MUCPSO: A Modified Chaotic Particle Swarm Optimization with Uniform Initial- ization for Optimiz- ing Software Effort Estimation	Predict the effort (ML)	not spec- ified	work items	Proposing a modified chaotic particle swarm optimization to optimize three effort estimation methods, i.e., Use case points, COCOMO, and Agile.	Three datasets re- trieved from the prior work for the three estimation methods.	Compared the prediction performance with three particle swarm optimiza- tion variants and a nature- inspired algorithm. The evaluation is conducted 30 rounds to eliminate coinci- dence.	moderate - old dataset	none	none	none
	Arora et al. [11]	An efficient ANFIS- EEBAT approach to estimate effort of Scrum projects	Predict the effort (ML)	Not spec- ified	projects	Using a parametric-based approaches, i.e., adaptive neuro-fuzzy inference sys- tem (ANFIS) with EEBAT technique, to predict the ef- fort of a project	21 Agile projects from 6 software houses proposed by Ziauddin, et al.	Compared the prediction accuracy with the state- of-the-art meta-heuristic and machine learning ap- proach using nonparamet- ric tests.	none	none	none	none
	Bilgaiyan et al. [15]	Chaos-based modi- fied morphological genetic algorithm for software de- velopment cost estimation	Predict the effort (ML)	Project plan- ning	projects	Using a dilation-erosion perceptron to predict the effort of a project.	Five datasets from literature, i.e., Albrecht, Desharnais, Ke- merer, COCOMO, and KotenGray	Compared the prediction accuracy with the actual effort using an evaluation function (EF), PRED(x), and MMRE units.	moderate - report only relative accuracy units	none	none	none
	Bilgaiyan et al. [16]	Effort estimation in agile software devel- opment using exper- imental validation of neural network mod- els	Predict the effort (ML)	Not spec- ified	projects	Using Elman Recurrent Network and feedforward Back-Propagation Net- work models to predict the project effort based on the features of user story and	21 projects re- trieved from Ziauddin and Zia [133]	Compared the predicted effort with actual effort.	none	none	none	none

team.

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Conference acronym
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low - open-

source

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et al. [22]	model for estimating story points	effort (ML)	plan- ning or release plan- ning	items	Long Short-Term Memory and Recurrent Highway Network to estimate the Story Points of a work item.	16 open-source projects	tion performance with baselines (i.e., LSTM +RF, BoW+RF, Doc2vec+RF) based on 60(train)- 20(validate)-20(test) split, chronologically. Perform the evaluation with orig- inal and adjusted Story Points.				source projects may adopt Agile differently
Dan et al. [27]	An NLP Approach to Estimating Effort in a Work Environment	Predict the effort (ML)	Not spec- ified	work items	Using a Bi-LSTM model to classify the time taken to complete a user story based on their description.	One company dataset	Compared the predicted ef- fort with actual effort and compare with an LSTM model and a concatenated model.	high - the size of the dataset is not described	none	moderate - training a language model, but the language data is in Germany	high - it is unclear whether the projects were developed in Agile
Dantas et al. [28]	An Effort Estimation Support Tool for Ag- ile Software Develop- ment: An Empirical Evaluation	Predict the effort (ML)	Sprint plan- ning	work items	Using decision trees to pre- dict the time (in hours) to complete a user story based on the features ex- tracted from user stories and the features provided by the team.	530 user stories and 1,879 tasks from a company	Compared the predicted effort with the estimation of 24 professionals and the actual effort based on 10-folds cross validation / we compared the values of Magnitude of Relative Error from the teams' estimations with the values provided by the tool.	none	none	none	none
Dragicevic et al. [31]	Bayesian network model for task effort estimation in agile software development	Predict the effort (ML)	Project plan- ning	work items	Using a Bayesian Network model to estimate the ef- fort of a task based on soft- ware entities, tasks com- plexity, and knowledge and skills of the developers.	160 tasks from a company	Evaluated the prediction performance based on 10-folds cross-validation.	moderate - small dataset	none	none	none
Farahneh and Issa [34]	A Linear Use Case Based Software Cost Estimation Model	Predict the effort (ML)	Not spec- ified	projects	Using a linear model to pre- dict the project effort based on project size and pro- gramming language.	66 projects retrieved from Issa et al.	Compared the predicted effort with actual effort and compare with a baseline.	none	none	none	high - it is unclear whether the projects were developed in Agile
Fu and Tan- tithamtha- vorn [38]	GPT2SP: A transformer-based agile story point estimation approach	Predict the effort (ML)	Sprint plan- ning	work items	Using a GPT-2 pre-trained language model to predict the Story Points of a work item.	16 open-source projects from Choetkiertikul et al.	Evaluated the prediction accuracy with the actual effort (in MAE) and compared the performance with nine baseline approaches in within-project and cross-projects scenarios.	none	none	none	low - open- source projects may adopt Agile differently

Using a combination of 23,313 issues from Compared the predic- none

Long Short-Term Memory 16 open-source tion performance with

Choetkiertikul A deep learning Predict the

et al. [22] model for estimating effort (ML)

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Sprint

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work

items

	Govil and Sharma [43]	Estimation of cost and development effort in Scrum-based software projects considering di- mensional success factors	Predict the effort (ML)	Not spec- ified	projects	Using a parametric-based algorithm that takes user story, story points, and success factors as inputs to calculate the effort and cost of the project	30 Scrum-based projects, vali- dated by industry professionals with experience in Agile.	Compare the accuracy of the proposed algorithm with the existing algo- rithm, and validating the result with annotators.	high unclear explanation where the 30 projects come from, and it is unclear why the dataset needs to be validated (and how).	none	none	none
	Gultekin and Kalipsiz [46]	Story Point-Based Effort Estimation Model with Machine Learning Techniques	Predict the effort (ML)	not spec- ified	work items	Using regression-based models to estimate the Story Points based on the features of work items.	56,687 issues, 3,834 iterations, from 5 OSS projects	Compared the predicted effort with actual effort.	none	none	none	none
	Gupta and Mahapatra [47]	Automated software effort estimation for agile development system by heuris- tically improved hybrid learning	Predict the effort (ML)	Not spec- ified	projects	Using a Deep Belief Network \	Artificial Neural Network - based technique to pre- dict the effort of a project.	Three publicly available datasets, i.e., COCOMO, NASA93, and CHINA	moderate - old datasets	none	none	none
n n	Hearty et al. [51]	Predicting project velocity in XP using a learning dynamic Bayesian network model	Predict the effort (ML)	Not spec- ified	sprints	Using a Bayesian Network model to predict the project velocity based on the process factors.	One company project	Applied the model to an in- dustrial case study to pre- dict the project velocity for each iteration.	moderate - report only relative accuracy units	none	none	none
	Karna et al. [61]	Data Mining Approach to Effort Modeling On Agile Software Projects	Predict the effort (ML)	Not spec- ified	sprints	Using a K-Nearest Neighbor technique to predict the effort of an iteration based on the features of work items and the estimator.	One company project	Compared the predicted effort with actual effort.	moderate - small dataset	none	none	none
	Kassem et al. [63]	Software Effort Esti- mation Using Hierar- chical Attention Neu- ral Network	Predict the effort (ML)	Not spec- ified	work items	Using hierarchical attention networks to classify user stories into a range of story points.	16 open-source projects from Choetkiertikul et al.	Evaluated the prediction accuracy with the ground truth story points and compared with four baselines.	none	none	none	low - open- source projects may adopt Agile differently
	Kassem et al. [64]	Story Point Estima- tion Using Issue Re- ports With Deep At- tention Neural Net- work	Predict the effort (ML)	Not spec- ified (plan- ning poker)	work items	Using Hierarchical Atten- tion Networks (HANs) at word and sentence levels for predicting Story Points of a work item.	16 open-source projects from Choetkiertikul et al.	Compared the prediction accuracy with two baselines, i.e., Deep-SP and BERT.	none	none	none	low - open- source projects may adopt Agile differently
	Kaushik et al. [65]	A fuzzified story point approach for agile projects	Predict the effort (ML)	Not spec- ified	projects	Using the fuzzified Story Points approach to calcu- late the project effort based on the cost drivers.	145 generated projects	Compared the prediction performance between fuzzy interval type 1 and type 2	high - using a generated dataset	none	high - using a generated dataset	high - using a generated dataset

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	Effort Estimation of Software Projects Us- ing Agile Methodolo- gies				particle swarm optimization algorithms to estimate software project effort.	Ziauddin and Zia [133]		relative accuracy units			
Malgonde and Chari [75]	An ensemble-based model for predicting agile software devel- opment effort	Predict the effort (ML)	Sprint plan- ning	work items	Using an ensemble-based method to predict the effort of a story.	503 user stories of 24 projects from university IT de- partment	Conducted experiments to compare the predic- tion performance of the ensemble-based approach with other approaches based on blocked cross- validation technique.	none	none	none	none
Marapelli et al. [76]	RNN-CNN MODEL: A Bi-directional Long Short-Term Memory Deep Learning Net- work For Story Point Estimation	Predict the effort (ML)	Not spec- ified	work items	Using a Bi-LSTM (RNN with CNN) model to predict Story Points based on the description of a user story.	16 open-source projects retrieved from Choetkier- tikul et al.	Compared the predicted effort with actual effort and compared the prediction performance with the approach of Choetkiertikul et al.	high - unclear explanation on the cross- validation method	none	none	low - open- source projects may adopt Agile differently
Miranda et al. [79]	An Analysis of Monte Carlo Simulations for Forecasting Software Projects	Predict the effort (ML)	Not spec- ified	work items	Using Monte-Carlo simulations to predict the effort and deliver time (based on Story Points) of a user story.	71 projects, 12,000 user sto- ries, 135,000 changes, 150 sprints, from a company dataset	Compared the model prediction performance with expert estimations based on 50\% hold-out. The prediction was evaluated in 3 aspects, i.e., delivery date, effort (hours) for each work item, and the impact of the size of historical data used.	none	none	none	none
Moharreri et al. [80]	Cost-Effective Super- vised Learning Mod- els for Software Ef- fort Estimation in Ag- ile Environments	Predict the effort (ML)	Sprint plan- ning	work items	Using machine learning models to improve the Planning Poker accuracy (predict the effort) based on the features extracted from Agile story cards.	Story cards from 10 teams in a com- pany	Compared the predicted effort with actual effort.	high - the character- istic of the 10 studied teams is unclear	none	none	none
Najm et al. [81]	An enhanced support vector regression model for agile	Predict the effort (ML)	Not spec- ified	projects	Using Support Vector Regression with Radial Bias Function kernel (SVR-RBF)	21 Agile projects from 6 software houses proposed	Compared the prediction accuracy with 10 base- lines using a leave-one-out	moderate - report only relative	none	none	none

Function kernel (SVR-RBF) houses proposed lines using a leave-one-out to predict the effort of a by Ziauddin et al. cross-validation.

project.

Estimating the effort using 21 projects re- Compare the predicted ef-

Ziauddin and Zia

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compare with other pro-

posed approaches.

fort with actual effort.

21 projects re- Compared the predicted ef-

trieved

artificial neural networks

(Radial Basis Function Neu-

ral Network and Func-

tional Link Artificial Neu-

ral Network) and a metaheuristic technique (Whale Optimization Algorithm).

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moderate - none

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Kaushik et The role of neu- Predict the

ral networks and

metaheuristics in

agile software de-

velopment effort

Khuat et al. A Novel Hybrid ABC- Predict the

projects cost estima-

tion

PSO Algorithm for effort (ML)

estimation

effort (ML)

al. [66]

[67]

Not spec- projects

Not spec- projects

	Nunes et al. [82]	iUCP: Estimating Interactive-Software Project Size with Enhanced Use-Case Points	Predict the effort (ML)	Not spec- ified	projects	Proposing a technique to estimate the project size based on use-case points estimation with the usage- centered design.	30 master students	Conducted an empirical ex- periment with master's stu- dents. The students devel- oped a group project using the proposed approaches.	high - tested the approach with master students only	none	none	high - stu- dents may not have sufficient experience in Agile software development
	Panda et al. [85]	Empirical Validation of Neural Network Models for Agile Soft- ware Effort Estima- tion based on Story Points	Predict the effort (ML)	Not spec- ified	projects	Evaluating different neural networks (GRNN, PNN, GMDH, and CCNN) to enhance the Story Points Approach estimation.	21 projects re- trieved from Ziauddin and Zia [133]	Compared the prediction performance among the four neural networks and the actual effort, based on 3-folds cross validation.	none	none	none	none
	Phan and Jannesari [94]	Heterogeneous Graph Neural Net- works for Software Effort Estimation	Predict the effort (ML)	Not spec- ified	work items	Using a heterogeneous graph neural networks model with FastText to predict the effort of a work item.	16 open-source projects from Choetkiertikul et al.	Compared the proposed approach with baselines (i.e., GPT2SP and Deep-SE) across three scenarios of estimation: within project, cross-project within the repository, and cross-project cross repository.	none	none	none	low - open- source projects may adopt Agile differently
ì	Phan and Jannesari [95]	Story point level classification by text level graph neural network	Predict the effort (ML)	Not spec- ified	work items	Using a Graph Neural Net- work to perform effort clas- sification of a work item based on textual data.	16 open-source projects from Choetkiertikul et al.	Evaluated the effectiveness of the approach through experiments and compared the results with TF-IDF ap- proach.	none	none	none	low - open- source projects may adopt Agile differently
	Porru et al. [97]	Estimating Story Points from Issue Reports	Predict the effort (ML)	Sprint plan- ning	work items	Using naive-bayes classifiers to classify the Story Points of a work item.	1 industrial project and 8 open source projects	Evaluated the prediction performance based on 10-folds cross-validation.	none	none	none	none
	Premalatha and Srikr- ishna [98]	Effort estimation in agile software devel- opment using evolu- tionary cost-sensitive deep belief network	Predict the effort (ML)	Project plan- ning	projects	Using an Evolutionary Cost-Sensitive Deep Belief Network (ECS-DBN) to predict the effort of a project.	160 work items from one small software com- pany	Compared the prediction performance using chronologically cross-validation.	none	none	none	none
	Prykhodko and Prykhodko [99]	A multiple non-linear regression model to estimate the agile testing efforts for small web projects	Predict the effort (ML)	Not spec- ified	work items	Using a multiple non- linear regression tech- nique to predict the effort of a work item.	40 small web projects (lack of detail about the dataset)	Evaluated the prediction accuracy with the actual ef- fort and compared it with linear and non-linear re- gression models (in MMRE, confidence intervals, and prediction intervals).	moderate - report only relative accuracy units	none	none	none
	Ramessur and Nagowah [100]	A predictive model to estimate effort in a sprint using machine learning techniques	Predict the effort (ML)	Sprint plan- ning	sprints	Using six machine learning models to predict the effort of a sprint.	2,100 simulated records	Compared the prediction performance among all models based on 10-folds random cross valida- tion, and cross-datasets prediction.	high - using a generated dataset	none	high - using a generated dataset	high - using a generated dataset

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projects

trieved

[133]

21 projects re-

Ziauddin and Zia

from

Empirical effort and

schedule estimation

models for agile pro-

cesses in the US DoD

prediction of Scrum

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hancement

Story Points

regression

model for agile soft-

ware development

effort estimation

Sharma and

Chaudhary

[114]

Sakhrawi et

al. [108]

Predict the

effort (ML)

Predict the

effort (ML)

Project

bidding

ning

Predict the

projects

changes

Using initial function

groups, and peak staff

inputs to predict the size of a project during the bidding phase.

Regression model to esti-

mate the COSMIC func-

tional size of a software

Story Points of issue

reports based on the

developer-related features.

Using multiple Linear Re-

gression models to predict

the project effort.

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requirements.

Maintenancerequirement Using a Support Vector

change.

36 agile and hy-

brid projects in

93 user stories

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US DoD

Compared the prediction

accuracy with the final ef-

Compared the predicted ef-

fort with actual effort using

70\%-30\% hold-out strat-

egy. Compared the predic-

tion performance between

the models trained using

COSMIC sizing and Story

built based on text features.

fort with actual effort

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fort and schedule

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adopt Agile

differently

	Sharma and Chaudhary [115]	model for soft- ware development effort estimation using polynomial regression for hetero- geneous projects	Predict the effort (ML)	Project plan- ning	projects	Using a polynomial regression technique that considering multiple project-related parameters to predict the effort of a project.	21 projects from Python proce- dural projects, Zia et al.'s dataset agile projects, and a company dataset for object-oriented projects.	Compared the prediction accuracy with the actual effort in R-squared and MMRE.	none	none	none	none
	Tawosi et al. [122]	Investigating the effectiveness of clustering for story point estimation	Predict the effort (ML)	Sprint plan- ning	work items	Using a combination of LDA and hierarchical clustering to group issues based on their topic similarities to predict effort of work items	26 open source projects with a to- tal of 31,960 is- sues.	Compared the prediction accuracy in MAE with a random guessing.	none	none	none	none
	Vyas and Hemrajani [54]	Predicting Effort Of Agile Software Projects Using Linear Regression, Ridge Regression And Logistic Regression	Predict the effort (ML)	Not spec- ified	work items	Using Linear, Logistic, and Ridge regression techniques to predict the required man-hours of a user story.	21 projects retrieved from Ziauddin and Zia [133]	Compared the prediction performance of the models based on random cross val- idation (20\% for testing)	none	none	none	none
)	Wińska et al. [132]	Reducing the uncer- tainty of agile soft- ware development us- ing a random for- est classification algo- rithm	Predict the effort (ML)	Release plan- ning	work items	Using complexity factors in effort classification for a work item.	70k issues across four major re- leases from a bank	Applied the proposed solu- tion in a commercial envi- ronment, and analyzed the impact of each complexity factor.	none	none	none	none
	Aslam et al. [12]	Risk Aware and Quality Enriched Effort Estimation for Mobile Applications in Distributed Agile Software Development.	Predict the effort (para- metric)	Not spec- ified	projects	Using a parametric-based approach to considers size, complexity, quality, novelty, type, and risk to predict the effort of a project.	128 generated user stories	Compared the prediction accuracy with the generated actual effort.	high - using a generated dataset, report only relative accuracy units, the definition of MER accuracy unit is not described	none	high - using a generated dataset	high - using a generated dataset
	Basri et al. [13]	An Algorithmic- Based Change Effort Estimation Model for Software Development	Predict the effort (para- metric)	Not spec- ified	requirement changes	t Extending the COCOMO II estimation method to es- timate the size of require- ment changes.	6 traditional and Agile software projects	Compared the predicted effort with actual effort.	moderate - report only relative accuracy units	none	none	none

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[19]	estimation technique in agile development	effort (parametric)	ified		approach to gather infor- mation of the projects from stakeholders, to be used as inputs for a parametric-based calcula- tion method for project level estimation.	projects of differ- ent sizes and user stories.	proach on the projects, fol- lowed by a developer sur- vey to understand the de- velopers' perception.				
Choudhari and Suman [23]	Phase wise Effort Estimation for Soft- ware Maintenance: An Extended SMEEM Model	Predict the effort (para- metric)	Maintenan	cemaintenand phases	the Using an algorithmic method to estimate the effort of a phase in software maintenance.	A case study with three Request for Changes	Used the method to predict the effort in a case study.	moderate - small dataset	none	none	none
Kang et al.	Model-Based Dy- namic Cost Estima- tion and Tracking Method for Agile Software Develop- ment	Predict the effort (para- metric)	Sprint plan- ning	sprints	Using the Kalman Filter to estimate and track the team velocity.	One case study consists of 32 user stories	Compared the performance of the model with the traditional methods through a case study.	moderate - small case study	none	none	none
Parvez [86]	Efficiency Factor and Risk Factor Based User Case Point Test Effort Estimation Model Compatible with Agile Software Development	Predict the effort (para- metric)	Project bidding	projects	Adjusting the Use Case Points using algorithmic method based on efficiency and risk factors	4 mobile and web applications	Compared the predicted effort with actual effort.	none	none	moderate - not report the accuracy using any well-known metrics	none
Paz et al. [91]	An Approach for Effort Estimation in Incremental Software Development using Cosmic Function Points	Predict the effort (para- metric)	Not spec- ified	releases	Estimating the effort of an increment using the Cosmic Function Points and COCOMO's effort adjustment factor.	2 student projects	Compared the predicted effort with actual effort.	high - con- ducted the experi- ment using student projects	none	none	high - stu- dents may not have sufficient experience in Agile software development
Raslan and Darwish [101]	An Enhanced Framework for Effort Estimation of Agile Projects	Predict the effort (para- metric)	Project plan- ning	projects	Using a combination of Story Points and CO- COMO II methods to estimate the project effort.	10 projects dataset ex- tracted from CO- COMONASA2	Compared the predicted effort with actual effort.	moderate - old dataset, and report only relative accuracy units	none	none	none
Rosa et al. [106]	Early Phase Cost Models for Agile Software Processes in the US DoD	Predict the effort (para- metric)	Project bidding	projects	Constructing an equation that consider different variable combinations and investigate whether the variable should be consid- ered in the estimation for	20 industrial projects	Used the three variations of the approach to predict the actual effort.	none	none	none	none

project bidding.

Butt et al. Prediction based cost Predict the Not spec- projects Using a structured Two ongoing Applied the proposed ap-

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Singal et al.	Integrating software	Predict the	Project	projects	Using a parametric-based	Two industrial	Compared the prediction	none	none	none	none
[117]	effort estimation with	effort (para-	plan-		(formula) that considers	datasets from an	accuracy with CoCoMo II				
	risk management	metric)	ning		risk exposure with other	Indian IT firm,	(for waterfall projects) and				
					factors to calculate an inte-	one for waterfall	Story Point approach (for				
					grated effort for a software	(45 projects) and	agile projects).				
					project.	one for agile					
						(30 projects)					
						development.					

	Authors	Title	Planning level	Automated / Manual	Purpose and techniques	Dataset used / Par- ticipants	Evaluation method performed	GRADE- Individual Study Bias	GRADE- imprecision	GRADE- Inconsistency	GRADE- indirectness
	Algarni and Magel [2]	Applying soft- ware design metrics to de- veloper story: A supervised machine learning analysis	Sprint planning	Manual	Proposing a developer story artifact to capture functional information and used it for the prediction approach.	30 open source java systems	Used machine-learning models that were trained based on the developer stories to predict the effort. The pre- diction performance was measured using 10x10-folds cross-validation.	moderate - re- port only rel- ative accuracy units	none	none	low - open-source projects may adopt Agile differently
	Buglione and Abran [18]	Improving the user story Agile technique using the INVEST criteria	Sprint planning	Manual	Proposing a process to apply the INVEST criteria to improve the quality of user stories.	One case study company	Evaluated the applicability of the IN- VEST process in an industrial con- text and record the lessons learned.	high - lack of detail on the application in industrial set- ting	none	none	none
	Grapenthin et al. [44]	Supporting Feature Estimation with Risk and Effort Annotations	Sprint planning	Manual	Proposing a system to help the team annotate user stories with symbols that highlight risks and effort drivers for effort estima- tion.	203 soft- ware fea- tures from 8 student teams	Conducted empirical analyses to examine whether the annotations could improve the team understand- ing of the project and increase the estimation accuracy	high - ex- periment conducted with students	none	none	high - student teams may not have sufficient software develop- ment experience
42	Hannay et al. [50]	Agile Uncertainty Assessment for Benefit Points and Story Points	Not speci- fied	Manual	Proposing a process to use a three-points estimation to illustrate uncertainty of the estimated effort	8 epics	Used Monte-Carlo simulations to demonstrate the prediction of project effort based on the three-points estimates.	moderate - small dataset	none	none	none
	Taibi et al.	Operationalizing the experience factory for effort estimation in agile processes	Sprint planning	Automated	Proposing a system to help the team decide whether to collect a measure based on its Return on Invested Time.	7 company projects	Compared the estimation performance between the projects that did not use the system and the projects that used the system.	none	none	none	none
	Tanveer et al. [120]	Utilizing change impact analysis for effort esti- mation in agile development	Sprint planning	Automated	Proposing a framework to integrate effort estimation with change impact analysis to help the team estimate effort of software change.	3 Agile teams from SAP SE	Evaluated the usefulness with Agile development teams and collected the feedback.	none	none	none	none
	Usman et al. [129]	Developing and using check-lists to improve software effort estimation: A multi-case study	Sprint planning	Manual	Proposing a checklist to help the team recall rele- vant factros of the tasks be- ing estimated to improve the estimation accuracy.	Participants from 3 companies	Examined the estimation accuracy and the perceived usefulness of the proposed checklists.	none	none	none	none

Table 13. Summary of the selected studies that proposed an approach to support the effort estimation practice (Section 4.3.2).

Pasuksmit	Story points		Sprint	Automated	Perform data analyses to	Seven open	Compared the classification accu-	none	none	none	low - open	-source	
et al. [89]	changes in agile		planning		study the change of Story	source	racy with four baselines.				projects	may	
	iterative	devel-			Points. Using machine	projects					adopt	Agile	
	opment: An empirical study				learning techniques to pre-	with 19349					differently		
					dict Story Points changes	work items.							
	and a prediction				of a work item.								
	approach												
Pasuksmit	Towards Reliable		Sprint	Automated	Using machine learning	Seven open	Compared the prediction accuracy	none	none	none	low - open-source		
et al. [90]	Agile Ite	erative	planning		and deep learning ap-	source	of the three predictive classifier with				projects	may	
	Planning	via			proaches to predict the	projects	two baselines and performed a quali-				adopt	Agile	
	Predicting	Doc-			documentation changes	with 17731	tative assessment on the reasons for				differently		
	umentation				before effort estimation of	work items.	the correctly predicted documenta-						
	Changes of	f Work			a work item.		tion changes						
	Items												