An Insight into the Capabilities of Professionals and Teams in Agile Software Development: An Update of the Systematic Literature Review

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Original scientific article

***Abstract*—Agile Software Development (ASD) confronts the challenge of effectively measurement and predicting the capabilities of software engineers and teams to improve individual performance, team efficiency, and project success. This study delves into exploring and identifying gaps and research prospects in assessing and predicting human capabilities within ASD. Thus, we conducted a Systematic Literature Review, building upon a prior review from 2001 to 2016 by different authors. To encompass primary studies published after 2016, we extended to 2022. Further, our study extends the scope of the previous SLR with a new research question to identify key attributes in publications focused on agile team formation. Our findings disclosed new attributes for evaluating and predicting the capabilities of professionals engaged in ASD, such as Openness to Creativity and Agile Adaptation. These attributes boost individual performance, contribute to ameliorated team productivity, and facilitate the precise composition of teams. Moreover, this study expands our prior study, providing more details on capability identification and research design, extends the analysis of attributes and prediction models, provides a more granular discussion of discoveries and comparisons with prior review, and more in-depth discussion about practical implications and thoroughly examines study validity. We observed that technical metrics were more prevalent than social and innovative aspects. Also, the study identified the prediction of agile capabilities as an emerging research domain necessitating further scrutiny due to the scarcity of existing models. The majority of studies (78%) supplied detailed metric descriptions, facilitating the evolution of the capabilities repository and supporting future investigations in this domain. Ultimately, these findings can aid agile practitioners in formulating team composition decisions based on individuals' and teams' appraised and foreseen abilities.**

***Index Terms*—Systematic literature review, individual capability, team capability, capability prediction, capability measurement, agile teams, agile software development, software engineering, software development.**

I. Introduction

In Agile Software Development (ASD), the people, their interactions, knowledge, and skills are vital to succeed [1], [2]. Given the criticality of human aspects in ASD [3], measuring and predicting professionals' capabilities help to improve individual performance and teams' productivity [4].

Models, theories, and discoveries in Evidence-Based Software Engineering evolve rapidly, necessitating up-to-date research [5]. This dynamic nature raises concerns about the relevance of many Systematic Literature Reviews (SLRs) in Software Engineering (SE). For example, Nepomuceno and Soares [6] found that many authors (68%) desire updates for their studies. Therefore, considering the significance of Vishnubhotla et al.'s study [4], and its average of 17 references with an annual mean of 3.4 on Google Scholar, reviewing its conclusions is crucial for the progression of this field and the identification of new insights.

The urgent need to update our understanding of ASD competencies is driven by the field's rapid evolution and increased adoption of ASD in industry [7], [8], [9]. This update is crucial for optimizing human resources in organizations to achieve project success [10], [11]. Moreover, identifying ASD competencies and capabilities poses a considerable challenge and is essential for various project management activities, such as task assignment [12], teamwork quality [13], and team formation [14], [15], [16]. Recognizing this, it becomes evident that a detailed understanding of specific competencies needs to be improved in current research, particularly in agile team formation.

Addressing this need, the previous SLR by Vishnubhotla et al. [4] did not explore specific attributes used in agile team formation. Our study addresses this significant gap, extending the scope of the previous SLR with a new research question (RQ) [17] to identify critical attributes for effective agile team formation. We investigate the capabilities identified in the SLR conducted by [18] and those pinpointed in primary studies highlighted by Costa et al. [19] within the context of agile team formation, and this paper summarizes our findings. Thus, we offer practical and updated insights, enhancing software engineering practices for researchers and industry practitioners.

This paper extends the SLR conducted by Vishnubhotla et al.[4] and presents current findings to address this research gap. The principal objective of this article is to update and expand the understanding of competencies and capabilities in the context of Agile Software Development (ASD). Unlike previous SLR [4], this study explicitly identifies critical attributes in publications focused on team formation within the ASD context. Recent survey studies have delved into specific aspects connected with measurement and predicting

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capabilities, including personality type [20], personal and organizational competencies [21], and individual attributes [11]. Our study makes a valuable contribution to the existing body of knowledge by identifying 18 novel primary investigations and new parameters for measuring and predicting the capabilities of professionals in the context of ASD. These newfound attributes have the potential to enhance the productivity of individuals and teams and provide substantial support for the precise allocation based on a ranking of professionals' capabilities [22], contributing with effective team formation [23]. Additionally, our study has revealed three innovative methods for measuring capabilities absent in the original SLR.

Moreover, this paper expands Cunha et al. [18] with additional contributions, including more details on (i) how we identified the capabilities in each attribute category, (ii) the research design used in the selection process, (iii) the information about the attributes, prediction models, SE domains, and types of applications, (iv) the review results associated with each primary studies' context, (v) more granular discussion of discoveries and comparison with the previous SLR, (vi) implications of the research and practice, and (vii) more in-depth discussion about the study's validity threats. Given this, this article eases replicating the study and presents new findings.

This paper is structured as follows: Section II introduces foundational concepts and reviews the relevant literature. Section III accounts for our adopted research methodology. The results are presented in Section IV, followed by a comprehensive discussion in Section V. Section VI outlines the study's limitations and discusses potential threats to validity. Finally, Section VII offers our concluding remarks and explores avenues for possible future research.

II. Background and Related Work

This section presents background information related to capabilities in ASD, as well as the background concepts (Section II-A) and the previous research on assessing and predicting the capabilities (Section II-B).

A. Capabilities in Agile Software Development

Within the realm of ASD, software engineer capabilities are a subject of discussion, often described using various other terms such as competencies, skills, attributes, knowledge, and traits. Existing studies shed light on these concepts. For instance, in Mendes et al. [24], the capabilities significantly impact individual and team performance. Another study by Assyne et al. [25] categorizes capabilities into soft and hard skills, recognizing their nuanced distinctions. Precisely defined capabilities are emphasized in a study by Wiedemann et al. [26], which introduces competence models tailored to specific roles. In Gren et al. [27], although not explicitly discussing capabilities, team-level skills are defined as non-technical and originate from interactions and support.

Vishnubhotla et al. [4] introduced three categories of attributes: technical, social, and innovative, which are paramount at individual and team levels. In our current study, we adopt these categories as the foundational framework and organize our analysis around three dimensions: the professional dimension, encompassing skills, knowledge, and technical competencies; the social dimension, which focuses on interpersonal interactions and teamwork; and the innovative dimension, which centers on skills geared toward innovation-driven endeavors.

In alignment with these diverse perspectives, our study aims to establish a clear definition and investigation of capabilities within the context of ASD. In our research, *competence* refers to an individual's ability to perform a specific task [22], while *capabilities* refer to the potential for growth and adaptability in different contexts [28]. *Attributes* are personal traits that may influence performance, such as personality traits, values, and attitudes. We addressed these factors considering three perspectives: professional (e.g. skills, knowledge, and technical competencies), social (e.g. interpersonal interactions and teamwork), and innovative (e.g. innovation-based skills).

B. Related Work

Secondary studies reported in the literature focus on identifying software engineers' essential capabilities and competencies, although with varying nuances. For instance, the reviews conducted by Restrepo-Tamayo et al. [20] and Gilal et al. [29] focused on non-technical factors to support team formation and Assyne et al. [21] concentrate on obtaining an overviewing of competencies in SE. Restrepo-Tamayo et al. [20] identified 14 procedures to build software teams from 26 primary studies. They observed that personalities are related to individual capabilities as the persons' characteristics and are widely measured using psychometric tests. They further stated that traits could support the measurement and assignment of roles.

Gilal et al. [29] evaluated 4878 papers from different sources between 2000 and 2014, which resulted in 17 primary studies. They focused on finding the effective personality preferences of programmer roles from different experimental settings: individuals, teams, academics, and industry. Many contributions were cited, such as the fact that combining the intuiting and feeling traits isn't a suitable personality choice for the programmer role. However, they did not present specific findings for companies that employ ASD.

Assyne et al. [21] performed a systematic mapping study on software engineering competencies. By analyzing 60 primary studies, they identified 49 competencies and 14 competencies frameworks. Although their research contributes to the theoretical and practical discussions on competencies in SE, they only focused on personnel and organizational competencies and showed an overviewing of the theme. Further, they did not investigate measures of capabilities in ASD.

A recent study by Costa Filho et al. [11] focused on human aspects of ASD. The authors presented the results of an SLR aimed at understanding the competencies of an agile team for managing activities in an agile environment. Although the SLR provided insights into the relevance of the research topic, the authors did not provide an in-depth analysis of individual factors (e.g. for software engineers) and focused only on the team level.

The previous SLR [4] search was conducted across four major databases using relevant keywords and Boolean operators. Studies were included based on criteria such as publication date, language, field, empirical evidence, and focus on ASD while excluding non-empirical studies, secondary studies, and studies not relevant to ASD or individual/team capabilities.

Included studies were assessed for quality using a defined scoring system. Only studies with a score above five are included in the analysis. Data was extracted from the included studies using a designed form and reviewed for accuracy. A comprehensive analysis of 16 studies revealed various attributes capable of measuring and predicting the capabilities of both individual software engineers and their teams. The study identified these attributes and explored the diverse instruments used for their measurement.

Considering a robust methodology design for the research goal of the original study, we utilized many of the research questions and inclusion and exclusion criteria as the quality assessment criteria. However, we updated a prior systematic review via forward snowballing as suggested by Wohlin et al. [30], searching Google Scholar for post-2016 citations of the original work or its studies to avoid publisher bias. Further, two researchers independently screened these results, bypassing search strings to prevent guideline breaches. This streamlined method effectively pinpointed new relevant studies for the review.

Adopting the original study 's [4] methodology was effective, and applying a new search period demonstrated the method's flexibility. We suggest additional clarification on quality criteria, specifically to reduce subjectivity in scoring, for example, by adding weightings, since responses to these questions may not reflect expected scores. Initially, we encountered confusion with the inclusion and exclusion criteria, but a pilot study clarified their application and significance, optimizing our analysis.

In contrast to these studies, our investigation expands the evaluation of measuring capabilities within SE, considering both individual and team outlooks, encompassing professional, social, and inventive qualities. Additionally, we have unearthed novel variables capable of enhancing the assessment and measurement of software engineers' and teams' capabilities. Ultimately, our study delves into pivotal determinants that can fortify personnel management across diverse domains within the software engineering field.

III. Research Design

In this research, we expanded the previous SLR [4], which focused on examining the competencies of professionals and teams in ASD from 2001 to 2016. Following the guidelines outlined in Wohlin et al. [30], we employed forward snowballing, utilizing the study by Vishnubhotla et al. [4] and its primary studies as our initial dataset. Given that our study represents an extension of the SLR by Vishnubhotla et al. mention vishnubhotla2018insight, we adopted a study design that closely mirrored the original. Subsequently, we present our study design and highlight the disparities compared to the original approach. We summarize the steps of our research in Figure1.

A. Research Questions

In our study, we rigorously re-examine the understanding, measurement, and validation of capabilities in ASD through RQ.1a, RQ.1b, and RQ.3 to ensure that our approach accurately reflects current industry practices. We delve into emerging trends and methodologies (RQ.2a and RQ.2b), investigating new attributes as predictors of success and innovative techniques for prediction modeling, thereby contributing to ASD's advancement and reassessing findings from the original SLR [4]. Furthermore, we explore essential capabilities for developing various types of software applications (RQ.4a) and skills critical across different software engineering domains like healthcare or finance (RQ.4b). This aspect of our research is crucial for aligning agile teams' skills with specific sectoral and technological requirements. Additionally, we address a significant gap from the original SLR [4] by focusing on specific attributes vital for effective agile team formation (RQ.5), enriching our understanding of necessary capabilities within ASD's dynamic landscape.

- *RQ.1a.* How are individual and team capabilities of software engineers being defined/understood in ASD?
- *RQ.1b.* Which attributes are used to measure the individual and team capabilities of software engineers in ASD?
- *RQ.2a.* If applicable, which attributes are being used as predictors of individual and/or team capabilities of software engineers in ASD?
- *RQ.2b.* If applicable, which technique(s) are being used to build prediction models?
- *RQ.3.* Which data collection mechanisms are being used to measure attributes?
- *RQ.4a.* If applicable, what type of software applications are being developed by agile teams?
- *RQ.4b.* If applicable, which software engineering domains are being focused on?
- *RQ.5.* Which individual attributes for measuring and predicting capabilities in Agile Software Development are utilized in the literature on Team Formation?

B. Search Strategy

We conducted a forward snowballing search following the guidelines outlined by Wohlin et al. [30]. These guidelines recommend a single iteration of forward snowballing using Google Scholar, with the original SLR and its primary studies serving as the initial seed set. The procedure involved the following steps:

- *(i)* We utilized the original [30] and their primary studies as the seed set.
- *(ii)* Employing Google Scholar, we retrieved papers that either cited the original SLR [30] or any of its primary studies. This approach helps eliminate biases in favor of specific publishers [31]. We only searched for papers published after 2016 and used the PoP software (available at http://www.harzing.com/pop.htm).
- *(iii)* We applied forward snowballing without iterations, a method considered adequate by Wohlin et al. [30]. Any paper related to an SLR topic should reference either the SLR itself or at least one of its primary studies.
- *(iv)* To minimize the risk of erroneously excluding relevant studies (i.e., false negatives), we involved two researchers in the initial screening process. We opted not to use a search string, as some retrieved studies might not reference all of our seed set, which could deviate from the guidelines set forth by Wohlin et al. [30].

C. Study Selection

Figure 2 illustrates the paper selection process. The first step is to identify all the papers that cited the ones on our seed set using the PoP software. A single researcher performed the study selection and conducted an initial screening. In this step, we removed duplicates and the grey literature [4].

The next phase involved the selection of pertinent papers. Conventional peer review, a common approach to mitigate bias, was employed in the original SLR [4]. Nevertheless, when two researchers assess the entirety of the papers, this method can become labor-intensive. As an alternative, we adopted the approach suggested by Pérez et al. [32]. In this approach, two reviewers examined a smaller subset of papers, and their consensus was quantified using Cohen's Kappa coefficient. We will elucidate this method in the subsequent discussion.

The process encompasses four distinct stages:

1) *Pilot Study:* In this preliminary phase, a random selection of 15 papers is made from the pool of identified studies, a methodology inspired by Pérez et al. [32]. These papers are designated for evaluation by both researchers.
2) *Review and Analysis:* Each researcher meticulously examines the title, abstract, keywords, and, when deemed necessary, the sections referencing citations and conclusions of each candidate study.
3) *Decision Annotation:* The researchers document their determinations regarding the inclusion or exclusion of the studies. A study is incorporated if it offers a clearly defined and objective approach to assessing, measuring, or predicting capabilities within Agile Software Development (ASD) using established techniques, metrics, models, or tools.
4) *Agreement Measurement:* The process culminates in Cohen's Kappa coefficient calculation [32], indicating the agreement level between the researchers.

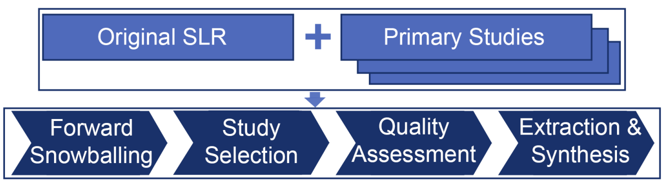

Fig. 1. Review steps [18].

Exclusion Criteria. Exclude a study if it presents at least one of the following characteristics: (i) Grey literature like non-refereed thesis works, technical reports, conference summaries, newsletters, extended abstracts, and magazine articles; (ii) Opinion-based reviews without any empirical evidence; (iii) Secondary studies or tertiary studies; (iv) Studies discussing training activities in educational institutions and knowledge transfer practices. (v) Non-professional subjects like students working in an academic setting; (vi) Study that did not investigate individual or team capability; and (viii) Study is not in the context of ASD.

Inclusion Criteria. The inclusion criteria are (i) Studies published after 2016; (ii) Studies written in English; (iii) Studies published within the field of computer science and engineering & software engineering; (iv) Studies backed by empirical evidence, which may involve quantitative, qualitative, case study, or mixed methods; (v) Studies focusing on ASD; (vi) Studies discussing team building criteria, with a focus on selecting individuals to agile teams; (vii) Studies presenting capability measurement and prediction methods for individuals/teams; and (viii) Studies discussing individual/team attributes that affect performance/productivity of an agile team.

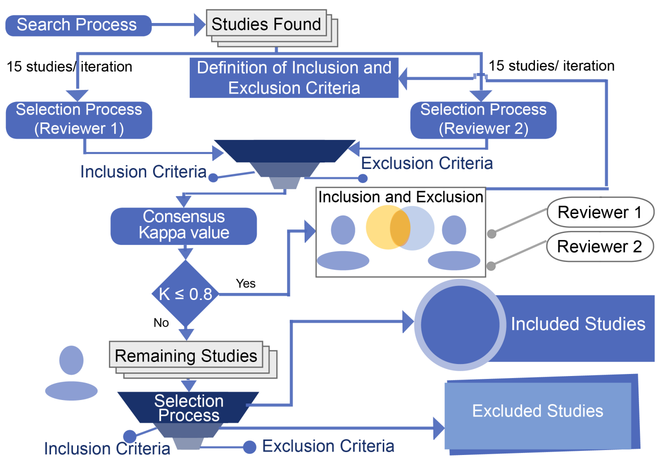

Fig. 2. Study selection process [18].

D. Quality Assessment

Once the papers were selected, the quality assessment was performed, adhering to the procedure established in the original study [4]. Two researchers carried out this procedure. The first researcher conducted the quality assessment using the attributes defined in the original SLR, while the second researcher checked for any conflicts. Any conflicts identified during the quality assessment were resolved through a meeting. In addition, the scoring criteria suggested by Kitchenham and Brereton [33] were adopted. Consequently, each question was rated as Yes=1, Partial=0.5, or No=0 point (See the supplementary material[1]).

We calculated each paper's total quality score by adding the papers' scores for each question. We excluded articles with a quality score below 5 points, as in the original SLR.

E. Data Extraction and Synthesis

One data extractor and one data checker performed the extraction, as recommended in [34] [35]. A data extraction form was designed based on the research and quality assessment questions. The data checker confirms that the data on the extraction form by the data extractor was correct. Finally, the data extractor and checker organized a synchronization meeting to inspect the extracted data.

F. Strategy for selecting Team Formation Studies

We conducted an analysis of all capabilities identified after the data extraction process, with those highlighted in primary studies outlined in the Systematic Mapping Study by Costa et al. [19] within the agile team formation context.

We applied two specific criteria to choose studies from Costa et al. [19] for the analysis of attributes. Firstly, we only included original studies that were centered on the formation of professional teams in the industry-specific context of ASD. Secondly, we ensured that the studies' findings were either a

[1]Supplementary Material: https://figshare.com/s/5024fec55fbceca82981

procedure or a technique, as classified by Costa et al. [19]. This selection process was carried out by an individual designated as the researcher extractor, who was responsible for picking out relevant studies. Subsequently, another individual, termed the researcher checker, reviewed and confirmed these selections during a coordination meeting.

we cross-referenced and compared our literature analysis with the attributes employed in agile team formation.

IV. Results

This section presents the results of our study, accounting for changes in the practice and research into the capabilities of professionals and teams in ASD. It also reinforces some of the results of the original SLR.

A. Results of the Selection Process

As a result of searching for relevant papers using forward snowballing, we identified 1283 papers. After performing the initial screening, we removed 944 entries, which left us with 339 papers to evaluate.

Using the Kappa-based study selection method, we assessed agreement between two researchers while selecting the studies given the inclusion and exclusion criteria. For this, we needed two iterations to reach a consensus (i.e., $k > 0.80$). In the first iteration, the researchers disagreed on including one study because researcher 2 (R2) misunderstood the exclusion criterion (vi). Both researchers discussed reaching a consensus regarding this criterion.

Next, we conducted a second iteration of the Kappa-based study selection, which resulted in a perfect agreement between both researchers ($k = 1$) [36]. From there on, a single researcher evaluated the remaining papers. As a result of conducting this step, we ended up with 20 relevant studies. Moreover, finally, after applying the quality assessment, we ended up with 18 primary studies.

B. Overview of Primary Studies

This section gives an overview of studies selected by our review. We disponibilize the complete list of primary studies in the supplementary material. We must mention that we adopted $(P + studyID)$ to reference the primary studies in this paper. We selected 20 primary studies from a set of 1283 based on search, selection, and quality criteria. Table II presents the distribution of studies based on quality score. It is essential to highlight that two studies received scores below five, and we labeled them as "Borderline" and "Poor". Therefore, we ended up with a list of 18 primary studies to be further analyzed. Table I presents basic information of each included paper, which consists of paper/study identification, paper title, and the paper reference.

We observed that most studies address team level only (61%), followed by five studies that discuss individual level (27%), and two studies that discuss both team and individual levels together (12%). Studies that addressed together social and technical factors are predominant (50%) (P1 [37], P2 [38], P3 [39], P6 [42], P7 [43], P8 [44], P10 [46], P15 [51], P18 [54]). Studies that consider social only factors represent 44% (P4 [40], P12 [48], P13 [49], P9 [45], P11 [47], P14 [50], P16 [52], P17 [53]). Finally, 1 study (P5 [41]) (6%) discusses technical factors only (See supplementary material).

TABLE I
BASIC INFORMATION OF THE INCLUDED PAPERS

Paper ID	*Title*	*Reference*
P1	Realising individual and team capability in agile software development: A qualitative investigation	[37]
P2	Understanding the perceived relevance of capability measures: A survey of Agile Software Development practitioners	[38]
P3	The essential competencies of software professionals: A unified competence framework	[39]
P4	Non-technical individual skills are weakly connected to the maturity of agile practices	[40]
P5	A Search-based Software Engineering Approach to Support Multiple Team Formation for Scrum Projects	[41]
P6	Agile Self-selecting Teams Foster Expertise Coordination	[42]
P7	Using qualitative system dynamics in the development of an agile teamwork productivity model	[43]
P8	Decision support system for assigning members to agile teams	[44]
P9	A theory of scrum team effectiveness	[45]
P10	Long Term Learning of Agile Teams	[46]
P11	How (un) happiness impacts on software engineers in Agile teams?	[47]
P12	An examination of personality traits and how they impact on software development teams	[48]
P13	Model of foresight work habits of agile software team members by personality traits	[49]
P14	The influence of teamwork quality on software team performance	[50]
P15	Integrating development and operations in cross-functional teams-toward a DevOps competency model	[51]
P16	A teamwork effectiveness model for agile software development	[52]
P17	The impact of project team characteristics and client collaboration on project agility and project success: An empirical study	[53]
P18	People Factors Influencing Project Success in Software Development: A Survey of Agile Development Teams in Indonesia	[54]

TABLE II
QUALITY SCORES OF PRIMARY STUDIES [18].

Quality Score (QS)	*Quality level*	*Number of studies*
QS<3	Poor	1
QS≥3 and QS<4	Borderline	1
QS≥4 and QS<5	Fair	0
QS≥5 and QS<6	Good	3
QS≥6 and QS<7	Very Good	7
QS≥7 and QS≤8	Excellent	8

Moreover, we identified three studies that presented measurement methods and one study (P4 [40]) that showed a capacity prediction method. The recognized methods to measure capabilities were period of experience (P5 [41]), systems dynamics (P7 [43]), and interactive assessment by questionnaire (P12 [48]). The context of all studies is an industrial environment, except for 1 study (P3 [39]) that extended its application to an academic environment.

The annual publication count, predominantly in journals, is outlined in the supplementary material. The pattern illustrates a steady annual study count, generally from three to four articles, except for 2020. The decrease in publications during that period could be linked to the impact of the pandemic, as the number of studies experienced a resurgence in 2021.

C. Responses to Research Questions

This section discusses the study's research questions and the trends observed in the primary studies, attributes, and data collection mechanisms.

RQ.1a. How are individual and team capabilities of the software engineers being defined/understood in ASD?

This question focuses on identifying how primary studies interpret individual and team capabilities. We found six studies that offer valuable definitions. Study P1 [37], defined capability related to individuals and teams, while study P3 [39] defined competence about individuals. Studies P4 [40], P6 [42], P15 [51], and P18 [54] expressed capabilities pertaining to teams.

Mendes et al. (P1 [37]) expressed that capabilities relate to individual and team performance. Assyne et al. (P3 [39]) defined competence in SE as "a complete set of abilities, skills, knowledge, and capabilities needed to engage in software development effectively." They categorized competence into soft and hard skills. Soft competencies are associated with an individual's behavior in interacting with others from the team, while hard competencies are related to learnable skills, knowledge, abilities, and attitudes.

Gren et al. (P4 [40]) defined team-level skills concerning non-technical skills. They stated that a team as an entity could have good planning skills as an output of collaboration, interaction, and mutual help. Rejab et al. (P6 [42]) defined team-level skills as knowledge and skills required for the software project. Wiedemann et al. (P15 [51]) stated that competency models precisely describe the skills, knowledge, attitudes, and traits needed for a job position or role. Fadilah et al. (P18 [54]) associated capability with the team and defined high commitment and technical expertise as team capabilities that can reduce risks and increase project success.

The definitions expressed in the studies focus on social and professional factors of individuals (e.g. technical expertise, knowledge, characteristics, and traits) and teams (e.g. interaction, outputs, and mutual help) to improve their skills and increase the team performance, aiming to increase the chances of project success. This vision of these factors aided us in identifying the attributes raised in question 1b.

RQ.1b. Which attributes are being used to measure individual and team capabilities of software engineers in ASD?

The primary studies have explored team selection, personality traits, composition criteria, and long-term learning in measuring software engineers' individual and team capabilities in ASD. Based on the original SLR, we classified the attributes identified into professional, social, and innovative categories [4]. The complete list is available in the supplementary material.

Figure 3 offers an overview of the attributes identified and analyzed over time. This visualization provides valuable insights into the attributes' focus, magnitude, and nature, shedding light on whether any of these attributes represent new findings compared to the original SLR. The data indicates that while specific competencies remain consistently significant, such as social attributes within teams, others appear to exhibit variations in importance over the years, for example, software security. Social skills are highly sought after in agile environments, encompassing both personal skills [21] and managerial competencies of teams [11]. Among the individual attributes, seven studies (P1 [37], P2 [38], P3 [39], P4 [40], P12 [48], P13 [49], and P15 [51]) contributed to their identification, with software construction boasting the highest number of attributes, totaling 14.

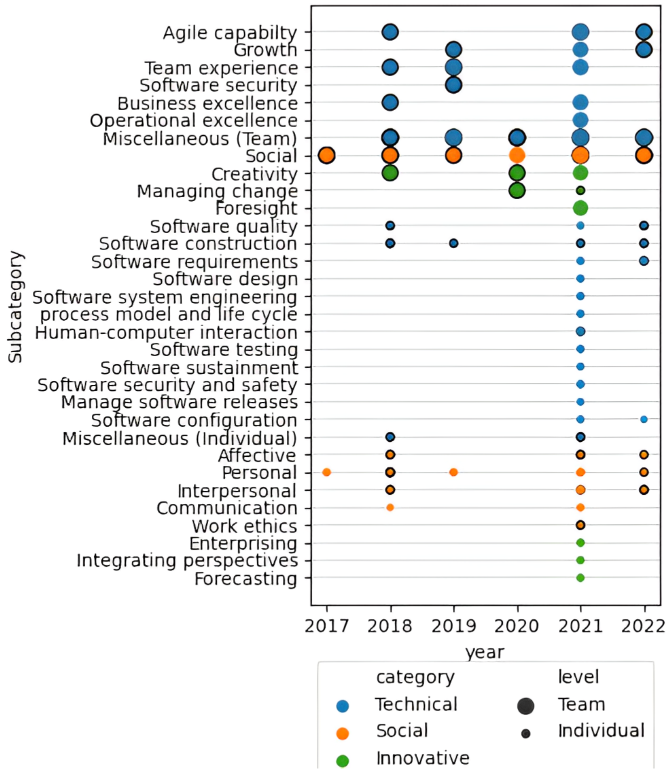

Fig. 3. In-depth analysis of subcategories of software engineers' capabilities [18].

More assertively, while the original study [4] identified seven attributes used to measure social capabilities for teams, our update expanded this number to 29, including those discovered by the previous study (Table III). This represents a significant leap in the acquisition of updated information, reinforcing the relevance of our investigation, which is reflected in the data from the following table.

In terms of professional capabilities within teams, the most frequently cited attributes were technical expertise (P2 [38], P6 [42], and P18 [54]), diversity of competencies (P1 [37], P6 [42], and P17 [53]), testing experience (P8 [44] and P15 [51]), domain knowledge (P2 [38] and P15 [51]), programming language (P2 [38] and P7 [43]), and experience with various tools (P2 [38] and P7 [43]). As demonstrated by Costa et al. [55], technical expertise remains crucial in forming agile teams. As for social attributes in teams, communication (P2 [38], P7 [43], P11 [47], and P16 [52]), adaptability (P7 [43], P16 [52], and P17 [53]), motivation (P2 [38], P7 [43], and P11 [47]), and problem-solving (P8 [44], P15 [51], and P17 [53]) were the most commonly mentioned attributes.

We found in P17 [53] that team autonomy, competency diversity, and client collaboration significantly impact project agility, directly influencing a team's adaptive performance and project success. Similar observations in studies P9 [45] and P10 [46] support these findings.

Innovative team attributes identified include creative exploration and foresight skills (P2 [38]), openness to creativity and agile adaptation (P11 [47]), and task variety/innovation

TABLE III
SOCIAL ATTRIBUTES FOR TEAM

Sub category	Attribute	Study ID	original SLR
Social	Adaptability	P7,P16,P17	
	Collaborative members	P11	
	Coordination	P7	
	Communication	P2,P7,P11,P16	✓
	Confidence	P11	
	Motivation	P2,P7,P11	✓
	Mutual trust	P7,P16	
	Proactive members	P11	
	Problem solving	P8,P15,P17	
	Team Leadership	P7,P16	
	Team autonomy	P9,P17	
	Knowledge Dissemination	P10	
	Team member rotation	P10	
	Customer Collaboration	P10,P17	
	Catching Recurrent Information	P10	
	Team Reflection	P10	
	Coordination of Expertise	P14	
	Value Sharing	P14	
	Trust	P14	
	Socio-relational	P15	
	Commitment	P18	
	Interpersonal adaptability	P17	
	Handling work stress	P17	
	Morale	P2	✓
	Value diversity	P2	✓
	Internal competition	P2	✓
	Cooperation	P2	✓
	Cohesion	P2	✓
	Preference to work with	P6	

(P7 [43]). P1 [37], contributed ten measures for individual capabilities and 5 for team capabilities. P2's survey[38], using Vishnubhotla et al.'s framework [4], highlighted the importance of non-technical skills (e.g. accountability, communication) in agile teams and identified seven new individual attributes (including code reviewing, work pace, self-reliance) and one new team attribute (decision-making ability).

Rejab et al. (P6 [42]) found that in agile team selection, self-selection is critical for managing expertise and ensuring diverse skills in various software domains (such as education and financial). They highlighted the importance of "preference for working with" as a criterion in team formation, underscoring the role of interpersonal relationships and past collaboration history in building effective teams. Then, a trend toward maintaining stable team compositions based on successful past collaborations.

Fatema and Sakib (P7 [43]) explored how various factors affect agile teamwork productivity and project success. Similarly, study P8 [44] introduced a decision support system prototype to automate team member selection, considering technical and social skills. This approach aligns with other research efforts [56] [57] [58] [59] focused on streamlining team formation by matching skills compatibility, aiming to enhance efficiency and accuracy.

Verwijs and Russo's study (P9 [45]) identified four key attributes for assessing agile team capabilities: responsiveness, continuous improvement, focus on stakeholder needs, and team autonomy. Their main finding is that agile team effectiveness is driven by the interaction of stakeholder concern and team responsiveness, requiring significant team autonomy, continuous improvement, and management support.

In ASD, recent studies have introduced 37 new attributes for evaluating professionals' capabilities: 17 professional, 19 social, and one innovative. Multiple studies highlighted features like programming language, personal attitudes, teamwork, leadership, and customer orientation. Each of the remaining attributes was discussed in individual studies, providing a comprehensive view of the evolving capabilities in ASD. Further details are available in the supplementary material.

We identified 37 new professional, 18 social, and three innovative attributes compared to the original SLR. Three studies featured competence diversity and adaptability. testing, mutual trust, team leadership, team autonomy, and customer collaboration appeared in two studies. The rest of the new attributes were unique to individual studies, with studies P11 [47] and P7 [43] specifically highlighting innovative team skills like openness to creativity, agile adaptation, and task variety/innovation.

Amorim et al. (P11 [47]) highlighted that communication, motivation, collaboration, and leadership are essential for ASD engineers' happiness. Yilmaz et al. (P12 [48]) and Kuko et al. (P13 [49]), in turn, linked personality traits to effective ASD team performance. Weimar et al. (P14 [50]) added Trust and expertise coordination as critical factors, while Wiedemann et al. (P15 [51]) focused on DevOps team capabilities. Strode et al. (P16 [52]) emphasized leadership and adaptability in team effectiveness. Fadilah et al. (P18 [54]) showed that team capability and personal traits are crucial for ASD project success. These findings underscore the importance of interpersonal and technical skills in ASD.

RQ.2a. If applicable, which attributes are being used as predictors of the individual or team capabilities of software engineers in ASD?

We identified only one study (P4 [40]) that analyzed whether individual non-technical skills can predict team-level performance in collaborative aspects. Gren et al. (P4 [40]) investigated the predictive power of 13 non-technical individual skills. They observed that five skills were significant in their results, namely teamwork, planning (iteration planning), organizing (customer access), Business-mindedness, and typing skills (customer acceptance tests). However, if we look at individual non-technical skills, there are better ways to predict the maturity of agile practices. The other abilities investigated in (P4 [40]) were Leadership, customer orientation, collaboration, decision-making, problem-solving, negotiation skills, and ability to meet project goals.

RQ.2b. If applicable, which technique(s) are being used to build prediction models?

The predictive model explored in (P4 [40]) utilized linear regression models to assess the correlation between measured agile practices and individual non-technical skills. The aim was to examine the predictive capacity through a linear regression analysis considering all skills as factors. The study revealed that the only model with an explained variance exceeding 10% success predicted "iteration planning" using planning and teamwork skills. Conversely, regression models derived from Customer Access and Customer Acceptance Tests demonstrated effect sizes below 10%, indicating a low predictive influence of individual non-technical skills. Further, individual skills such as communication, collaboration, decision-making, problem-solving, organization, and negotiation link to the team's ability to develop iteratively.

RQ.3. Which data collection mechanisms are being used to measure attributes?

We observed that 10 out of 18 primary studies used questionnaires as a means to measure attributes: 3 studies explored individual capabilities (P3 [39], P4 [40], P12 [48]), two explored capabilities at both the individual and team level (P2 [38], P13 [49]) and five explored only with capabilities of teams (P7 [43], P10 [46], P11 [47], P14 [50], P18 [54]). Moreover, seven studies used interviews: 3 being at the individual level (P3 [39], P6 [42], P15 [51]), one at the individual and team level (P13 [49]), and three at the team level (P7 [43], P11 [47], P16 [52]). Other data collector mechanisms were: focus group (P3 [39], P16 [52]), analysis of documents (P5 [41], P6 [42]), case studies (P9 [45], P16 [52]), observations (P6 [42]), semi-structured interviews (P1 [37]), personality test (P13 [49]), monitoring of progress (P13 [49])(See supplementary material). The variety of mechanisms identified suggests no one-size-fits-all approach to measuring agile capabilities. Thus, organizations should consider using multiple methods to understand the team's strengths and weaknesses comprehensively.

RQ.4a. If applicable, what type of software applications are being developed by agile teams?

Only three primary studies reported information about the types of developed software applications. Two studies (P2 [38], P6 [42]) reported e-commerce systems. Embedded systems were reported in P2 [38], Mobile in P2 [38] and P6 [42], and Automotive reported in P2 [38].

RQ.4b. If applicable, which software engineering domains are being focused in studies?

Three studies (P6 [42], P17 [53]) reported telecommunication and educational domains. We also found health domain in 3 studies (P11 [47], P6 [42], P17 [53]) and government applications in the other two primary studies (P18 [54], P17 [53]).

The study addresses attributes at the individual level in Finance/Banking, Infrastructure Services, and Media/Social Networking domains. Team-level considered attributes in other domains, except Logistics/Shipping and Entertainment/Recreation.

Finance/banking is the most discussed domain among the studies, covering social and technical attributes for teams and individuals. Three studies addressed domains like government applications, telecommunication, and Education, each focusing on different aspects such as social attributes for teams, technical and social attributes for teams, and technical and social characteristics at individual and team levels.

All domains discussed innovative skills, except human resources, biotechnology, security applications, accounting, and engineering/construction. Social attributes like coordination of expertise, value sharing, and trust were only considered in finance/banking and government applications domains (See supplementary material).

RQ.5. Which individual attributes for measuring and predicting capabilities in Agile Software Development are utilized in the literature on Team Formation?

Our analysis found that of the 69 social attributes identified in primary studies [18], 35 were relevant in team formation studies. From 73 technical attributes listed [18], 11 were identified. Of 22 innovative attributes, 5 were discussed in the team formation context.

Table IV outlines the individual attributes in team formation literature, divided into social, innovative, and technical categories. Key attributes frequently mentioned include Communication, Collaboration, and personality traits like Introverts & Extroverts, Intuition & Sensing, Thinking & Feeling, Judging & Perceiving in the social category. In the technical category, Programming language and Programming experience were notable.

V. Discussion

In this section, we present an overview of our findings (see Section V-A), compare our findings with the results of the original SLR (see Section V-B), and discuss our results in light of their implications for research and practice (see Section V-C).

A. Summary of Findings

The findings reveal a comprehensive understanding of professionals' capabilities in ASD. The effectiveness of teams is notably enhanced through the cultivation of trust, value-sharing, and Coordination of expertise (Weimar et al., P14 [50]). Addressing stakeholder concerns and responsiveness demands essential elements, namely team autonomy, continuous improvement, and robust management support (Verwijs and Russo, P9 [45]).

The most frequently cited subcategory was team-focused technical, such as Agile Capability, while other individual subcategories cited the least, such as Enterprising. The many attributes associated with Software Construction emphasize its critical role in successfully developing software products for ASD. The emergence of new attributes, such as testing, programming language, and problem-solving, may be associated with the increased adoption of agile methods [72], by requiring specific capabilities to handle complex tasks.

However, the literature highlights the need for a comprehensive approach to assessing capabilities in ASD. The trend toward using social measures reflects the use of agile methods [72], [8], which encourages a multidisciplinary approach, including non-technical skills like communication, teamwork, and conflict resolution. Combining social and technical aspects is crucial for achieving success in ASD [27].

The Finance sector accentuates individual attributes, emphasizing self-reliance. Social attributes for teams, including Coordination of expertise, value-sharing, and trust, find explicit consideration in the Finance and Government domains. Despite a general appreciation for innovative skills, the Human Resources, Biotechnology, Security, Accounting, and Aerospace domains need to pay more attention to this aspect. Observing self-selected teams across domains such as Education and finance (Rejab et al., P6 [42]), we recognized their potential to support expertise management, foster interdependence, and ensure diverse skills.

The relatively unexplored 'work with' preference factor is crucial for team formation, helping prevent long-term dissatisfaction and boosting members' confidence in coordinating their expertise [73]. The preference for maintaining team compositions over time is because assembling a team is more than just finding candidates with specific skills. Many experts may appear suitable for a role in real-world situations. However, their performance within a specific team remains

TABLE IV
COMPARISON OF INDIVIDUAL ATTRIBUTES: PRIMARY STUDIES VS. AGILE TEAM FORMATION LITERATURE

Category	Sub category	Attribute	[60]	[61]	[62]	[63]	[64]	[65]	[66]	[67]	[68]	[69]	[70]	[71]
Social	Affective	Aptitude												
		Person's attitudes												
		Person's initiative												
		Teamwork									✓			
		Leadership												
	Comm.	Communication	✓											
		Oral communication	✓											
	Interpersonal	Customer orientation					✓							
		Collaboration					✓	✓		✓				
		Seeks help					✓							
		Helps others					✓							
		Teamwork oriented					✓				✓			
		Willingness to Confront					✓		✓					
	Personal	Introverts & Extroverts		✓	✓		✓							
		Intuition & Sensing		✓	✓		✓							
		Thinking & Feeling		✓	✓		✓							
		Judging & perceiving		✓	✓		✓							
		Formal Education				✓								
		Decision making							✓					
		Negotiation skills							✓					
		Openness					✓							
		Conscientiousness					✓							
		Agreeableness					✓							
		Neuroticism					✓							
		Tenacity					✓		✓					
		Education				✓								
		Perseverance					✓	✓						
		Pro-active/initiator/driver					✓							
		Thoroughness					✓							
		Sense of mission					✓							
		Strength of conv.					✓							
	Work ethics	Flexibility							✓					
		Responsibility								✓				
		Honesty/ ethics								✓				
		Task prioritization									✓			
Innovative	Creativity	Generating ideas												
		Creative problem solving												
	enter- prising	Gathering/evaluating information							✓					
	Integ. persp.	Openness to ideas	✓											
	Mng. chng	Intelligent risk-taking							✓					
Technical	SW constr.	Programming Language				✓						✓		
		Manage Software Construction							✓					
	SW config.	Manage SW releases							✓					
		Plan SW configuration management							✓					
		Conduct SW configuration management							✓					
	SW security &safety	Quality											✓	
	SW proc.& LC model	Process implementation & management							✓					
	Diverse	Accurate effort estimate												✓
		Domain knowledge				✓								
		Prior work experience					✓							
		Programming experience					✓					✓		

to be determined, mainly due to factors like interpersonal relationships and team dynamics [74].

Identified social capabilities, particularly collaboration, have proven instrumental in enhancing decision-making [75]. Such insights have positively impacted developers' professional status, underscoring the importance of combining social and technical aspects for success in ASD (Gren et al., P4 [40]).

Lastly, while some subcategories have received new attributes over the years, others, such as Operational Excellence, Communication, and Foresight, have yet to add any new attributes. Some possible causes include (i) Stability, (ii) Low priority given to specific areas, (iii) Difficulty in measurement, and (iv) Lack of innovation. However, attention to these areas can lead to issues in productivity and resource allocation.

B. Comparison with Original SLR

We identified variations in the number of attributes compared to the original SLR [4]. At the individual level, we discovered additional attributes in professional subcategories, such as Software Construction. Table V shows attributes from our review not addressed in the original SLR [4]. For instance, in Software Construction, we identified six new attributes: Current implementation track record, Software Development, Programming language, Software design, Proficiency in code reviewing, and Site Reliability Engineering (SRE). The emergence of SRE reflects the evolving software engineering landscape, driven by the need for enhanced self-sufficiency.

TABLE V
COMPARATIVE STUDY: PROFESSIONAL INDIVIDUAL ATTRIBUTES

Sub category	*Attribute*	*Our study*	*original* SLR
Software quality	Delivered quality	✓	
	Productivity	✓	
	Test and Quality engineering	✓	
	Maintenance	✓	
	Product audits	✓	✓
	Statistical control	✓	✓
Software construction	Current implementation track record	✓	
	Debugging and testing	✓	✓
	Detailed design and coding	✓	✓
	Integrating and collaborating	✓	✓
	Managing software construction	✓	✓
	Software Development	✓	
	Programming language	✓	
	Software design	✓	
	Site Reliability Engineering	✓	
	System integration and verification	✓	✓
	System validation and deployment	✓	✓
	System sustainment planning	✓	✓
	Software construction planning	✓	✓
	Proficiency in code reviewing	✓	
Software requirements	Elicitation	✓	✓
	Documentation	✓	
	Project Management	✓	✓
	Requirements analysis	✓	✓
	Specification	✓	✓
	Validation	✓	
	Verification	✓	✓
Human -computer interaction	Accessibility	✓	✓
	Interaction style design	✓	
	Requirements	✓	✓
	Usability testing	✓	✓
	Visual design	✓	✓

Additionally, we noted an increase in social subcategories, such as Affective, Communication, Interpersonal, Personal, and Work Ethics. We found new attributes in Software requirements (7 vs. 5 in the original SLR), Human-computer interaction (5 vs. 4 in the original SLR), and Software Quality (6 vs. 5 in the original SLR). There was also an increase in social subcategories such as Affective (13 vs. 10 in the original SLR), Communication (4 vs. 3 in the original SLR), Interpersonal (10 vs. 6 in the original SLR), Personal (34 vs. 26 in the original SLR), and Work ethics (8 vs. 6 in the original SLR).

At the team level, 61% of primary studies discussed team attributes, compared to 43% in the original SLR. Attributes increased across all categories compared to the original SLR. The Innovative category expanded from 2 to 5 attributes, and the Social category grew from 7 to 29. In the professional category, subcategories such as Team Experience, Agile Capability, Business Excellence, and Growth increased. These findings contribute to the evolution of the capabilities catalog, supporting future research. Additionally, we identified three new measurement methods: experience time, system dynamic, and interactive assessment. Predicting capabilities in ASD remains challenging, with only one study discussed in both the original SLR and our review.

A notable gap in the ASD area pertains to predictors of software engineers' and teams' capabilities, with only one study presenting a prediction model in both the original SLR and our review. It demands the most effort in this area. Further research is crucial to understand how capabilities can be measured and to develop and evaluate effective predictive models, enhancing project management in diverse ASD contexts.

Our study pinpointed essential capabilities for agile team formation in ASD, uncovering attributes critical in social, technical, and innovative areas, aligned with industry needs [76]. This enriches the existing literature and is particularly useful when not all resources are highly specialized [77].

Academic research shows a strong focus on social aspects such as teamwork and communication [72], but less on individual initiative and leadership. Interpersonal and Personal attributes received more attention, reflecting the rise in agile methods [72], while Communication and Enterprising need more exploration.

C. Implications for Research and Practice

Our results highlight that while technical factors such as expertise receive extensive investigation by teams, innovative attributes still need to be explored, highlighting a discernible research gap that necessitates further exploration. Also, we found that collaboration, communication, satisfaction, and engagement contribute to happiness, and anxiety and insecurity aspects are mentioned. There is room to investigate skills for dealing with these aspects.

Further, we noted that predicting the professionals' capabilities in ASD remains challenging, and there is a lack of investigation into this area. Although one study demonstrated the benefit of predicting capabilities based on linear regression models, more investigation is needed regarding this activity. An insight for researchers is to investigate using intelligent techniques to support these activities. In identifying capabilities within ASD, researchers can enhance teamwork quality models, crucial for optimizing the success of agile projects [78].

Our results have some insights for industrial practitioners. There are several applications in different domains of software engineering (e.g. e-learning, health, and agribusiness). Consequently, a variety of capabilities can be identified within each domain. However, according to our findings, some factors seem more used for certain domains than others (e.g. Coordination of expertise in business and finance domains).

Using more significant attributes in a specific domain can be considered when choosing criteria for team compositions and their decision-making activities. Also, practitioners can benefit considerably from our discoveries by supporting training on necessary emerging technologies such as blockchain, which will play an increasingly important role in many domains (e.g. reducing transaction costs and making payments more transparent and automated).

For practitioners, our findings on key capabilities essential for forming agile teams are a practical guide for team selection, emphasizing the integration of social and technical skills for ASD success [75], [79]. Attributes like ”Person's attitudes,” ”Person's initiative,” ”Leadership,” and ”Creative problem-solving” are vital for dynamic teams but often overlooked.

These insights are valuable for industry, helping to refine team composition strategies. Using these attributes to design assessment tools and evaluation criteria can lead to effective, high-performing agile teams.

This effective collaboration links to improved decision quality [75], the promotion of valuable insights, and the facilitation of resolving complex challenges within a team context. Furthermore, collaboration to foster integrated perspectives in innovation [80]. In this sense, collaboration consists of working together, especially in an intellectual endeavor [81].

VI. Threats to Validity

This section presents the threats to validity and the actions to mitigate them by following the classification schema presented by Wohlin et al. [82].

A. Internal Validity

Search Method Incompleteness: Using only forward snowballing might miss relevant studies. To minimize this, we used forward snowballing, assuming that significant studies published after 2017 would cite the original SLR or its primary studies [30], focusing on recent and relevant works.

Study Selection Bias: There is a risk of bias in selecting studies. We countered this using a Kappa coefficient-based selection process [32], aligning with the original SLR's criteria. We then achieved 100% agreement among researchers after two iterations.

Data Extraction and Synthesis Bias: Data extraction and classification biases can impact result validity. We mitigated this by adopting the original SLR's extraction strategies and classification schemes [4]. Additionally, at least two researchers checked the extraction results, reducing errors and inconsistencies.

B. External Validity

Result Generalization: This review focuses on ASD studies post-2016, which may limit its broad applicability but aligns with current agile trends. The literature indicates that choosing the right skills impacts agile project success [2]. Therefore, the review's focus on recent ASD studies is essential for understanding the necessary skills and practices in agile environments.

Software Domain Diversity: The review covers various domains but may not include all areas, potentially limiting the conclusions' applicability. We acknowledged and discussed this possibility, illustrating the findings' diverse applications.

C. Construct Validity

”Capability” Definition and Measurement: Variations in defining and measuring ”capability” across studies can cause inconsistencies. We used the original SLR's classification scheme [4] to define and measure ”capability consistently.”

Construct Categorization Consistency: Inconsistencies could arise if the original SLR's [4] capability categories were unclear. We revised these definitions to ensure applicability to current studies and consistency with the literature, enhancing relevance and accuracy.

D. Conclusion Validity

Result Interpretation: Results interpretation could be biased by researchers' expectations. Involving multiple researchers in analysis and interpretation and using clear, consistent criteria reduced bias and ensured objective analysis.

Result Reproducibility: The review's dependence on qualitative methodologies and researchers' interpretations might challenge reproducibility. We detailed the methodology, including selection criteria, analysis methods, and interpretation processes, and presented data and analyses transparently.

VII. Final Remarks

This study presents an updated Systematic Literature Review (SLR) on measuring and predicting professionals' capabilities in Agile Software Development (ASD), driven by the critical role of human aspects in ASD and the field's rapid evolution and increasing adoption in the industry. It addresses gaps identified in a previous SLR, particularly regarding team formation attributes. Our work expands upon an earlier review by incorporating two new research questions focused on these specific areas. Our research uncovered 18 new primary studies, revealing 37 new individual and 58 team capabilities. These findings are crucial for software organizations in optimizing human resource management and facilitating the precise allocation of personnel based on diverse capability requirements. The study also paves the way for future research, particularly in developing predictive models for software engineers' competencies and methodologies for constructing such models. Future endeavors will aim to integrate these findings into a decision support system for effective team formation, with validation through collaboration with experienced ASD practitioners.

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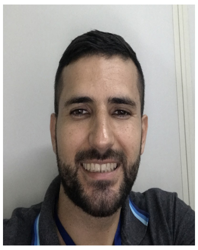

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