



Psychometric instruments in software engineering research on personality: Status quo after fifty years

Danilo Almeida Felipe^{a,*}, Marcos Kalinowski^a, Daniel Graziotin^b, Jean Carlos Natividade^c

^a Department of Informatics, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Rio de Janeiro - RJ, Brazil

^b University of Stuttgart, Institute of Software Engineering, Universitätsstraße 38, Stuttgart, Germany

^c Department of Psychology, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Rio de Janeiro - RJ, Brazil

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ABSTRACT

Context: Although software development is a human activity, Software Engineering (SE) research has focused mostly on processes and tools, making human factors underrepresented. This kind of research may be improved using knowledge from human-focused disciplines. An example of missed opportunities is how SE employs psychometric instruments.

Objective: Provide an overview of psychometric instruments in SE research regarding personality and provide recommendations for adopting them.

Method: We conducted a systematic mapping to build an overview of instruments used within SE for assessing personality and reviewed their use from a multidisciplinary perspective of SE and social science.

Results: We contribute with a secondary study covering fifty years of research (1970 to 2020). One of the most adopted instruments (MBTI) faces criticism within social sciences, and we identified discrepancies between its application and existing recommendations. We emphasize that several instruments refer to the Five-Factor Model, which despite its relevance in social sciences, has no specific advice for its application within SE. We discuss general advice for its proper application.

Conclusion: The findings show that the adoption of psychometric instruments regarding personality in SE needs to be improved, ideally with the support of social science researchers. We believe that the review presented in this study can help to understand limitations and to evolve in this direction.

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1. Introduction

Software Engineering (SE) activities are primarily performed by humans. However, many empirical studies have only focused on proposing new methods and technologies to support SE activities leaving human and social factors behind them underexplored (Feldt et al., 2008), impeding a more holistic view of the area.

Behavioral Software Engineering (BSE), proposed by Lenberg et al. (2015), is the body of knowledge of SE research that attempts to understand human aspects related to the activities of software engineers, software developers, and other stakeholders. The area has been the subject of recent research in the SE domain. Nevertheless, because BSE is relatively immature, some approaches adopted misled researchers mainly by not properly combining SE research with social sciences backgrounds, such

as psychology, to address human factors (Graziotin et al., 2015a, 2022).

Furthermore, measurement activities are an essential part of empirical software engineering research and most quantitative studies. In empirical studies, researchers and readers must possess a high degree of confidence regarding how the results of measuring resources can be interpreted in valid and reliable ways. These resources can be personnel, hardware, or software for an activity or process (Wohlin et al., 2012)

BSE research has encouraged the use of psychometric instruments as support to the understanding of human factors in a more systematic way (Feldt et al., 2008; Lenberg et al., 2015). In its turn, the Psychoempirical Software Engineering proposed by Graziotin et al. (2015a) deals with “denoting research in Software Engineering with established theory and measurements from psychology”. A problem addressed by the authors is the misuse of theoretical backgrounds of psychology, such as assuming a certain theory as the only truth in the research foundation; and also the improper use of psychometric instruments, some not validated within the psychology area or used to evaluate wrong human factors.

* Corresponding author.

E-mail addresses: dfelipe@inf.puc-rio.br (D.A. Felipe), kalinowski@inf.puc-rio.br (M. Kalinowski), daniel.graziotin@iste.uni-stuttgart.de (D. Graziotin), jeannatividade@puc-rio.br (J.C. Natividade).

Graziotin et al. (2022) has further highlighted the importance of properly adopting psychometric instruments in SE. They introduced introductory guidelines for SE researchers, including an example of psychometric validation with the R language. They covered topics such as operationalizing psychological constructs, item pooling, item review, pilot testing, item analysis, factor analysis, statistical property of items, reliability, validity, and fairness in testing and test bias. They report that “to improve the quality of behavioral research in SE, studies focusing on introducing, validating, and then using psychometric instruments need to be more common”. Our study echoes this request.

We notice that information on *whether and how psychometric instruments are adopted in SE research* remains vague and dispersed in many studies. As far as we know, one study has partially synthesized this knowledge concerning a specific construct, personality¹: a period of forty years (1970 to 2010) about personality in SE research is mapped by Cruz et al. (2015). Still, there is only a brief discussion and characterization of the instruments and their use in the software engineering context (e.g., education and pair programming), missing a critical assessment. This status quo remains unchanged more than ten years later and deserves to be challenged.

There is also a need to find out whether SE research over the years has been adopting these instruments coherently with well-known recommendations. Although some authors have outlined this on a smaller scale (McDonald and Edwards, 2007; Usman and Minhas, 2019), a large-scale study has not been done to get a big picture.

In order to synthesize this knowledge in a structured manner, **our objective is to present an overview and reflections on the use of psychometric instruments in SE research on personality.**²

We intend to consolidate findings on the use of psychometric instruments in SE research. Therefore, we searched for new studies using psychometric instruments by applying an update strategy to a systematic mapping on personality-related SE research by Cruz et al. (2015). It is noteworthy that our study does not strictly correspond to an update of the previous study, as we focus specifically on the use of psychometric instruments. Given that the population of studies to analyze the instruments is the same, i.e., primary studies reporting SE research on personality, new studies within this same population can be identified by following the guidelines for the search strategy to update secondary studies by Wohlin et al. (2020).

More specifically, we classify and discuss the objective of the studies, reported limitations on their use, SE constructs related to the psychometric instruments, the type of research, and empirical evaluations. Additionally, we discuss aspects of the most used instruments under the lens of literature guidelines and involved a social science researcher active with psychometric and personality-related research (the last author) to provide critical feedback to the SE community.

Our main contribution concerns updating evidence on personality-related SE research in order to cover fifty years of research, with a particular focus on psychometric instruments. We carefully assessed the need for an update of the evidence (Mendes et al., 2020), and we followed guidelines on the search strategy to update systematic literature studies (Wohlin et al., 2020). The previous mapping study covered forty years of research and identified 90 research papers (Cruz et al., 2015). Applying the search strategy led us to identify 106 additional papers published within the ten subsequent years (2011 to 2020). More specific contributions related to the psychometric instruments include:

- Outlining the use of psychometric instruments in SE research on personality over fifty years.
- Observing remaining discrepancies between one of the most adopted instruments (MBTI) within recent SE research and existing recommendations in the literature. We also observed several studies using the Five-Factor Model, while specific advice on how to apply this model within the SE domain is missing. We discuss general advice from social science research.
- Identifying the most common objectives of studies employing psychometric instruments and the limitations of their application as reported by the authors.
- Relating the use of psychometric instruments within recent SE research to theoretical SE constructs, aiming at providing a better understanding on how such instruments are used within the context of *actors applying technologies/interventions to perform activities on software systems*.
- Summarizing the type of research and the empirical evaluations in SE research employing psychometric instruments.

The remainder of this paper is organized as follows. Section 2 provides background on Behavioral Software Engineering, common personality models, and secondary studies that address personality in SE, focusing on psychometric instruments. Section 3 presents the systematic mapping protocol, derived research questions, update strategy for getting new evidence on psychometric instruments, and documented execution of the protocol. Section 4 presents the results organized by research questions. Section 5 provides a discussion on the evolution of psychometric instruments over the whole fifty-year period and reviews their use based on literature guidelines. Section 6 discusses threats to validity. Finally, Section 7 presents the concluding remarks, limitations, and future work.

2. Background and related work

This section introduces the theoretical foundation and related work to this study. To approach the theoretical foundation, we describe the broader context of this study (Behavioral Software Engineering), provide a definition of personality, and describe frequently used personality models in SE. Regarding related work, we focus on personality studies in SE, emphasizing existing secondary studies.

2.1. Behavioral Software Engineering (BSE)

BSE is defined as “the study of cognitive, behavioral and social aspects of software engineering performed by individuals, groups or organizations” (Lenberg et al., 2015). It involves dealing with existing relationships between SE and disciplines from social sciences, such as *work and organizational psychology*, the *psychology of programming*, and *behavioral economics* to get a broader understanding of SE practices.

Although software is developed by humans, for a long-time, SE research has focused intensively on the technical aspects (such as processes and tools) and less on human and social aspects (Feldt et al., 2008).

BSE introduces several constructs called BSE concepts. When operationalized in empirical research, they could provide insights to researchers and practitioners. Also, with adequate knowledge adopted from other disciplines, such as social sciences, it is possible to better understand the software engineer’s practices, as a human, in the execution of their activities. It is worth mentioning that BSE is restricted to software engineers and stakeholders, and not human aspects related to the use of the software (Lenberg et al., 2015).

¹ Personality is one of the most studied concepts in BSE research as pointed by Lenberg et al. (2015).

² Hereafter we refer to psychometric instruments related to personality simply as “psychometric instrument(s)”.

Still in the context of BSE, the authors present a definition for the body of knowledge research described earlier and also conducted a systematic literature review based on the definition. The findings report lack of research in some SE knowledge areas (e.g., requirements, design, and maintenance) and rare collaboration between SE and social science researchers. A list of 55 BSE concepts and respective units of analysis is raised and detailed. Concepts such as *cognitive style*, *job satisfaction*, *communication*, and **personality** are seen as more frequently studied, while concepts such as *intentions to leave* are underexplored.

2.2. Personality: Adopted definition and common models

In the present study, we focused on mapping the literature on BSE with a restricted scope in personality, observed as one of the most studied concepts and the one with the most significant relationship with other concepts (Lenberg et al., 2015). Despite being a human factor with different definitions, we need to adopt a consistent one with the consolidated literature in SE. A deeper review and discussion are not our scope and goal. However, we need to adopt definitions to support our decisions. For personality, we rely on the following definition used in Cruz et al. (2015):

Personality is generally viewed as a dynamic organization, inside the person, of psychophysical systems that create the person's characteristic patterns of behavior, thoughts, and feelings. Ryckman (2012) defined personality as "the dynamic and organized set of characteristics possessed by a person that uniquely influences his or her cognitions, motivations, and behaviors in various situations". We use these definitions because they are general enough to allow the inclusion of studies covering a wide range of personality theories and research methods. [...] The dispositional perspective encompasses the traits and types theory, which is one of the most used theories in organizational psychology (Anderson et al., 2001) and in studies on personality in software engineering.

Complementarily, Barroso et al. (2017) summarize personality models commonly used to identify personality traits in SE in dispositional perspective. Those models are the **Myers-Briggs Type Indicator** and the **Five-Factor Model**.

The Myers-Briggs Type Indicator (MBTI) is a model based on Jung's theory of personality types adapted by Isabel Myers and Katharine Briggs in a personality inventory, with the purpose of identifying dominant individual preferences over four dichotomous dimensions (Myers, 1998):

- *I-E dimension*: refers to the way that an individual directs their energy towards the world. Introversion (I) directs to the inner world of experiences, ideas, and internal experiences (imaginative world). Extraversion (E) to the outer world of people and objects (the real world).
- *S-N dimension*: refers to functions or the way of an individual's perception work. Sensing (S) people tends to rely on what can be perceived by the five senses; on the other side, intuitive (N) people rely on patterns and relationships.
- *T-F dimension*: refers to the processes of judging and make conclusions. Thinking (T) people tend to perform logical and objective impartial analysis. Feeling (F) people highlight personal or social values, in a harmonic way.

Table 1

Description of the Five-Factor Model broad dimensions.

	Higher scores	Lower scores
Extraversion	affectionate joiner talkative fun loving active passionate	reserved loner quiet sober passive unfeeling
Neuroticism	anxious temperamental self-pitying self-conscious emotional vulnerable	calm even-tempered self-satisfied comfortable unemotional hardy
Openness to experience	imaginative creative original prefers variety curious liberal	down-to-earth uncreative conventional prefers routine uncurious conservative
Agreeableness	softhearted trusting generous acquiescent lenient good-natured	ruthless suspicious stingy antagonistic critical irritable
Conscientiousness	conscientious hardworking well-organized punctual ambitious persevering	negligent lazy disorganized late aimless quitting

- *J-P dimension*: is an extended dimension based on Jung's theory, this refers to the way that an individual prefers to deal with the outside world. Judging (J) people prefer to be decisive using the judging processes (T-F dimension). Perceiving (P) people prefer to be more spontaneous using perception processes (S-N dimension).

Given the dimensions described earlier, an individual can be placed in one of 16 possible combinations of personality (INTP, ESFJ, ISFJ, and so on).

Unlike the MBTI, the Five-Factor Model (FFM) does not provide a classification of people into types. Instead, this model allows assessing levels of latent traits underlying behaviors, levels that vary from person to person on a continuum (at least, in theory). The FFM has proved to be one of the most consensual perspectives in describing personality structure (McCrae and Costa Jr., 2008). This model describes personality based on broad five factors, which are latent traits with a high explanatory scope on behaviors: *Extraversion*, *Agreeableness*, *Conscientiousness*, *Neuroticism*, and *Openness to experience*.

The FFM emerged from strictly empirical approach and gained prominence in the 1990s. Starting from the idea that language could provide data to characterize personality traits (see John et al., 1988), researchers, using factorial analysis techniques, found five-factor structures to explain the correlations between the items in their instruments (John, 2021). The model proved even more consolidated when researchers, using personality instruments developed under other theories, also found a five-factor structure (e.g., Costa Jr. and McCrae, 1988; Lanning, 1994).

Table 1 provides descriptions by Feist et al. (2012) of the Five-Factor Model, in which a person tends to show higher or low scores in characteristics by each broad dimension.

Often the Five-Factor Model is refereed in the literature as Big Five [Model]. Barroso et al. (2017) points out an existing

distinction between then in theoretical basis, causality, and measurement between the two models, distinguishing the Five-Factor as a derivation of the Big Five, in which the latter assumes that personality traits are important for social interaction. At the same time, the former is a model that provides causes and contexts. A deeper review of personality models is beyond our scope and we consider the Five-Factor Model as the main one.

Given the definition of personality and an overview of common personality models, in the next section we highlight secondary studies on the dispositional perspective of personality. Some of them were captured by our secondary study protocol described in Section 3.

2.3. Personality and psychometrics in software engineering

According to [Michell \(1999\)](#), “psychometrics is concerned with theory and techniques for quantitative measurement in psychology and social sciences” ([Michell, 1999 apud Feldt et al. 2008](#)). In addition, [Feldt et al. \(2008\)](#) state that “[...] in practice, this often means the measurement of knowledge, abilities, attitudes, emotions, **personality**, and motivation”. The use of psychometric instruments in SE is encouraged, especially in empirical research, as a way to emphasize hitherto unexplored human factors and to help understand how they affect the research landscape ([Feldt et al., 2008](#)). This is our focus in this study, given the importance of measurement activities in empirical research.

In [Barroso et al. \(2017\)](#), personality models utilized in 21 papers are mapped onto three main ones: Myers–Briggs Type Indicator (MBTI), Five-Factor Model, and Big Five. The study covers the period of 2003 to 2016 and includes peer-reviewed publications in the IEEE, ACM, and Elsevier digital libraries. In addition to the personality models used, inconclusive findings are also identified on the influence of software engineers’ personalities on professional activities. However, there is no mapped information about the psychometric instruments that operationalize these models.

As far as we know, [McDonald and Edwards \(2007\)](#) is the first study that brings to attention on the use of psychometric instruments in SE research, beyond providing guidelines for the use of two of them (MBTI and 16PF). In addition, is highlighted that one of the authors is from social sciences and a certified professional regarding these instruments.

[Cruz et al. \(2015\)](#) performed a systematic mapping on personality in SE research using the dispositional perspective. In addition to reporting on the most common SE topics addressed, such as *education* and *extreme programming*, they reported which personality tests (a.k.a psychometric instruments) were most commonly used, which resembles this study. However, the authors only reported brief information on personality-related psychometric instruments without deep discussion about them regarding their use in SE. They provide a valuable list of instruments and relate them to some SE topics, but their scope did not include analyzing how these instruments were applied and the limitations reported by the authors.

[Usman and Minhas \(2019\)](#) investigate ethical topics raised by [McDonald and Edwards \(2007\)](#) on the adoption of MBTI-based tests in a sample of 8 studies obtained in the final set compiled by [Cruz et al. \(2015\)](#) published after 2007, and complemented with 7 studies returned in string-based search on Scopus³ in the years of 2016 and 2017, totaling a sample of 15 studies. Their results indicate that the use of psychometric instruments in SE is inadequate. The authors found problems in all of the analyzed studies, including the reliability and validity of MBTI (there are different versions of this instrument). The authors also highlight

possible causes, such as not exploring literature guidelines and lack of collaboration with social science researchers. However, the study reported is initial and limited to analyzing only the use of MBTI in a small sample of studies.

Still, [Graziotin et al. \(2015b\)](#) claims that the use of psychometric instruments should be cautious, in addition to the proper theoretical background used. The authors then propose the *Psychoempirical Software Engineering* that aims “to denote research in SE with proper theory and measurement from psychology”. In the same study, the authors provide broader steps when adopting psychometric instruments in SE research and exemplify scenarios using the *affect* construct. Nonetheless, the steps initially do not cover personality.

Building on the previous study, [Graziotin et al. \(2022\)](#) conducted a survey of the psychometric theory literature guided by *The Standards for Educational and Psychological Testing*. They repackaged the synthesized knowledge as introductory guidelines for SE researchers, including an example of psychometric validation with the R language. The reviewed topics were operationalizing psychological constructs, item pooling, item review, pilot testing, item analysis, factor analysis, statistical property of items, reliability, validity, and fairness in testing and test bias. The paper provides guidelines that encourage a culture change in SE research toward the adoption of established methods from psychology.

3. Systematic mapping protocol

Systematic mapping is a method to build a classification scheme of an area providing a visual summary of the state of research in a structured way ([Petersen et al., 2008](#)). It aims at providing an auditable and replicable process with minimal bias.

This section describes each step of our research method based on guidelines in the literature. Section 3.1 introduces the mapping goal and research questions. Section 3.2 describes the search strategy for collecting new evidence. Section 3.3 presents the study selection criteria and discusses quality assessment, and Section 3.4 presents the Data Extraction Form and our classification scheme. Concluding, Section 3.5 documents how the mapping protocol was started.

3.1. Mapping goal and research questions

Our systematic mapping aims at providing an overview of the use of psychometric instruments in SE research. To guide our investigation, and to obtain an overview of the state-of-the-art, trends and gaps, we describe the following Research Questions (RQs) as follows:

- **RQ1:** Which psychometric instruments have been applied in SE research regarding personality?
- **RQ2:** What are the objectives of the studies?
- **RQ3:** What are the limitations faced by the use of psychometric instruments reported in the studies by the authors?
- **RQ4:** To which SE constructs are those psychometric instruments related?
- **RQ5:** Which types of research do the studies refer to?
- **RQ6:** Which types of empirical studies have been conducted?

In the following section, the search strategy is presented. It was developed by the first author and reviewed by the second one.

³ <https://www.scopus.com/>

3.2. Search strategy

3.2.1. The need to update evidence on psychometric instruments

This mapping started in a traditional way of conducting secondary studies (string-based search in digital libraries with snowballing steps), according to consolidated literature (Petersen et al., 2008, 2015; Kitchenham, 2007; Mourao et al., 2017). Later, new guidelines emerged, and we noticed that they could help conduct our study (Mendes et al., 2020; Wohlin et al., 2020), given the awareness we had about comprehensive secondary studies on human factors in SE (Cruz et al., 2015; Lenberg et al., 2015).

We defined Cruz et al. (2015) as a candidate study to be considered as we wanted to start our immersion into BSE using a narrower scope, focused on personality, to allow a comprehensive overview and a focused critical assessment. Cruz et al. (2015) identified 90 studies published within a time range of forty years, whereas Lenberg et al. (2015) defined 55 BSE concepts (e.g.: *personality, job satisfaction, communication*, etc.) in a large scale study that considered 250 papers. The narrower focus by Cruz et al. (2015) would also allow us to apply our update search strategy to get new evidence (discussed in Section 3.2.2) with reasonable efforts.

We also argue that personality is a BSE concept presented in Lenberg et al. (2015) as one of the most studied together with others (such as *group composition, communication, and organizational culture*). We believe that updating evidence regarding psychometric instruments of Cruz et al. (2015) study yields significant results regarding our objective described in Section 1, which is also within BSE's scope. Thus, we decided to update the mapping study by Cruz et al. (2015).

We used the 3PDF decision framework recommended by Mendes et al. (2020) with a specific focus on identifying the need of updating evidence on psychometric instruments, using as a basis the evidence contained on this subject in the mapping study conducted by Cruz et al. (2015). We conducted the evaluation process by answering the seven 3PDF questions, which are listed and answered hereafter (in Steps 1.a. to 3.b.) and illustrated in Fig. 1.

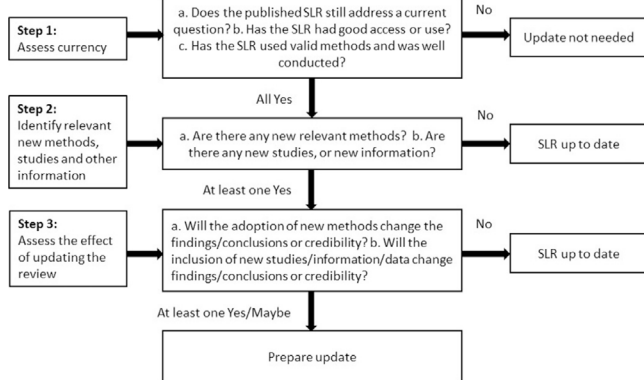


Fig. 1. 3PDF framework recommended by Mendes et al. (2020).

Step 1.a.: Does the published SLR still address a current question? Yes. Regarding the currency of the evidence on psychometric instruments contained in the specific literature mapping by Cruz et al. (2015), their study has been used to subsidize information on psychometric instruments in dozens of current studies on personality, including studies recently published in some of the main software engineering journals. For instance, a recent paper by Russo and Stol (2022), addressing gender differences in personality traits of software engineers, refers to Cruz et al. (2015) to emphasize that software engineering has adopted

several instruments to measure personality. As additional examples, Glasauer (2023) and Amin et al. (2020) also cite the paper by Cruz et al. (2015) to back information on the main psychometric instruments being used.

Considering that the study by Cruz et al. (2015) only covers until 2010, arguments on the main instruments being used would ideally need to be backed by more recent evidence. Hence, there is a need to update the status quo on psychometric instruments to cover the entire half a century.

Step 1.b.: Has the SLR had good access or use? Yes. Like (Mendes et al., 2020), we used in the cut-off point the same yearly average citation value of 6.82 documented by Garousi and Fernandes (2016) to consider a paper for good access or use. In August of 2020, Cruz et al. (2015) had a yearly average citation value of 30.8 in Google Scholar. Furthermore, we identified recent papers indicating that part of its access and use refers to backing up evidence on psychometric instruments.

Step 1.c.: Has the SLR used valid methods and was it well-conducted? Yes. Regarding the methods, Cruz et al. (2015) present an extension of preliminary results published previously in Cruz et al. (2011) with improvements, such as a refined search string increasing the sensitivity and coverage; adding backward snowballing steps; review of research questions and extended presentation of results. Finally, the authors present clear steps in their mapping protocol and are based on well-recognized guidelines for conducting secondary studies in software engineering (Kitchenham, 2007).

Step 2.a.: Are there any new relevant methods? Yes. We identified new guidelines to efficiently search for evidence to update secondary studies in software engineering (Wohlin et al., 2020). As Cruz et al. (2015) used valid methods (Step 1.c.) to identify evidence including psychometric instruments, we decided that we could confidently use their findings as a basis for updating such evidence using the identified guidelines.

Step 2.b.: Are there any new studies or new information? Yes. The papers included in the original mapping study had each a considerable number of citations in a preliminary verification in Google Scholar. There is more than a decade of evidence on psychometric instruments not incorporated by Cruz et al. (2015), which covered only until 2010.

Step 3.a.: Will the adoption of new methods change the findings, conclusions or credibility? Yes, potentially. We adopted a new method concerning the mapping protocol and addressed different research questions to get a big picture of psychometric instruments in software engineering research, which we believe generates new and important findings. Cruz et al. (2015) has a relevant research question on psychometric instruments, but there is little discussion of its results beyond listing and counting frequencies.

Step 3.b.: Will the inclusion of new studies/information/data change findings, conclusions or credibility? Yes. Regarding new potential findings, we had prior knowledge of a series of studies (Grazier et al., 2015a, 2017, 2018) used as control papers as a strategy to ensure good literature coverage in our protocol. These studies are not covered by Cruz et al. (2015) because they were published later. They discuss the use of psychometric instruments in SE on the theoretical basis of other areas (such as social sciences and psychology), which can support SE research in general.

It is noteworthy that, although we identified the need for an update, our goal and research questions differ, as we focused on psychometric instruments. The authors of the original study focused on characterizing the SE research on personality. Hence, we share the same population of studies to be analyzed. Although their study also mapped the instruments by answering the research question "What personality tests are administered

in the studies, and to what type of participants (professionals or students)?”, they did not openly provide a detailed spreadsheet of extracted data. This limited us to work only with the information reported in their paper.

3.2.2. Strategy to collect new evidence

We adopted the guidelines proposed by Wohlin et al. (2020) as a strategy to search for new evidence based on an existing secondary study. They are the following:

- **Use a seed set containing the original secondary study and its included primary studies:** Cruz et al. (2015) included 90 papers in their final set. However, we excluded their mapped paper S86 from our seed set because it is a book chapter, and we did not find evidence of publication in a scientific journal or conference to be approved in IC1 (see Section 3.3). As suggested in the guidelines, the original study itself Cruz et al. (2015) was included, obtaining a seed set of 90 studies.
- **Use Google Scholar to search for papers and apply forward snowballing, without iteration:** We used the Publish or Perish 7 tool Harzing (2020) to assist this step. The tool has features related to bibliometric analysis, including retrieving citations from publications using Google Scholar. Thus, we conducted the forward snowballing on the seed set using the tool in August 2020 and exported the results for treatment in JabRef,⁴ a bibliographic reference manager. Also, a new forward snowballing step was conducted in January 2021, aiming at covering research from 2020. All screening steps were conducted using JabRef.
- **Include more than one researcher in the initial screening to minimize the risk of removing studies that should be included (false negatives):** One researcher was included to assist in the initial screening of studies and discussions were held with a third researcher.

3.3. Study selection

Petersen et al. (2015) argue that only studies that are relevant to answer the RQs must be considered. Our inclusion criteria (IC1) consists of **primary studies published in journals, conferences, and workshops reporting SE research using psychometric instruments regarding personality that were published after 2010**.⁵ The exclusion criteria applied to filter the raw set of studies from forward snowballing are presented in Table 2.

This mapping study aims to provide an overview of the use of psychometric instruments in SE research published in peer-reviewed venues. Therefore, we focus on classifying the type of contribution by discovering objectives, the use of psychometric instruments, and the type of research to understand the overall publication landscape without applying a formal quality assessment. The procedure involved reading titles and abstracts and looking for evidence of psychometric instruments. If it was not enough for clarification, the paper's introduction and the conclusion were read. Still, if not sufficient, the full text of the study was read.

As shown in Table 2, we only included papers written in English (EC1), peer-reviewed (EC2), and complete (EC3). Due to the volume of papers, it was necessary to adopt an objective and impartial filter strategy based on keywords in the title and abstract (EC4). Focusing on the scope of the study itself, papers that did not deal with personality or related concepts (EC5) in SE studies (EC6) were also eliminated. Papers that used simulated or secondary personality data without applying a psychometric instrument (EC7) were also not considered.

Table 2
Exclusion criteria.

Criteria	Description
EC1	Papers that are not written in English.
EC2	Grey literature. Such as books, theses (bachelor's degree, MSc or PhD), technical reports, occasional papers, and manuscripts without peer-review evidence.
EC3	Papers that are only available in the form of abstracts, posters, short versions, and presentations. First, we check whether the paper's information is a short version according to the venue. If not available, we excluded papers with less than six pages.
EC4	Papers that did not include in their title or abstract terms defined by Cruz et al. (2015) as regarding personality. There are: “personality”, “psychological typology”, “psychological types”, “temperament type”, and “traits”.
EC5	Papers addressing other psychometric constructs (e.g., behavior, cognition, abilities, roles, etc.), not corresponding to the adopted definition of personality (cf. Section 2.3).
EC6	Papers that do not meet the inclusion criteria, i.e., papers that do not contribute to SE.
EC7	Papers that use secondary personality data (available datasets, reused data collected in previous studies, etc.).

Table 3
Data extraction form.

Information	Description
Study Metadata	Paper title, author's information, venue, psychometric instrument (name, version, and application process), and year of publication.
Objective (RQ1a)	Study objective: we employed open coding (Glaser, 1992) to extract information.
Limitations (RQ1b)	Limitations on the use of psychometric instruments (if exists), such as what were the difficulties of adoption/application and data interpretation. We employed open coding (Glaser, 1992) to extract data.
Purpose of the psychometric instrument in the study (RQ1c)	What constructs represent the purpose of the psychometric instrument in the study. In SE, constructs are derived from one of the classes: <i>people, organizations, technologies, activities, or software systems</i> (Sjøberg et al., 2008). We employed open coding (Glaser, 1992) to extract data.
Research Type (RQ1d)	For research type facets we used the taxonomy proposed by Wieringa et al. (2005), containing the following categories: <i>evaluation research, solution proposal, validation research, philosophical paper, opinion paper, or experience paper</i> . Petersen et al. (2015) recommendations were followed in this categorization.
Empirical Evaluation (RQ1e)	Classification of the empirical study in the following categories of Wohlin et al. (2012): <i>experiment/quasi-experiment, case study, or survey</i> .

3.4. Data extraction and classification scheme

The data extracted from each paper of the final set is shown in Table 3.

⁴ <https://www.jabref.org/>

⁵ Cruz et al. (2015) already had mapped 1970 to 2010.

3.5. Applying the systematic mapping protocol

The first step to execute the mapping protocol was to conduct forward snowballing on the seed set as described in Section 3.2.2, which generated 6702 entries (step 1 of Fig. 2). Between September and October of 2020 we conducted an initial screening of duplicates and of studies with year less than or equal to 2010, given that Cruz et al. (2015) cover a range from 1970 to 2010.

Many entries were provided by Google Scholar/Publish or Perish 7 export feature with incomplete or incorrect data (e.g., journal studies categorized in the entry as books or miscellaneous, and truncated title or abstracts). After removing duplicate entries and when possible, the data for each published study were complemented and registered in JabRef to perform a more reliable exclusion per year. The result of this initial screening resulted in 2974 entries (step 2 of Fig. 2).

Thereafter, another screening was conducted regarding the exclusion criteria EC1 and EC2. The removal was performed based on the metadata provided in the title, abstract, and journal/booktitle field entries. When it was not possible to easily identify, a verification was made through the URL of the entry or by searching the source on the internet. This exclusion was conducted between October and November of 2020 (step 3 of Fig. 2). These exclusion steps reduced the set to 1718 entries.

Thereafter, we removed entries from 2020 and applied EC4, which resulted in 369 entries of 2011 to 2019 (step 4 of Fig. 2). The removal was conducted aiming at completing our ten-year coverage by replacing them with a new forward snowballing conducted in January 2021 to more consistently include research from 2020. In this new snowballing, we considered only papers from 2020 and applied the same previous ECs, which resulted in a candidate set of 403 entries (step 5 of Fig. 2).

In 2021, we applied the other exclusion criteria (EC3, EC5, EC6, and EC7) by reading the remaining studies in the candidate set and extracting data from the selected ones (step 6 of Fig. 2). Two additional researchers assisted in this step covering two years each (2017 to 2018 and 2019 to 2020), using a prepared web form with detailed advice for data extraction. All exclusions/inclusions and extracted data were carefully reviewed. As a result, 106 studies were included and had their data extracted. The list of papers and the extracted data can be found packaged online in Felipe et al. (2022).

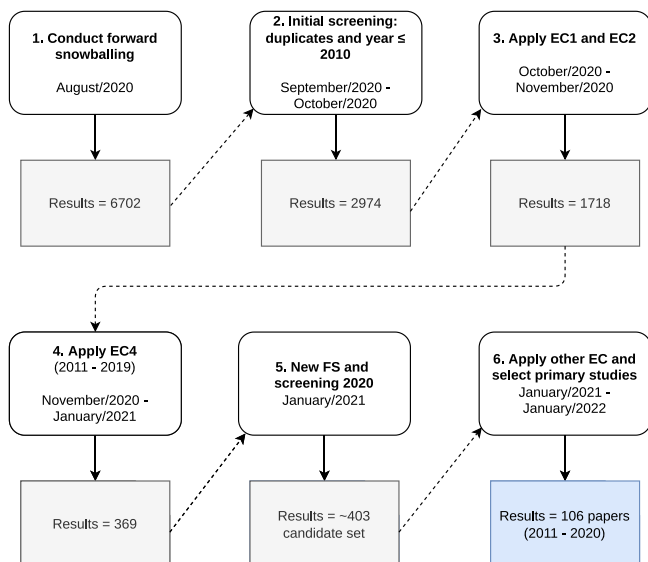


Fig. 2. Steps of mapping execution.

In the next section we present the results extracted and organized by our RQs. Bibliographic references of the selected studies are presented in Appendix A.

4. Systematic mapping study results

This section presents the results of the mapping study. First, we provide an overview of the included studies, followed by answers of defined RQs based on the information extracted from the included studies (Sections 4.1 to 4.7).

4.1. Overview

We identified 106 additional primary studies that employ psychometric instruments in SE research on personality, ranging from 2011 to 2020.⁶ The temporal distribution of the studies is depicted in Fig. 3. We can observe that the time range of 2014 to 2016 holds the highest frequency of studies. Indeed, when screening and extracting data process, this period required more effort due to also having a larger volume of papers to be analyzed.

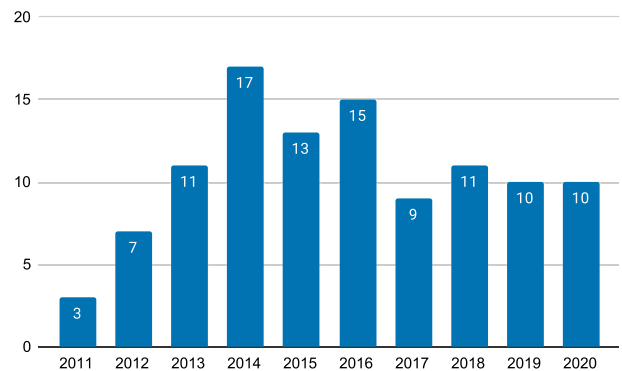


Fig. 3. Temporal distribution of selected primary studies.

Nevertheless, it is possible to observe that we identified 40 additional papers ranging from 2017 to 2020. In fact, while we found 106 studies in our investigated ten-year range (2011 to 2020), Cruz et al. (2015) found 90 studies in the previous 40-year range (1970 to 2010).

Most of the studies (62 out of 106) were published in journals, which reinforces our effort in data extraction due to fewer restrictions on document size generally required. Followed by conference (39 out of 106) and workshop (5 out of 106) publications. The latter could have a low number due to more restrictions in document size, hence not approved by our ECs, as we were looking for complete research papers.

4.2. RQ1. Which psychometric instruments have been applied in SE research regarding personality?

The frequency of instruments is illustrated in Fig. 4. The most used instrument refers to versions of the Myers-Briggs Type Indicator (MBTI), a finding also reported in Cruz et al. (2015). It is noteworthy that we observed a recent reduction regarding the use of MBTI, which we will further address in Section 5. For illustration purposes, instruments used in only one study are not shown in the chart. An overview of the complete list can be found in Table 4.

To facilitate the instruments' categorization, we compared details of the versions reported through bibliographic references

⁶ We refer to the identification of studies from our protocol as S(NUMBER), where (NUMBER) begins to account from 91, given that Cruz et al. (2015) has 90 mapped studies.

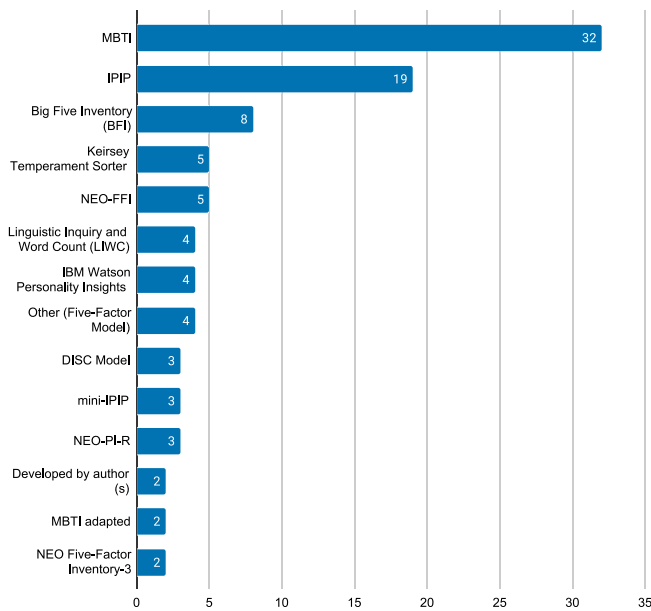


Fig. 4. Frequency of used psychometric instruments.

and specific information available to understand if they were referring to the same instrument. In these cases, we kept the details on the version in our repository but consolidated them for analysis purposes (e.g., MBTI, mapped across multiple versions).

It is also noteworthy that a variety of instruments that operationalize the Five-Factor Model of personality are used (e.g., IPIP, BFI, NEO-FFI, mini-IPIP, NEO-PI-R, and NEO Five-Factor Inventory-3). Together with the MBTI, this model stand out as the main theoretical background for instruments applied in SE research. Although the instruments based on the Five-Factor Model are the majority in sum, we consider each one of the instruments shown in Table 4 as an individual instrument in our analysis.

4.3. RQ2. What are the objectives of the studies?

During the data extraction, it was possible to observe the following major objectives with open and axial coding procedures (Glaser, 1992)⁷.

Investigate the effect of personality: in this major coded objective, data on personality is used as an intervention to investigate phenomena. We identified this one with several specificities illustrated, as shown in Fig. 5 and listed below for minor objectives with more than two papers. Such specificities aim to *investigate the effect of personality*:

- in pair programming teams compositions [S92, S96, S103, S106, S113, S115, S193, S196];
- in the quality of software developed [S95, S123, S133, S140, S164, S173, S177, S182] and their respective perceived satisfaction [S95, S133];
- regarding influence on project management activities [S100, S130], including communication [S134] and collaboration [S177];
- in academic contexts, such as analyzing achievements [S102, S120, S122, S125, S169], resilience [S141] or learning outcomes [S144, S175] of students;
- in development preferences [S104, S110, S114];

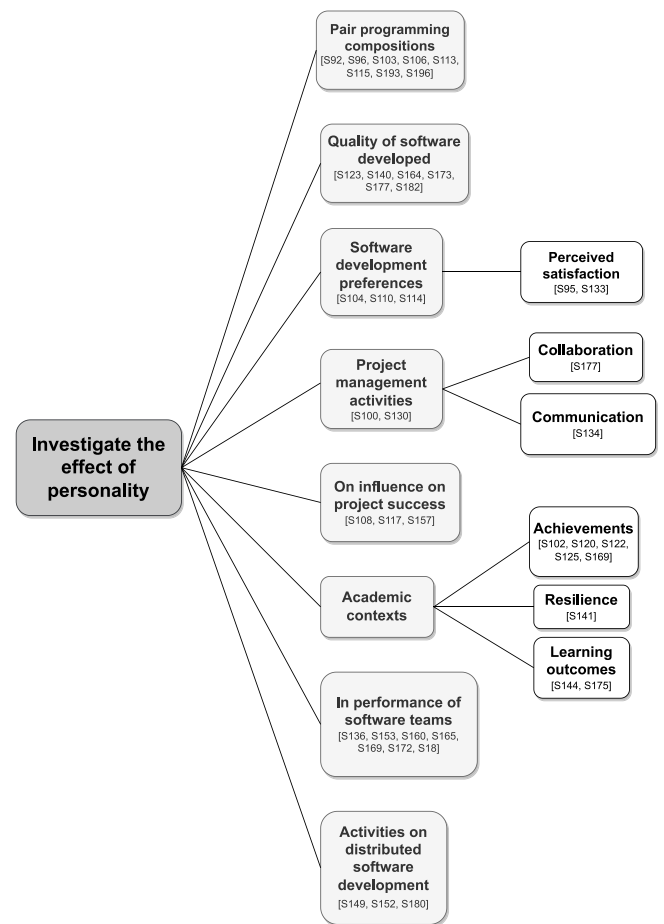


Fig. 5. Tree structure of *Investigate the effect of personality* major code.

- on the influence on project success [S108, S117, S157];
- in performance of software teams [S136, S153, S160, S165, S169, S172, S187]; and
- in activities on distributed software development [S149, S152, S180].

Furthermore, the effect of personality has also been investigated in other topics, such as the use of CASE [S101, S170] and static analysis tools [S143], implementing a new technology [S109], performance of software engineer [S127, S146], programming styles [S135, S150], software testing performance [S105], team climate and productivity [S139, S195], requirements engineering activities [S142], knowledge management activities [S159, S162], software engineer burnout tendencies [S179], collaboration [S176], creativity [S189], and on the use of software repositories [S194].

Characterize software engineer personality: as shown in Fig. 6, some studies aimed to discover patterns in personality of software engineering professionals [S93, S119] and more specifically to mapping these patterns to roles and required skills [S99, S107, S111, S129, S132, S138, S158, S161, S179, S184, S185, S188, S190, S191, S192] or preferences in software aspects [S112, S126, S166]. Characteristics of software engineering personality are also explored in distributed software development [S116]; considering common profiles of personality by region or organization-context [S131, S137]; to relate them with other psychometric constructs over time [S118]; and with respect to distinguishing profiles within different computer major courses [S147].

⁷ An overview of qualitative coding, in the context of grounded theory for SE research, has been offered by Stol et al. (2016).

Table 4
Psychometric instruments mapped organized by studies.

Psychometric instrument	Studies	Count
MBTI	S91, S93, S99, S101, S110, S111, S112, S119, S120, S122, S123, S126, S127, S129, S130, S137, S138, S151, S155, S158, S162, S163, S165, S167, S168, S169, S172, S173, S177, S179, S181, S196	32
IPIP	S92, S106, S113, S124, S128, S132, S135, S136, S139, S146, S150, S161, S164, S171, S174, S178, S182, S186, S195	19
Big Five Inventory (BFI)	S100, S104, S114, S125, S141, S175, S183, S189	8
Keirsey Temperament Sorter (KTS)	S96, S103, S108, S131, S147	5
NEO-FFI	S117, S133, S140, S153, S174	5
Linguistic Inquiry and Word Count (LIWC)	S116, S134, S149, S194	4
IBM Watson Personality Insights	S152, S176, S180, S188	4
Other (Five-Factor Model)	S107, S143, S145, S192	4
DISC Model	S109, S148, S157	3
mini-IPIP	S118, S142, S156	3
NEO-PI-R	S95, S102, S110	3
Developed by author(s)	S121, S184	2
MBTI adapted	S94, S154	2
NEO Five-Factor Inventory-3	S97, S98	2
NEO-PI3	S105	1
IPIP based	S115	1
Five-Factor Stress	S144	1
Other (Unspecified)	S159	1
Student Styles Questionnaire	S166	1
EPQ-R	S170	1
IPI	S185	1
16 Personality Factors (16PF)	S187	1
HEXACO Model	S191	1
Quick Big Five (QBF)	S193	1

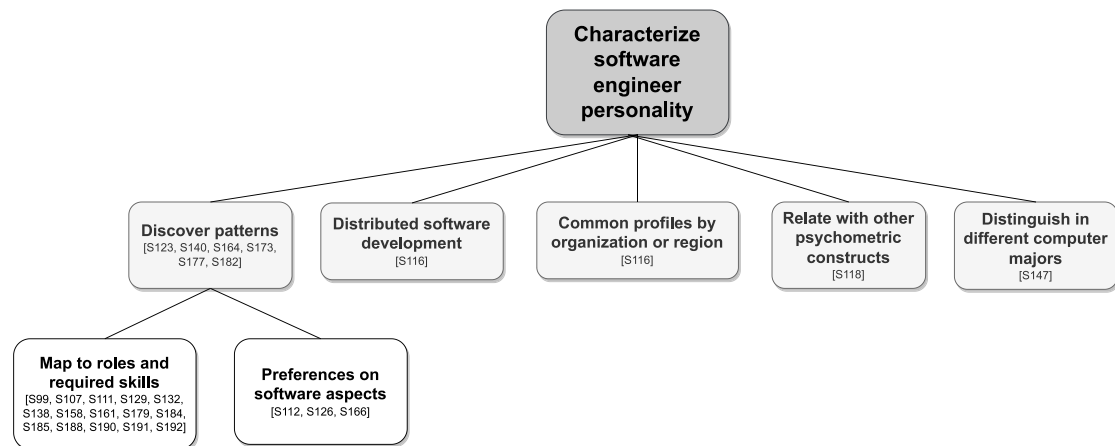


Fig. 6. Tree structure of characterize software engineer personality major code.

Predict performance or preferences: four studies used information on personality to perform predictions (see Fig. 7). This objective involves development team's performance algorithms and tools in order to optimize resources [S91, S97, S98] and predict preferred roles of software engineering professionals [S181].

Propose an approach: in this objective, some proposal is given to support research or practical activities in SE (Fig. 8). For instance, proposing approaches to measure personality [S121, S148, S154, S175, S186] and to interpret statistically data in domain

of SE [S156]; to personalize SE activities [S124]; to create links between human factors (like personality) with software diversity [S128]; to investigate turnover intentions [S145]; to relate individual characteristics to development performance [S183]; to perform team compositions [S151, S173]; and to conduct task assignments [S167, S168].

Investigate the relation of personality: this objective is related to check whether personality has any relationship with a research object (see the structure in Fig. 9). Personality relationships are

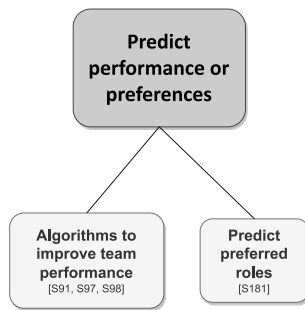


Fig. 7. Tree structure of predict performance or preferences major code.

investigated with learning outcomes [S144], burnout tendency [S178], choices in major degree in computing [S155], class grades considering gender [S163], learning effectiveness [S174], project success [S157], and task selections [S162].

It is noteworthy that we decided on a completely new coding without a direct influence from previous results to capture the essence of the new results more precisely (Seaman, 1999). However, we can compare our mapped objectives with the most frequent research topics mapped by Cruz et al. (2015). Listing them (highlighted): **pair programming**, in investigate the effect of personality; **education**, during the data extraction, we identified studies that contributed to educational purposes or used an academic scenario to reach the research goal in all major codes described earlier; **team effectiveness**, in predicting team performance; **software process allocation**, **software engineer personality characteristics**, **individual performance**, and **team process** in all of our major codes. It can show us that these topics are still being researched.

4.4. RQ3. What are the limitations faced by the use of psychometric instruments reported in the studies by the authors?

Less than half of the primary studies (43 out of 106) reported limitations related to the adoption of psychometric instruments in SE research. An overview of our coded limitations is described in the following.

Possible misuse of psychometric instrument: the authors of [S95, S132, S152, S157, S187] declare that adopting the psychometric instrument to the objectives of research could affect the validity of the study, but this limitation is mitigated by relying on the literature. Other threats concern not involving psychologists in the research design [S130, S148, S187], use of non-intuitive platforms, and poor instructions on instruments' application [S178]. The lack of a data set for performing benchmarks is also reported [S180].

Choice of a short version of psychometric instrument: the statistical power of personality data in the studies may be compromised by the adoption of shorter versions of the instruments, so they could result in less accurate results [S118, S156, S191], hence compromising the research goal. Furthermore, Graziotin et al. (2022) reports that shortening validated measurement instruments in a non-systematic way may drastically reduce psychometric reliability and validity properties, to the point that we cannot be confident anymore of our interpretation of results.

Personality may not be a representative construct: the use of personality as an investigated human factor may not be a good choice for the research design [S128] and encountered correlations may not assure causality [S135, S150].

Bias on subjects responses: the authors indicate that subjects' administration of psychometric instruments can become a threat in cases of factors like lack of honesty or loss of concentration of

the subjects [S96, S97, S110, S113, S143, S146, S149, S164, S172, S177, S178, S184, S190, S195] sometimes caused by the absence of control of researcher employing certain empirical approaches (like surveys). This limitation is generally mitigated by ensuring they made aware that the response data obtained is anonymized and used only for research purposes.

Statistical power of psychometric instrument: the dichotomous approach of MBTI-based instruments could affect results in scenarios when a person is in a center of a scale due to the instruments' statistical structure [S96, S103, S182]. Others report that personality traits data should be measured by adopting other psychometric instruments in order to achieve better results [S100, S104, S111, S158, S163, S173] but without suggesting any other instrument; in case of identification of personality traits from textual analysis, the amount of chunk text may not be sufficient [S176]. Moreover, the one scale/trait of the psychometric instrument showed low internal validity, being excluded from the study [S170].

Paid subjects: participants were paid to participate in the study, which may have influenced them somehow [S105].

Issues with dictionary to measure personality from text: adequacy of language dictionaries to measure personality from textual analysis may be a threat. Also, the data extracted to measure personality may not be representative of a person [S116, S134, S194].

Construction issues on proposed psychometric instrument: the adequacy of psychometric instrument to SE context may deal with validity issues. These issues were mitigate using expert judgments and a series of incremental refinements [S160].

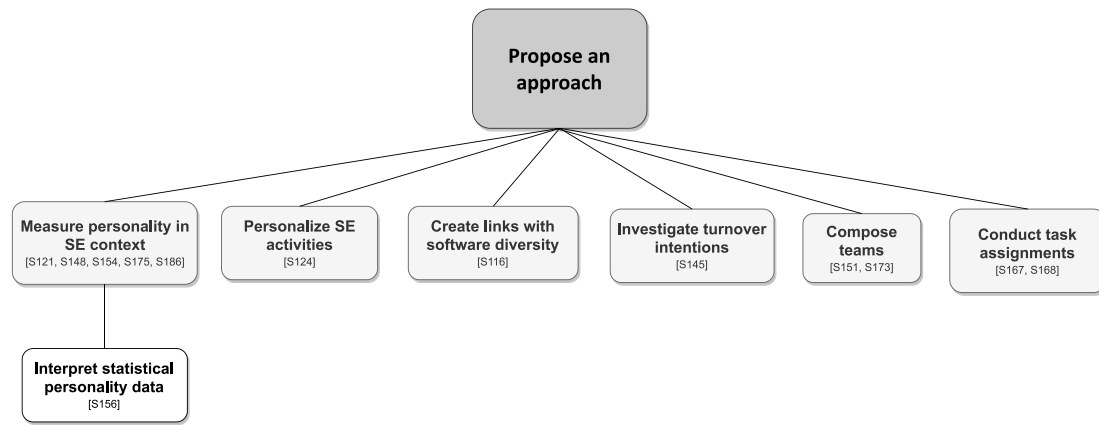
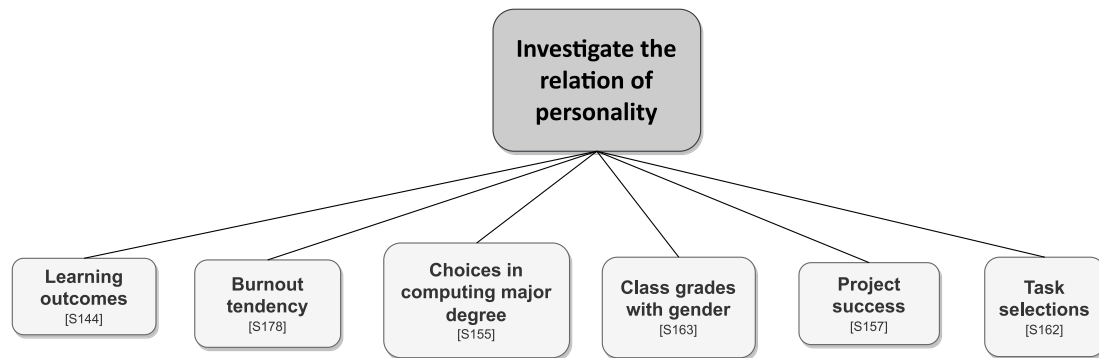
4.5. RQ4. To which SE constructs are those psychometric instruments related?

Regarding SE constructs, we used the framework to describe theories proposed by Sjøberg et al. (2008) and its archetypal classes as support for open coding constructs. This framework is largely used in SE research to present theories. In it, the archetypal classes interact together in the following way: an *actor* applies a *technology* (we believe that *intervention* is more appropriate in the context of psychometric instruments) to perform certain *activities* on a *software system*. In Tables B.5 to B.8 (Appendix B) we list and describe the coded SE constructs to which the psychometric instruments are related within the identified studies, organized by archetypal class.

Fig. 10 depicts the relationship network between the constructs described in the aforementioned tables. We can observe that constructs of class **Actor** researcher and *academic setting* are the majority, indicating the application of studies in an academic setting due to scope limitations of the research design or for purely investigative purposes by researchers. In the **Intervention** class, *personality traits data* represents the most common coded construct and is typically measured by some psychometric instrument and used to investigate its influence on SE activities.

Regarding the **Activity** class, the constructs *software engineer characterization*, *team building*, *assessment of activities execution*, *pair programming*, and *mapping of suitable roles* have a higher frequency. All of them are related to the previously mentioned constructs in classes **Actor** (*academic setting and researcher*) and **Intervention** (*personality traits data*).

Still, the activities described earlier are also strongly related to the constructs of the **Software System** class. It is possible to observe that *software engineer characterization* is typically not related to any specific software system (code *none*), indicating no direct reference or use to software systems in these studies. The code *tool* indicates the use of some technique using software/algorithms/games/logic rules to support the studies. Moreover, *class assignments* were specially related to *team building* and

Fig. 8. Tree structure of *propose an approach* major code.Fig. 9. Tree structure of *investigate the relationship of personality* major code.

pair programming, where SE teams were built based in academic contexts based on personality data. It is noteworthy to mention the use of a *software repository*, in which software artifacts of different kinds are stored.

Please note that RQ1c aims at answering what parts of SE theory the psychometric instruments are related to. There may be similarities with the overall objectives of the mapped studies (RQ1a), but RQ1c is specifically focused on the context of used instruments in the primary studies and their relations to SE theory elements.

4.6. RQ5. Which types of research do the studies refer to?

We used the following research type facets taxonomy defined by Wieringa et al. (2005) and the advice for distinguishing between the categories contained in Petersen et al. (2015).

- **Validation Research:** these papers investigate the properties of a solution proposal that has not yet been implemented in practice.
- **Evaluation Research:** these papers investigate a problem or an implementation of a technique in practice.
- **Solution Proposal:** in these papers, a solution for a problem is proposed, it can be either novel or a significant extension of an existing technique.
- **Philosophical papers:** these papers sketch a new way of looking at things, a new conceptual framework, etc.

- **Opinion papers:** these papers contain the author's opinion about what is wrong or good about something, how we should do something, etc.
- **Personal experience papers:** in these papers, the emphasis is on what and not on why. The experience may concern one project or more, but it must be the author's personal experience.

Fig. 11 depicts the distribution of research types facets by year. It is possible to note that validation research over-represented the set of mapped studies either in distribution per year and in total (85 out of 106). This facet includes empirical studies, as well as the less frequent evaluation research (11 out of 106). The difference between them indicates that most empirical research has been conducted in academic scenarios for initial validation purposes and does not propose and measure new proposals in industrial scenarios. This is somehow expected due to possible difficulties in using industrial practitioner subjects as part of research designs.

Few solution proposals have also been mapped (10 out of 106), which typically represent new research proposals with some limited evaluation required for publication or no presentation of empirical evaluation, therefore they were not classified as either evaluation or validation research.

4.7. RQ6. Which types of empirical studies have been conducted?

Fig. 12 depicts the frequency of empirical evaluations adopted by year, with 96 out of 106 studies. When analyzing the figure,

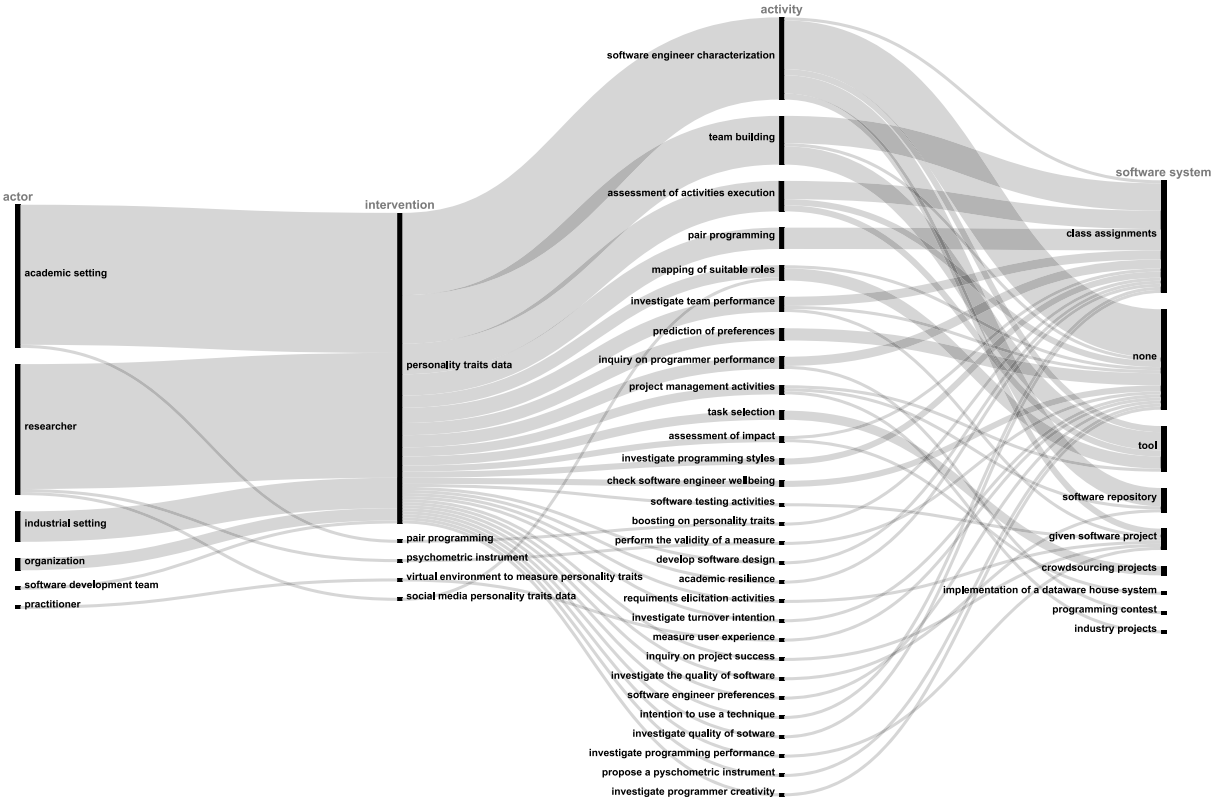


Fig. 10. SE constructs related to the psychometric instruments.

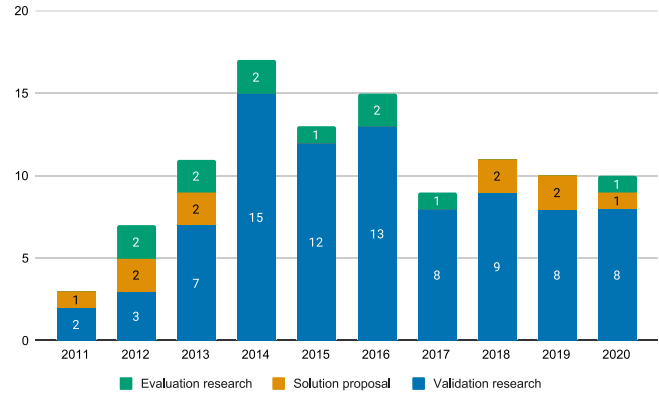


Fig. 11. Frequency of research type per year.

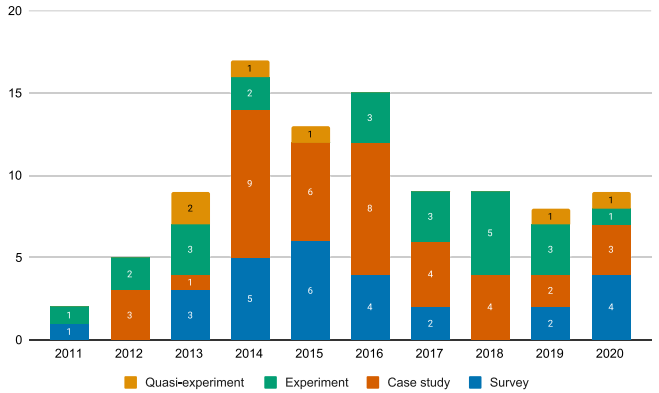


Fig. 12. Frequency of empirical evaluation types per year.

it is possible to observe that survey and case study strategies have been frequently adopted through the years. In the case of surveys, studies generally use this empirical strategy to apply psychometric instruments. It is noteworthy that case studies represent a high frequency of empirical approaches. Many studies document the research design as experiments (which we see in figure less frequent), but in an inconsistent way with the definition of experimental/quasi-experimental design (Wohlin et al., 2012). In these cases, we classified the empirical evaluation type as case studies. Experiments and quasi-experiments are shown less frequently. This

may be explained due to the complexity of handling personality as a variable in controlled experiments.

5. Discussion

To outline how the use of psychometric instruments in SE research on personality evolved over the last fifty years, we manually integrated the data from our study with the corresponding data from the study by Cruz et al. (2015). Unfortunately, there was no public access to the data extracted in their mapping. However, the paper contains a table listing the psychometric instruments used in each of the papers included in their study.

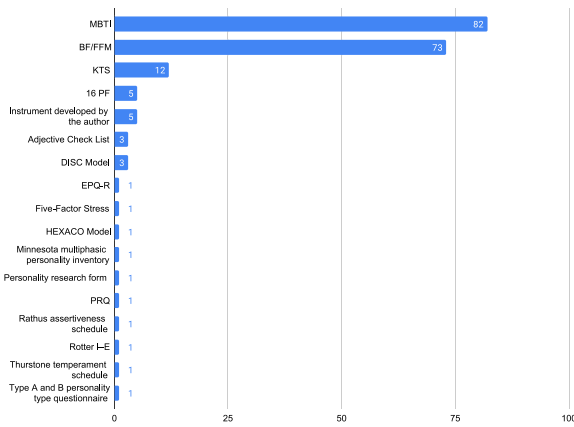


Fig. 13. Frequency of psychometric instruments adoption.

Therefrom, we prepared a new spreadsheet for this particular analysis, which is available in our online repository. For aggregation purposes, similarly to what had been done by Cruz et al. (2015), we grouped a variety of instruments (e.g., IPIP, BFI, and NEO-FFI) that operationalize the Five-Factor Model into the BF/FFM category.

Fig. 13 shows the overall usage of psychometric instruments in SE research from 1970 to 2020. It is possible to observe that MBTI and FFM stand out as the most used theoretical backgrounds for instruments applied in SE research.

Additionally, we wanted to understand if there were trends in the most adopted instruments over time. While the complete data is available in our online repository, we included only MBTI and the FFM instruments in this analysis, as none of the other instruments had comparable recent use. Fig. 14 shows how often MBTI and FFM instruments appear in SE research published from 1970 to 2020. While the first paper using MBTI was published in 1975, the first paper using FFM was published almost thirty years later, in 2003. It is possible to observe a reduction in the use of the MBTI and an increase in the use of the FFM after 2018. While we avoid risking any kind of causal inferences, the study by Cruz et al. (2015) might have shed some light on criticisms regarding the use of MBTI for personality-related research (Boyle, 1995; McCrae and Costa Jr., 1989). With respect to the FFM, on the other hand, studies mainly support it as a reliable and valid theoretical background for measuring personality. For instance, the study by McCrae and Costa Jr. (1987) provided evidence for the convergent and discriminant validity of the FFM across different measurement instruments and different observers. The study by McCrae and Costa Jr. (1997) examined the cross-cultural generalizability of the FFM, finding support for the model in 50 cultures and languages.

Given the prevalence of the MBTI and FFM, hereafter, we discuss the use of their related instruments based on the data we extracted from the papers ranging from 2011 to 2020. Unfortunately, there was no public access to the data extracted in the mapping by Cruz et al. (2015), not allowing aggregating analyses on limitations of the usage of the instruments during this period. Furthermore, our specific focus on the instruments led us to extract more detailed information in this particular regard (cf. Table 3). Nevertheless, we believe that this analysis is still meaningful, given that a more recent ten-year period actually better reflects the *status quo*.

Regarding the MBTI, while there is no consensus in the literature regarding the validity of this instrument (Boyle, 1995; McCrae and Costa Jr., 1989), we found specific guidelines on how to apply it within SE research (McDonald and Edwards, 2007).

To confront the usage of the MBTI instruments with the existing guidelines, we used the extracted data on the instruments (actual name, version/bibliographic references), how they were employed (covering from administration to data interpretation), and the reported limitations.

Not following the recommendations of these guidelines, most studies did not report any bibliographic references and explicit versions of the instrument. Furthermore, most studies also did not report anything different from “we use *x* to measure personality” regarding instruments application or “*x* is widely used in SE research to measure personality” to support the choice of the instrument.

Following the guidelines, we extracted data from a reader’s perspective looking for “explicit details of types of test used, administration process, the qualifications of the testers” (McDonald and Edwards, 2007) by answering the following derived questions:

Has the study documented the participation of a qualified tester? Only one study claims the participation of an MBTI certified practitioner to process data [S138]; however, by using surveys as empirical approach more refinements in data interpretation were limited.

Are there details to justify the choice of MBTI? No, the choice is primarily justified by the wide use and acceptance of this instrument by previous SE studies [S151, S163, S167, S168, S169, S172, S173] or by brief claims about the validity of the instrument and professional widespread use [S155].

Are there details about versions of MBTI? One study claims the use of *Form M* or *Form G*, but no references to specific versions were documented [S112, S138, S181]. Others document the use of some free tests [S129] in an unspecified version [S126]. Also, some applied the psychometric instrument through a website [S169, S172, S177] or in a printed version [S155]. Most studies document (Myers, 1998) as a bibliographic reference when they refer to MBTI, but this reference is about the model and its theoretical foundation, not the specific psychometric instrument.

How was MBTI administered? One study mentions having provided a participation consent form [S165]. Other studies document that instruments were self-administered by subjects through a survey empirical strategy [S130, S137, S138, S181] or in a range of time without further details (longitudinal study) [S122]. One study did not measure personality by means of MBTI but proposed a solution mapping its dimensions against adequate soft skills in requirements elicitation techniques [S179].

How were the results of MBTI interpreted? In general, the identified studies did not report on the result interpretation. In one study, an interview followed the administration of the psychometric instrument to obtain refinements of the resulting personality traits [S112]. Additionally, one study reported the algorithm to interpret the results [S137].

In sum, we can see that despite existing literature, there is a lack of concern about how to handle personality and psychometric instruments in SE. McDonald & Edwards’ guidelines date from 2007. More recently, we had a critical review by Usman and Minhas (2019) including a sample of Cruz et al. (2015) studies (see our background and related works in Section 2.3). The results of their review are consistent with our observations, leading us to the same conclusion that there was no significant progress in improving the adoption of the MBTI in SE research over the years. The scenario is even worse when considering the lack of consensus in the literature regarding the validity of this instrument.

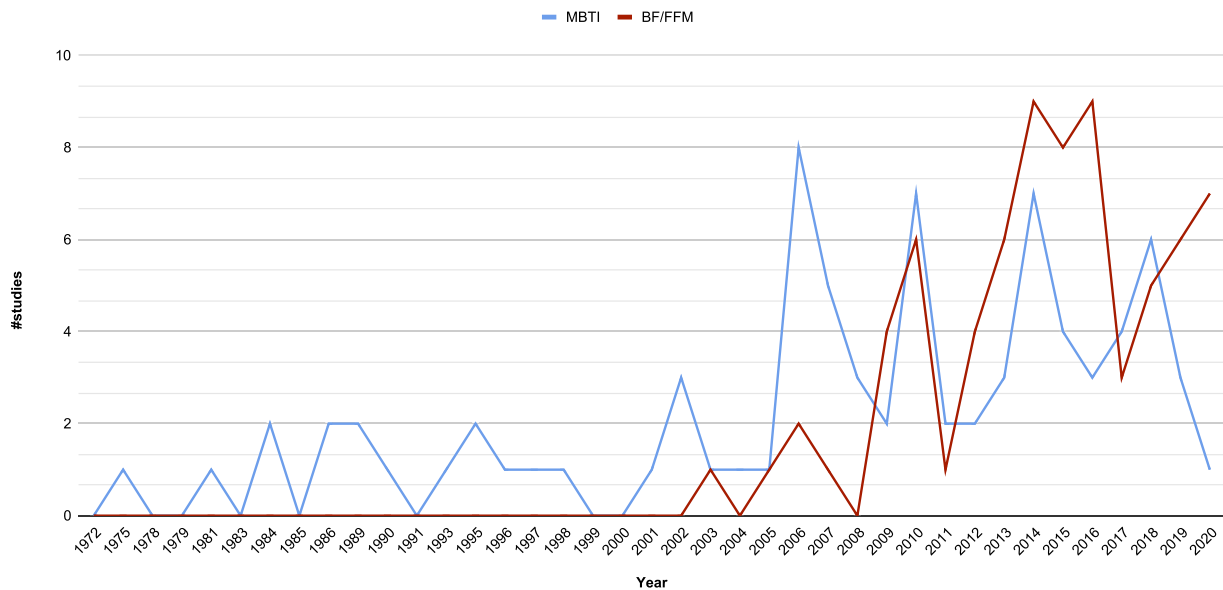


Fig. 14. Usage of psychometric personality instruments in SE research over the years.

Regarding the FFM, despite its relevance in social sciences, we found no specific guidelines for its application by SE researchers. However, considering the coded limitations of the use of psychometric instruments reported in the studies, we observed that most studies lack details on the application of these instruments. We understand that researchers are usually restricted by document size in research papers. However, given the majority of studies mapped in journals, which are generally more extensive and detailed in terms of text, we believe that more details on how a relevant human factor as personality is handled should be provided (or at least be made available in open science repositories).

In general, we put forward that certain basic steps should be followed when administering personality tests. It is noteworthy that the last author is a psychology researcher focused on personality-related research. Hereafter we provide some general advice adapted from the international guidelines for test use of the International Test (Commission, 2001), which are widely accepted within the field of psychology.

- The instrument used needs to show evidence of validity for the target population, and the more evidence, the better. *I.e.*, there is a need for evidence that the test accurately assesses the personality within our population of interest. For instance, as there is limited validity evidence of personality instruments for SE professionals, one should provide arguments that allow to relate the representativeness of the sample to a population for which such evidence exists. The NEO-FFI provides evidence of the test's validity with college students and working adults in its own manual (Costa and McCrae, 1992). Therefore, if the study sample concerns the target population of adult software developers, a researcher could relate to such evidence arguing that adult software developers represent working adults. Researchers should look for supporting evidence of validity for the target population in the scientific literature, and new studies should be conducted when there is no such evidence.

- The instrument needs to be applied properly so that the environment does not interfere with the participant's responses. *I.e.*, the way to apply the instrument needs to be consistent with the level of attention and comfort required to answer it. For example, consider a personality instrument with complex phrases that are difficult to understand. In that case, one must apply the test in a calm, interruption-free environment. In the context of SE professionals, this would ideally be out of the company.
- To interpret the scores obtained from the instrument, norms that are appropriate to the respondent population should be used. For example, suppose a researcher wants to interpret the Openness to Experience scores of adult woman software developers from the United States using NEO-FFI. This researcher should be aware that NEO-FFI has different norms for men and women adults from the United States, with different norms for men and women (Costa and McCrae, 1992). Hence, it is important to understand that norms vary depending on the test used and the population studied and that a test result is only useful when the interpretation is based on the specific norms of the target population. In this example, using the men's norms to interpret the woman's results would not be helpful.

Following these basic steps of seeking evidence of validity, standardizing the application, and using appropriate norms for the population is fundamental for a gold-standard use of psychological instruments. Hence, before using items (adjectives, descriptors, phrases, stimuli) to assess the Five Factors, there is a need for evidence that those items accurately measure the Five Factors. The instrument needs to be applied properly so that the environment does not interfere with the participant's responses, and appropriate norms need to be used to interpret the results. For example, someone will most likely introduce, or increase, measurement error by taking a German instrument, translating it into Brazilian-Portuguese, applying it in a Brazilian context, and interpreting the results based on the Germany's scores.

Furthermore, instruments may come with specific instructions, including details on their existing evidence of validity, how the instrument should be applied, and how the scores should be interpreted. In case instructions, or technical manuals, are provided, they ease the application of the international guidelines for test use by already specializing them for the instrument. For instance, the Big Five Inventory (BFI) instrument (John et al., 2008) has specific advice available on the website of the Berkeley Personality Lab.⁸

It is noteworthy that the advice we herein provide for the personality-related context is consistent with the more generic guidelines compiled for psychometrics in BSE (Graziotin et al., 2022).

6. Threats to validity

In this section, we discuss the findings of our study regarding its threats to validity. We list the possible threats and procedures we took to mitigate those issues hereafter according to Petersen et al. (2015).

Theoretical validity: with respect to our search strategy, we relied on empirically assessed guidelines to search for new evidence. Based on the set of 90 studies covering forty years of personality research in SE, we identified 6702 new studies to be analyzed in a single forward snowballing iteration using Google Scholar and included 106 additional studies. We believe that as a result, we had good coverage of the literature within the last fifty years.

Regarding study selection, the exclusion of short papers and grey literature can threaten the representativeness of the sample of selected studies. However, we adopted this strategy to prioritize complete and peer-reviewed studies. We noticed that short papers frequently did not provide the necessary information to answer our research questions during initial data extraction efforts.

Furthermore, given the huge quantity of papers to be analyzed (6702) we filtered out papers that did not include terms related to personality in the title and abstract. This decision was taken to make the study selection effort viable. We included synonyms and believe that this did not lead to relevant studies being excluded.

Finally, concerning the data extraction process, a threat can be the main control of one researcher in the mapping study execution, which can bring some bias to results in different ways. This threat was mitigated by exhausting reviewing extracted data and consensus meetings with the second author. We had support from two additional researchers in the extraction process to cover years 2017 to 2020, but the researcher that extracted data for the remaining years (2011 to 2016) reviewed their extraction. Still, the data extraction process is error-prone. To improve the reliability in this process, all extracted data is auditable and openly available to the community.

Descriptive validity: our protocol is based on solid guidelines and an update of a comprehensive mapping study. The open coding method for answering our research questions may not help to provide an easily understandable overview. We incorporated axial coding procedures when answering research questions that primarily use open coding accordingly to Table 3 (RQ2 and RQ3).

Regarding transparency, we documented the entire process and packaged all generated artifacts organized by the followed steps (see Fig. 2) in order to turn it available to the community. They allow further analyses and replication of our protocol. Studies that were not included are flagged with their respective exclusion criteria.

Generalizability: The present mapping study is restricted to the dispositional personality perspective in SE research. More perspectives that could interest some target audiences may have been adopted in the SE literature. However, they were not captured by this protocol, and it is not our focus.

7. Conclusions

This study aimed to provide a comprehensive overview on psychometric instruments used in SE research regarding personality. Therefore, we updated evidence of a broad existing secondary study (Cruz et al., 2015). We provided a detailed protocol based on specific guidelines to assess the need for an update and to define an effective search strategy for identifying new evidence. The original secondary study included 90 studies covering 1970 to 2010, we identified 106 additional studies covering 2011 to 2020.

By analyzing these additional studies and answering our research questions, we contribute to the Behavioral Software Engineering (Lenberg et al., 2015) body of knowledge on the following topics with respect to personality:

- *Status Quo:* Outlining the use of psychometric instruments in software engineering research on personality over fifty years and observing remaining discrepancies between the application of the psychometric instruments within recent SE research and existing recommendations in the literature. Within fifty years of SE research involving personality, we could not observe significant improvements. We also involved a social science researcher active with personality-related research in the analyses to provide additional advice to the SE community.
- *Common objectives:* we observed common objectives of mapped studies that use personality, employing coding procedures to provide an overview of the most studied topics. *Investigate the effect of personality* in some SE activity contexts had the highest frequency, followed by *characterize software engineer personality*, which aims to discover and distinguish the personality of software engineering professionals and systematizing it, mostly for mapping roles and skills.
- *Limitations:* the limitations regarding the adoption of psychometric instruments are poorly reported in the mapped research. In fact, less than half of the primary studies in our set reported some limitations on the adoption of psychometric instruments.
- *Theoretical constructs:* we mapped the use of psychometric instruments within recent SE research related to archetypal classes of constructs. We observed that the instruments are mainly used within the context of **actors academic setting** and **researcher** who applied the **intervention personality traits data** to perform **activities** such as *software engineer characterization*, *team building*, *assessment of activities execution*, *pair programming*, and *mapping of suitable roles*, mostly without considering a **software system** (*none*) and sometimes related to *class assignments* and *varied tools*.
- *Type of research and empirical approaches:* We provided a summary of the type of research and the empirical evaluations employing psychometric instruments. We observed that Validation research is the most common type of the mapped studies. It depicts research conducted in academic scenarios or not proposing something new and measuring in practice. With respect to the empirical evaluations, surveys and case studies are generally adopted.

⁸ <https://www.ocf.berkeley.edu/~johnlab/bfi.htm>

Overall, our study indicates that the adoption of psychometric instruments regarding personality in SE still needs to be improved. We discuss general advice from the area of social science and point readers to the recent guidelines by Gaziotin et al. (2022) on psychometrics in BSE as a first step toward improving the adoption in our discipline.

We believe that the scenario presented in our study helps to highlight this important issue and that the review and advice can help to guide the employment of psychometric instruments in SE research regarding personality.

CRedit authorship contribution statement

Danilo Almeida Felipe: Conceptualization, Data curation, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Marcos Kalinowski:** Conceptualization, Data curation, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Daniel Gaziotin:** Validation, Writing – original draft, Writing – review & editing. **Jean Carlos Natividade:** Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared the link to our data within our paper in the Zenodo open science repository.

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Appendix B. Dictionary of coded constructs related to SE

See [Tables B.5–B.8](#).

Table B.5
Coded constructs in class Actor.

Actor coded construct	Description	Studies	Count
academic setting	The study has an educational purpose or is applied in an academic setting due to scope limitations	S91, S92, S95, S96, S99, S101, S102, S103, S105, S106, S107, S110, S111, S113, S115, S120, S122, S125, S126, S133, S135, S136, S140, S141, S143, S144, S146, S147, S148, S150, S151, S155, S158, S162, S163, S165, S166, S169, S171, S172, S173, S174, S176, S177, S182, S193, S196	47
researcher	The study author(s) act primarily for investigative purposes	S93, S104, S108, S112, S114, S116, S117, S118, S119, S121, S123, S124, S128, S129, S131, S132, S134, S137, S138, S139, S145, S149, S152, S156, S159, S161, S167, S168, S170, S175, S178, S179, S180, S181, S183, S185, S186, S187, S188, S189, S191, S192, S194	43
industrial setting	The study is applied in a industrial setting	S109, S130, S142, S153, S157, S160, S164, S184, S190, S195	10
organization	The scope of the study is not clear (where does the study data come from?). The code was adopted to be comprehensive.	S97, S98, S100, S127	4
practitioner	The study is clearly applied and focused on practitioners	S154	1
software development team	A software development team was the interventor in the study	S94	1

Table B.6

Coded constructs in class Intervention.

Intervention coded construct	Description	Studies	Count
personality traits data	The study has data on personality traits measured by some psychometric instrument	S91, S92, S93, S94, S95, S96, S97, S98, S99, S100, S101, S102, S103, S104, S105, S107, S108, S109, S110, S111, S112, S113, S114, S115, S116, S117, S118, S119, S120, S122, S123, S124, S125, S126, S127, S128, S129, S130, S131, S132, S133, S134, S135, S136, S137, S138, S139, S140, S141, S142, S143, S144, S145, S146, S147, S148, S149, S150, S151, S152, S153, S155, S156, S157, S158, S159, S160, S161, S162, S163, S164, S165, S166, S167, S168, S169, S170, S171, S172, S173, S174, S176, S177, S178, S179, S180, S181, S182, S183, S184, S185, S186, S187, S188, S189, S190, S191, S192, S193, S194, S195, S196	102
pair programming	The study adopted pair programming to assess some impact	S106	1
psychometric instrument	The study adopted a psychometric instrument to be adapted/validated	S121	1
social media personality traits data	The study has data on personality measure using social media data as source	S175	1
virtual environment to measure personality	The study used an virtual environment to measure personality as intervention	S154	1
software development team	A software development team was the interventor in the study	S94	1

Table B.7

Coded constructs in class Activity.

Activity coded construct	Description	Studies	Count
characterization of software engineer	The study characterizes, in some extent, the software engineering professional. It means: comparison of SE and other professionals, discover (and/or compare) personalities for some purpose.	S93, S108, S112, S116, S118, S119, S127, S129, S131, S132, S134, S137, S138, S147, S148, S149, S152, S155, S156, S160, S165, S179, S180, S184, S191, S194, S195	27
team building	The main activity of the study is to build software development teams with more than two members	S91, S94, S95, S97, S98, S99, S102, S111, S124, S133, S144, S153, S158, S171, S172, S174	16
assessment of activities execution	The main activity of the study is to assess software artifacts and processes in a software activity	S101, S117, S120, S122, S125, S126, S143, S159, S169, S182	10
pair programming	The main activity of the study is to build pair programming teams	S92, S96, S103, S113, S115, S193, S196	7
mapping of suitable roles	The main activity of the study is to mapping software engineer roles (developer, tester, project manager, etc.)	S107, S161, S175, S185, S192	5
investigate team performance	The main activity of study is investigate performance of a software team	S136, S139, S173, S176, S190	5
inquiry on programmer performance	The main activity is assess programmer performance in coding activities	S123, S128, S146, S163	4
project management activities	The main activity is related to software project management activities	S100, S130, S188	3
task selection	The main activity is related to selection of tasks to development	S162, S167, S168	3

Table B.8

Coded constructs in class Software System.

Software system coded construct	Description	Studies	Count
class assignments	The study used a software system for academic settings, previously developed for some specific purpose (be tested, refactored, ...) or developed during the conduction of the study by students	S92, S95, S96, S99, S102, S103, S106, S113, S115, S117, S120, S123, S125, S126, S133, S135, S136, S140, S141, S144, S146, S147, S150, S151, S158, S163, S169, S170, S171, S172, S173, S174, S176, S177, S182, S193, S196	37
none	No software system was used in the study	S93, S104, S110, S112, S114, S118, S119, S121, S122, S127, S129, S131, S132, S137, S138, S139, S145, S153, S154, S155, S159, S160, S161, S165, S166, S178, S179, S181, S186, S187, S189, S191, S195	33
tool	The study used a machine learning/computational intelligence, some kind of algorithm, gamecard, or CASE tools	S91, S94, S97, S98, S100, S101, S107, S111, S124, S143, S148, S156, S175, S185, S192	15
software repository	The study used a software repository that stores some kind of software artifacts, (e.g. code, documents, or tasks)	S116, S134, S149, S152, S164, S180, S188, S194	8
given software project	The study uses software (or requirements of it) that has not yet been developed, but it was during the conduction of the study	S105, S108, S142, S157, S183, S184, S190	7
crowdsourcing projects	The study has crowdsourcing projects as a software system	S162, S167, S168	3
implementation of a dataware house system	The study used data from implementation of a dataware house system	S109	1
programming contest	The study used what is developed in a programming contest	S128	1
industry projects	The study used data regarding industrial projects	S130	1

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Daniilo A. Felipe received his M.Sc. degree from the Department of Informatics of the Pontifical Catholic University of Rio de Janeiro (PUC-Rio) and a Bachelor's in Information Systems from the Federal University of Ceará. His main research interests are experimental software engineering, human factors in software engineering, software quality, and data science techniques for data extraction in unstructured documents. He is currently a researcher at the Tecgraf Institute and collaborates in the Software Science Lab at PUC-Rio. Contact him at dfelipe@inf.puc-rio.br.

Marcos Kalinowski is professor at the Department of Informatics of the Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Brazil, where he heads the Software Science Lab. His research focuses on empirical software engineering, software engineering for machine learning, requirements engineering, software process and product quality, and human factors in software engineering. He has co-organized several conferences and workshops in the software engineering community and serves further as area editor for the *Journal of Systems and Software*. Contact him at kalinowski@inf.puc-rio.br.

Daniel Graziotin is a tenured Akademischer Rat at the Empirical Software Engineering group, Institute of Software Engineering, University of Stuttgart, Germany, where he performs as head of the division for Human Aspects of Software Engineering. His research focuses on human, behavioral, and psychological aspects of empirical software engineering, studies of science, and open science. He is academic editor at the *PeerJ Computer Science* journal and the *Research Ideas and Outcomes* journal, editorial advisory board member at the *Journal of Open Research Software*, and editorial board member at the *Empirical Software Engineering* journal. Contact him at daniel.graziotin@iste.uni-stuttgart.de.

Jean C. Natividade is professor at the Department of Psychology of the Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Brazil, where he heads the Laboratory on Social Psychology (L2PS). His research focuses on psychometrics, romantic relationships, personality, and social psychology. He holds a Ph.D. in Psychology from the Federal University of Rio Grande do Sul (UFRGS), with a sandwich period at Ohio State University (USA). Contact him at jeannatividade@puc-rio.br.