Human Aspects in Software Development: A Systematic Mapping Study

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Abstract. Software development is a process that requires a high level of human talent management to ensure its success. This makes it a topic of interest to the software industry and research. Considering this interest, it is evident the need to know the aspects that have been studied, how they have been measured, and what data analysis methods have been used. This paper presents an analysis of the human aspects associated with the software development process, identifying procedures and methods used to analyze data and its measurement. A systematic mapping with a sample of 99 studies identified by their relationship with the proposed topic was used as the research method. The main findings show that one of the most studied is personality. This aspect is related to the performance of software development teams and is a key variable for its conformation. Concerning the most used data source, we find the survey based on self-reporting. Finally, descriptive statistics is the most frequent method of analysis, which is performed prior to other methods such as correlation or regression analysis. The results suggest a wide spectrum of human aspects to be studied in Software Engineering, and interesting potential for analysis by identifying interesting methods other than self-reporting.

Keywords: Metrics · Human aspects · Software development · Systematic mapping study

1 Introduction

There is a growing interest in studying human aspects in Software Engineering (SE), mainly because software development is a people-centered process [1], therefore human aspects have become a fundamental part of their measurement programs [2]. Previous studies indicate that the people and tasks associated with team processes are key to the success and effectiveness of software development projects [3]. In addition, human aspects must be taken into account in the estimation of productivity [4].

Research related to the identification of relevant human aspects in software engineering has been carried out [5]. However, it has been identified that the measurement of these aspects is difficult and therefore represents a challenge for both industry and research [6]. Consequently, the objective of this study is to identify the human aspects that have been studied in the context of SE, analyzing measurement instruments and data processing methods.

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Considering the objective mentioned above, a systematic mapping is performed with a sample of 99 studies published in a time window between 2010 and 2021. Scientific databases such as Science Direct, Springer, IEEE, and ACM were used. The descriptive analyses described in this work are related to the year of publication, authors' country of affiliation, type of study, human aspects treated as dependent variables, human aspects treated as independent variables, measurement instruments used, and data analyzing methods.

The findings of this mapping allow us to identify the human aspects most studied in SE. A company may focus investment efforts by identifying the instruments that have been used to measure human aspects of interest. A higher education institution or research center will be able to identify those human aspects that have not been worked on and allocate research resources to promote projects aimed at the expansion of knowledge in the area.

Another interesting finding is the identification of tools for capturing data and analyzing data methods related to the measurement of human aspects in SDT. This identification can guide the definition of innovative methodologies and proposals, with advantages over traditional ones, and that can be easily incorporated in academia and industry to improve teamwork.

This article is structured as follows. Section 2 is related to the importance of human aspects in software development. Section 3 presents the systematic mapping protocol followed in this article. Section 4 presents the overall results of the mapping and answers the research questions. Section 5 presents implications for practice and research, and the limitations of the study. The conclusions are in Sect. 6.

2 Human Aspects in Software Development

Human aspects have an important impact on SE [7]. A software product requires human intervention [8] and its development is an intellectually challenging activity that demands collaborative work [9].

Several studies indicate that SDT performance is affected by technical, non-technical (soft), organizational and environmental factors [10]. Non-technical factors include those related to people [11, 12].

Skills such as communication, emotional intelligence or leadership are required in jobs related to Information Technology [13]. However, organizations must understand the importance of these types of aspects, as well as diversify the skills of developers to enrich talent and contribute to the work of building software [14].

Since people-related factors have raised the interest of SE researchers, there is a set of 57 social and human factors that, according to a tertiary review, influence the productivity of SDT [5]. This set was adjusted to 13 factors by a conceptual analysis supported by psychology and software engineering [15] and corroborated through a survey-based study [16]. The results indicate that this set of social and human factors are perceived as influencing SDT productivity. However, the magnitude of this influence is still unknown because non-technical factors are difficult to measure [6].

Finally, considering the importance of Human Factors in Software Development, this topic can be considered a subfield of Empirical Software Engineering [17], where psychological knowledge plays an important role [6].

3 Systematic Mapping Protocol

Systematic mapping is a particular type of literature review focused on understanding the behavior of a field of knowledge at the research level and the main challenges that are still to be solved [18]. This mapping considers both primary and secondary research, and adopts the protocol used by Brereton et al. [19], which includes three phases:

- Phase 1: study planning, where research questions, scope, research criteria, and study selection criteria are defined.
- Phase 2: execution of the study, which includes the selection and classification of studies.
- Phase 3: analysis of results and response to each of the research questions.

3.1 Phase 1: Study Planning

Planning the study involves defining the research questions, scope, research criteria, and selection criteria. According to the object of study, the systematic mapping is focused on characterizing the scientific production on measurement of human aspects in software development. Therefore, the research questions are:

- RQ1: What human aspects are measured in Software Engineering?
- RQ2: What are the sources of data used to quantify human aspects in software engineering?
- RQ3: What data analysis methods are used in Software Engineering to analyze data related to human aspects?

The limits of the research according to the guidelines proposed by Petticrew and Roberts [20], the population of interest are people who are part of software development teams or companies without considering a specific geographic location. Research published as of January 2010, inclusive, was considered, and the review of the selected studies was conducted by an expert in SE and another in engineering research.

The search for publications was performed in the IEEE Xplore, ACM, Science Direct, and Springer databases to cover the objective of the systematic mapping. The terms that can account for the topic of interest are related to "measurement instruments" or "evaluation" of "human factors" or "human aspects" in Software Engineering or Development, so the search string used was:

(assessment OR "measuring instruments") AND ("human factor" OR "human aspect" OR "soft skill") AND ("software engineering" OR "software development").

The term "human aspect" was used because it is an area of research in software engineering, related to human resource management [21]. This area includes the analysis of "soft skill" that is usually related to "human factor" [6]. On the other hand, the term "assessment" was used because it is widely used in clinical psychology [22], while the term "measuring instrument" is broader [23].

The study classification procedure began with a review of the title, keywords, and abstract of each candidate study to identify the relationship with the topic of interest. In some cases, it was necessary to review other sections such as the introduction and conclusions, when the previous ones were not conclusive to identify the respective relationship with the topic of interest.

It is necessary to define the criteria required to make decisions regarding the inclusion or exclusion of studies in the systematic mapping to select the candidates that will be part of the initial sample of studies. Table 1 presents the inclusion and exclusion criteria considered in this mapping and used to select the studies.

Table 1. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
- Studies involving human aspects in software engineering - Studies published since 2010	- Studies without complete available document - Studies not written in English - Duplicate investigations

3.2 Phase 2: Execution of Study

The execution of the study is the mapping phase that allows the aspects planned in the previous phase to be implemented. That is, to search according to the search string defined in the selected databases and based on the inclusion and exclusion criteria, to select the studies and then classify them.

The execution of the search string in the identified databases yielded an initial capture of 1533 studies. The application of the established selection criteria and the review of the general elements of each document (title, abstract and keywords, and introduction and conclusion, when necessary), led to the selection of 99 studies, representing 6.46% of the total number of studies reported in the initial capture (Fig. 1).

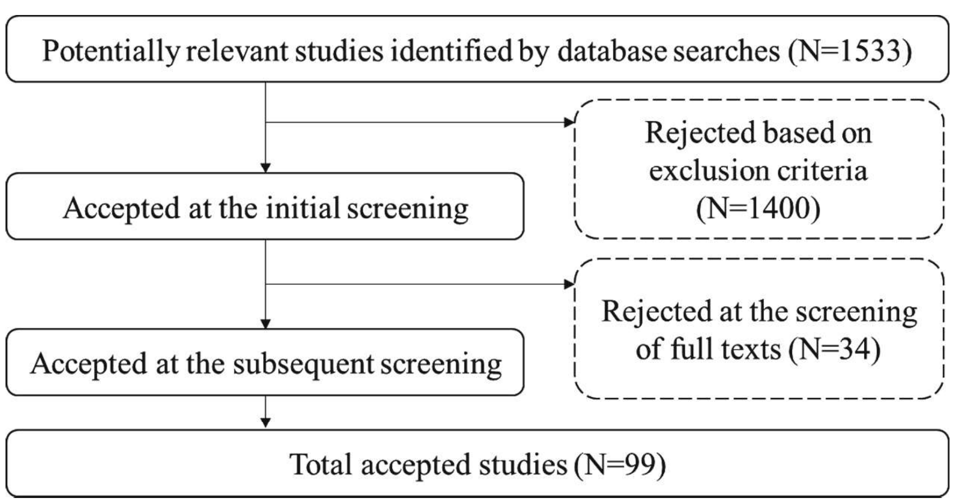

Fig. 1. Flow diagram of the data collection procedure

The number of studies captured and selected in each database is presented in Table 2. Relevant information on the 99 selected publications can be found at https://github.com/lmrestrepo/HA-SD.git.

Table 2. Number of studies by database consulted

	Science Direct	Springer	IEEE	ACM	Total
Captured studies	623	473	250	187	1533
Selected studies	35	18	10	36	99

Once the studies of interest were selected, they were classified according to a) year of publication, b) country of affiliation of the authors, c) type of study (case study, observation, experiment, document analysis), d) human aspects treated as dependent variables, e) human aspects treated as independent variables, f) measurement instruments used, and g) data analyzing methods.

4 Phase 3: Analysis of Results

This section presents the results obtained by classifying the selected studies. This phase aims to answer the three questions posed in the planning phase of this systematic mapping.

4.1 General Results of the Study

Figure 2 shows the behavior of studies by year considering publications in journals and academic events. There is an increasing trend of studies related to the measurement of human aspects in SE between 2011 and 2014. However, from 2014 onwards, an oscillatory behavior is presented suggesting a stabilization of the topic of interest for the last 7 years.

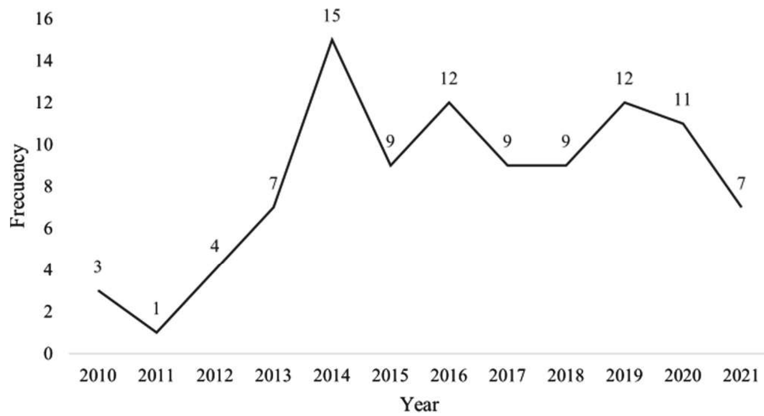

Fig. 2. Number of studies per year

Table 3 lists the first five of each type of publication, according to the number of studies that were selected. In total, 54 studies in journals (54.55%) and 45 studies in academic events (45.45%) were considered.

Table 3. Number of studies by type of publication

Journal name	#	Proceeding name	#
Information and Software Technology	19	CHASE Cooperative and Human Aspects of Software Engineering	7
The Journal of Systems and Software	9	EASE Evaluation and Assessment in Software Engineering	6
Empirical Software Engineering	8	ESEM Empirical Software Engineering and Measurement	5
Computers in Human Behavior	3	ICSE International Conference on Software Engineering	4
Transactions on Computing Education	2	EuroSPI Systems, Software and Services Process Improvement	2
Transactions on software engineering	2	SIGSOFT Software Engineering Notes	2

According to the countries of affiliation of the authors who have participated in the studies selected for this systematic mapping, 19.61% of the total number of authors reported are from Brazil, 8.12% are from Sweden, 6.44% are from Spain and 5.60% are from the United States. The continent with the most researchers working on the measurement of human aspects in SE is Europe with 46.78%, followed by South America (20.45%), and Asia (14.01%).

The survey study stands out (55 studies - 55.56%), where information is obtained from individuals through a questionnaire or an interview and then processed quantitatively or qualitatively, depending on the type of questions and the interest of the research. Some studies are related to literature reviews (17 studies - 17.17%).

Case studies (13 studies - 13.13%) are less frequent, but they are applied when it is desired to describe the behavior of an individual or a reduced set of individuals. Publications were found that rely on the analysis of documents (8 studies - 8.08%) such as organizational repositories and e-mails to study human aspects.

Studies were also found in which experiments or quasi-experiments were carried out in which some variables were controlled (3 studies - 3.03%). Finally, three laboratory studies were found in which electronic devices or sensors are used to collect data and, therefore, are performed under specific working conditions.

4.2 What Human Aspects are Measured in Software Engineering?

We founded research in which cause-effect relationships of human aspects with other variables were studied, where human aspects can be treated as dependent (explained) variables or as independent (explanatory) variables. In cases where no cause-effect relationships were studied, the variables were taken as independent variables.

Table 4 presents the variables and the number of studies associated with these variables (number greater than or equal to 2), classified as independent and dependent. In some studies, an aspect can be considered as an independent variable and in others as a dependent variable, as occurs with decision-making and motivation.

Table 4. Independent and dependent variables

Independent variable	#	Dependent variable	#
Personality	29	Performance	11
Experience	5	Team building	5
Communication	4	Productivity	5
Social interaction	3	Motivation	4
Team size	2	Quality	4
Commitment	2	Job satisfaction	3
Emotional intelligence	2	Yield	3
Trust	2	Team climate	2
Task characteristics	2	Decision making	2
Decision making	2	Role conflict	2
Motivation	2	Project success	2
Leadership	2		
Emotion	2		
Team autonomy	2		
Happiness	2		

As evidenced in Table 4, the human aspect that has been most studied in SE is personality, which is related to the fact that the software development process is predominantly social [24] and people-centered activity [17].

The literature reviews have been carried out regarding personality. One of the studies is related to the identification of personality aspects that have been of interest in SE [25]. Others have studied the relationship between personality and performance [26, 27] and team climate [28, 29]. One literature review studied the relationship between personality and decision making [30] and another compared the instruments used in SE to measure personality [31].

Personality has been included as an independent variable in research that studies cause-effect relationships. Table 5 consolidates the variables that have been related and the respective references. There is interest in studying how personality influences efficiency and how to build work teams and assign tasks to optimize the software development process.

Table 5. Studies related to personality like independent variable

Dependent variable	References
Performance, productivity, yield	[32–36]
Decision making	[37]
Communication	[38]
Team climate	[39, 40]
Team building, role assignment, task preference	[21, 41–49]
Attitude and behavior	[50–52]
Trust to reuse code	[53]

Experience is another human aspect that has been taken into account to estimate performance [32, 54]. Juneja [55] proposes an instrument to measure the performance of programmers based on experience among other aspects. Also, the relationship between experience and autonomy has been studied [56] and between experience and team process background [57].

Considering the 13 social and human factors that are perceived to influence SDT productivity [15], some of them are directly evidenced in this mapping and are related in Table 6.

One of the aspects that have been studied as a dependent variable is motivation because it favors efficiency in software development projects [74]. Also, factors that influence motivation have been studied [75], and one of the studies analyzed has focused particularly on the motivation of the engineers in charge of the tests [72]. In addition, a study was identified that proposes a way to measure motivation through sensors [76], and another study where the relationship between motivation and job satisfaction was studied [66, 69].

Job satisfaction is another human aspect of interest for researchers, and according to the above, its relationship with motivation. This mapping identified an instrument built

Table 6. Studies related to human aspects that are perceived as influencing productivity

Independent variable	Dependent variable	References
Communication	Project performance and success	[58–61]
Social interaction (interpersonal relationships)	Software quality, team tacit knowledge acquisition, and value creation	[62–64]
Emotional intelligence	Task preference and team performance	[43, 65]
Motivation	Job satisfaction and developer skills	[66, 67]
Commitment	Team building, motivation, and job satisfaction	[68, 69]
Leadership	Project success and team process history	[57, 59]
Collaboration	Team building and teamwork quality	[68, 70]
Autonomy (team)	Project results and quality of teamwork	[70, 71]
Cohesion	Quality of teamwork	[70]
Innovation (creativity)	Motivation	[72]
Job satisfaction	Turnover	[73]

to identify whether the clarity of equipment standards and psychological safety impact job satisfaction and SDT performance [77].

Team climate is an aspect that has attracted the attention of researchers. Soomro et al. [28] conducted a systematic literature review on personality traits that influence the climate of the SDT and, subsequently, Vishnubhotla et al. [40] build a regression model between both variables in agile teams.

Finally, decision-making has also been studied. Freitas et al. [30] did a literature review on the personality of decision-makers in SE, and then presented a regression model between both aspects [37].

4.3 What are the Sources of Data Used to Quantify Human Aspects in Software Engineering?

Table 7 presents the data sources most frequently used in the studies analyzed. Out of 176 records, considering that several sources can be used for an investigation, 22.73% correspond to questionnaires and 9.09% to interviews. Researchers can use instruments designed by themselves, use instruments designed and validated by other authors (e.g., psychometric tests), or make adaptations of instruments used in previous research. In this mapping, any of the three options is considered as ‘Questionnaire’.

Table 7. Number of studies by type of data source

Data source	#	Data source	#
Questionnaire	40	Organizational data	2
Interview	16	Self-Assessment Manikin	2
International Personality Item Pool	11	Maslach Burnout Inventory	2
Big Five scores	7	Scale of Positive and Negative Experience	2
Observation	4	Document analysis	2
Myers–Briggs Type Indicator	3	Team Climate Inventory	2
Electronic device	3	GitHub repository	2
Jazz repository (IBM)	3	Work Design Questionnaire	2

Surveys, case studies, and experiments are the main methods of empirical research in SE [78]. The surveys, supported by questionnaires and interviews, are the data sources that are most used in the investigations of this mapping.

Both the questionnaire and the interviews are empirical research tools used to collect information about the processes and skills of software developers through self-report [7]. In several investigations, they are used simultaneously, to obtain additional information that can be obtained using only one of these tools [42, 56, 79–84].

Concerning surveys (questionnaires and interviews), some limitations should be considered. One of these is to ensure that the sample size is representative of the population to be studied. The sample size is necessary to achieve the generalization of the findings. This limitation is due to its requirement in the identification of the unit of analysis [85]. In addition, Kitchenham et al. [86] recommend reporting the response rate and, presenting how study participants were recruited and selected, which may constitute an additional constraint for the management and administration of information and the collection process.

Instruments that have been designed and validated by other authors, employed iteratively in research, and which are usually called acronyms, are considered formalized (some even with restricted use by licensing), as in the case of personality instruments, team climate, job burnout, among others. Table 8 presents the formalized instruments found in this mapping, the aspect they measure, and the references of the studies in which they were used.

Table 8. Formalized instruments

Formalized instrument	Aspect	References
International Personality Item Pool (IPIP)	Personality	[33–37, 40, 43, 44, 46, 50, 53]
Big Five scores	Personality	[32, 35, 38, 39, 47, 51, 52]
Myers–Briggs Type Indicator – MBTI	Personality	[21, 45, 68]
Self-Assessment Manikin (SAM)	Visual stimuli	[83, 87]
Maslach Burnout Inventory (MBI)	Job Burnout	[88, 89]
Scale of Positive and Negative Experience	Feelings	[90, 91]
Team Climate Inventory (TCI)	Team climate	[39, 40]
Work Design Questionnaire (WDQ)	Job characteristics	[88, 89]
Multidimensional Work Motivation Scale	Laboral motivation	[92]
Belbin Self-Perception Test	Team roles	[68]
Team Tacit Knowledge Measure (TTKM)	Tacit knowledge of the team	[63]
Multifactor Leadership Questionnaire (MLQ)	Leadership	[59]
Positive And Negative Affect Schedule	Affect	[60]
Intrinsic Motivation Inventory (IMI)	Intrinsic motivation	[67]
Team Selection Inventory (TSI)	Team selection	[39]
Keirsey Temperament Sorter (KTS)	Temperament	[34]

Psychometric instruments are easy to apply and score and allow measuring the characteristics of interest of a person at a given time. However, the results can be affected by the individual's temporal events, the inherent interaction between the examiner and the examinee, and the possibility of distorting or simulating the examinee's responses [93].

In line with the above, Andersson et al. [94] made a comparison between the ratings given by behavioral observers and the self-evaluation ratings to measure team performance. In this comparison, from a quasi-experiment, they found that observation-based techniques are more reliable than those based on self-assessment. The observation allows corroborating the relationship between what the teams say they do and what they do [95, 96]. In addition, it allows for identifying the strategies that individuals use when facing stressful situations [80].

As an alternative to psychometric testing, the use of electronic devices has been proposed. Bordel and Alcarria [76] designed a device to automatically evaluate motivation in Industry 4.0 scenarios with Environmental Intelligence infrastructure. This device is based on body and environmental sensors that account for the physiological and emotional signals of the individual. Another proposal is that reported by Girardi et al. [87], who used an electronic device to identify the emotions of software developers while working on it. Also, Fritz et al. [97] report the use of psychophysiological sensors to detect when software developers are facing a difficult task and prevent them from making mistakes.

4.4 What Data Analysis Methods are Used in Software Engineering to Analyze Data Related to Human Aspects?

Table 9 presents the main data analysis methods reported in the studies selected in this mapping to analyze the data obtained related to human aspects, excluding those of a philosophical and opinion type. In total, 25 data analysis methods were reported, but this table only presents those that had a frequency of use greater than or equal to two.

Table 9. Data analysis methods

Method	#	Method	#
Descriptive statistic	48	Normality test	6
Correlation analysis	27	Cluster analysis	4
Regression analysis	22	Data mining	3
Mean comparison study	20	Linguistic analysis	3
Qualitative analysis	17	Machine learning	2
Factor analysis	11	Archetypal analysis	2
Reliability calculation (Cronbach's Alpha)	11	Bayesian statistic	2
Principal component analysis	7		

A recent systematic review of the literature indicates that the statistical methods most commonly used in SE are descriptive statistics, power analysis of statistical tests, the goodness of fit tests, parametric and non-parametric tests, error type I, confidence intervals, analysis of latent variables and finally, practical significance and size of the effect [98]. All the methods mentioned are confirmed in the set of studies on this mapping.

The predominant method is descriptive statistics, used in 60.00% of the studies where data analysis is possibly required. This method is usually used in the first steps of statistical analysis because it allows summarizes relevant information [98, 99] and usually includes measures of central tendency and dispersion [100]. This method is used in some studies to present preliminary results [45, 49, 55, 66, 101, 102], and in other studies is before the use of more advanced statistical methods [33, 34, 40, 42, 43, 47, 50, 52, 54, 57, 60, 63, 67, 70, 87–90, 103–106].

A recurrent analysis method is correlation analysis, used in 33.75% of the studies analyzed in this mapping in which data analysis was possibly required. These studies in some cases can lead to regression analysis (27.50%), and subsequently to the comparison of means (25.00%). Normality testing is required to do a Pairwise Comparison, but only six of the studies reported this. Regression models allow modeling a variable according to others and are usually accompanied by correlation studies [107]. These models have been used to estimate programming performance based on personality and cognitive styles [33]. Information is also reported where regression models are used to estimate decision-making from personality [37] and to estimate performance based on social interaction, transactive memory, and tacit team knowledge [63], among others.

Concerning studies that present designed instruments, they usually support their research in factor analysis (13.75%). On some occasions, it was accompanied by principal component analysis as an estimation method (8.75%). Feldt et al. [105] designed an instrument to measure willingness and openness to organizational change based on participation, knowledge, and the need for change. Marsicano et al. [57] propose a questionnaire called Teamwork Process Antecedents (TPA). This questionnaire aims to measure the background of equipment processes for use in research and the management of equipment in practice. In both cases, Cronbach's Alpha is reported as a measure of reliability. For its part, Gren [108] makes some recommendations to ensure the construct validity and reliability of the instruments, taking into account the stability and internal consistency. Likewise, Lloret-Segura et al. [109] present a guide for doing exploratory factor analysis.

Given the recent interest in analyzing human aspects in SE, which have a latent nature, it is necessary to use methods that work with this type of variables, as is the case of models of structural equations of partial least squares [110]. Xiang et al. [65] used structural equations to study the relationship between emotional intelligence and the shared mental model, and between the shared mental model and team performance in the analysis of requirements. Basirati et al. [81] used this method for to understand the impact of conflict on the success of software development projects for different types of conflicts and different environments.

Naturally, the use of analytical methods is not unrelated to software development [111]. The use of machine learning allows to calculate the probability of replacement of a person and resignation in a software development company [73] and, can be the basis for defining classifiers to predict difficult tasks [97]. For its part, data mining is a useful method when it is necessary to analyze large volumes of data [38, 68, 73].

The analysis method depends on the type of data being analyzed. Several studies present their results based on a qualitative analysis because of the use of open-ended interviews. In particular, semi-structured interviews allow flexibility but require intelligence, sensitivity, preparation, and agility on the part of the interviewer [112]. This method is used when the interest is to know the individual opinion of people who are part of a group [42, 56, 58, 69, 80, 81, 83, 84, 113–115]. In some cases, researchers prefer to use structured interviews with previously defined questions [70, 79, 95, 116].

5 Implications for the Practice and Research

The results of this systematic mapping suggest that human aspects such as personality and motivation have an impact on the performance of the SDT, so its measurement is a relevant aspect in organizations. Personality is an aspect to be considered for recruiting, selecting, and retaining talent, as well as for forming work teams. Concerning motivation, organizations should identify the aspects that promote it and, on that basis, verify the need to propose strategies to reach the desired levels.

Now, the list of human aspects is broad, and several of them have also been identified as influential in the performance of the teams. Therefore, organizations have at their disposal the tools designed and tested to be included in their management processes.

Concerning training programs in SE, training in soft skills is fundamental because it has been shown to influence the success of projects. For technical training, the fact that knowledge in statistics and data analysis methods is required to support studies of interdependence where human aspects are involved is highlighted.

The research on human aspects has been oriented to the study of the personality of the members of the SDT, in their relationship with performance and efficiency. It has also been analyzed how to take advantage of personality to form teams, although it is an area still to explore. Likewise, interest in other human aspects such as motivation, communication, or collaboration in SE has been identified. Recognizing the human aspects that are of interest in the area and that have not been studied exhaustively, represents an opportunity for future research.

According to the results, human aspects have traditionally been measured using psychometric tests, which can give biased results when situational. Therefore, in this aspect of the results, there is a challenge to be solved related to the use of measurement mechanisms. Mechanisms are needed to ensure consistency between what software developers say they do and what they do.

Finally, the use of statistical methods is a common practice for studies related to instrument design and for addressing analysis. These methods aim to identify relationships of interdependence, maintaining in all cases the mathematical rigor and data processing. However, emerging data analysis methods are identified that can respond to the needs of data analysis in this context and become complementary methods to enrich knowledge around work of this research.

5.1 Study Limitations

This study focused on scientific databases such as 1) Science Direct, 2) Springer, 3) IEEE and 4) ACM. A limitation associated with these databases is related to the possible exclusion of relevant studies on the measurement of human aspects in SE, published in other databases with less coverage. However, the four databases mentioned were selected for their wide scope in the areas of engineering, SE, and Computer Science, as well as their frequency of use among the scientific community as a source of recent and reliable information in the area.

This systematic mapping was carried out with 99 studies, published in journals or academic events. This amount may vary by including terms more specific to those used in this study (human aspects, human factors, soft skill). However, the sample of studies selected in this mapping made it possible to identify the aspects towards which the research has been oriented and to identify future work opportunities in the area.

6 Conclusions

This paper presents a systematic mapping that includes the review of 99 scientific studies related to the human aspects that have been of interest to measure in SE between 2010 and 2021. We analyzed the number of publications per year, by type of document, by country of affiliation of authors, by type of research, and by type of study.

Personality is the most studied human aspect in SE as an independent variable, mainly to explain the performance of SDT and to assign roles and form teams. However, there is a broad spectrum of human aspects that has already attracted the interest of some researchers, and where there are opportunities to delve deeper.

Human aspects are variables that are measured indirectly from other observable variables, so their latent nature allows surveys, through questionnaires and interviews, to be the most frequent source of data. The use of instruments based on self-reporting is frequent and, therefore, the results depend on the conditions under which the data were captured. Therefore, adopting methodologies that allow taking data that ensure consistency between what is done and what is said to be done is a challenge to be addressed.

Descriptive statistics was the most common method of data analysis, either to present preliminary results or as a method prior to others such as regression analysis or factor analysis. Statistical methods predominate in the analysis of the data obtained in these investigations, without forgetting the contribution of qualitative analysis when interviews are conducted. In any case, the usual practice of using several methods of analysis in the same study will depend on the nature of the data obtained.

This mapping suggests that the study of human aspects in HE is a topic of interest and is still under construction because there are several aspects that can be further explored. A systematic literature review for each aspect can clarify specific lines of work. Additionally, estimating the influence of human aspects on the efficiency, performance, or productivity of the SDT would allow designing intervention strategies focused on these aspects so that it is possible to improve the management of human talent in projects.

Future work is related to the use of specialized techniques in modeling the context as a dynamic system to determine the relationship between the different factors. One line of future work is related to broadening the scope of this research to include dimensions of social and human factors such as those related to happiness, stress management or anxiety, among others.

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