Human Capital in Software Engineering: A Systematic Mapping of Reconceptualized Human Aspect Studies

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Abstract The human capital invested into software development plays a vital role in the success of any software project. By human capital, we do not mean the individuals themselves, but involves the range of knowledge and skills (i.e., human aspects) invested to create value during development. However, there is still no consensus on how these broad terms of human aspects relate to the health of a project. In this study, we reconceptualize human aspects of software engineering (SE) into a framework (i.e., SE human capital). The study presents a systematic mapping to survey and classify existing human aspect studies into four dimensions of the framework: capacity, deployment, development, and know-how (based on the Global Human Capital Index). From premium SE publishing venues (five journal articles and four conferences), we extract 2,698 hits of papers published between 2013 to 2017. Using a search criteria, we then narrow our results to 340 papers. Finally, we use inclusion and exclusion criteria to manually select 78 papers (49 quantitative and 29 qualitative studies). Using research questions, we uncover related topics, theories and data origins. The key outcome of this paper is a set of indicators for SE human capital. This work is towards the creation of a SE Human Capital Index (SE-HCI) to capture and rank human aspects, with the potential to assess progress within projects, and point to opportunities for cross-project learning and exchange across software projects.

Keywords Human capital · Software engineering human capital · Human aspects · Systematic mapping

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1 Introduction

Software development involves a variety of human-intensive activities. Researchers refer to it as knowledge-intensive (Wohlin et al., 2015), with developers (i.e., humans) playing an important role the success of a software project (DeMarco and Lister, 2013). As an intangible asset, software development produces artifacts that lack physical substance (unlike physical assets such as machinery and buildings). Therefore, simply evaluating any software system in terms of the physical humans is not practical, as it involves a much more deeper investment of human activities related to the skills and knowledge that is created, retained and lost during development. The numerous metrics and frameworks defined to measure health is evidence of the difficulty when assessing the health of an OSS project (Crowston and Howison, 2006). To date, there is no single consensus on the broad terms related to human aspects in software engineering.

In economics, human investments are seen as capital – specifically intellectual capital, which is “the sum of all knowledge firms utilize for competitive advantage” (Nahapet and Ghoshal, 1998; Youndt et al., 2004; Wohlin et al., 2015) and can be characterized into different forms (e.g., human, social, relational, structural, etc.) Oxford handbook on Human Capital highlights the importance of human capital, that is, “all forms of intellectual capital including social and structural capital are arguably reducible to the human knower, thus human capital becoming the linchpin” (Burton-Jones and Spender, 2012). In software engineering, Wohlin et al. argues that intellectual capital is the bigger umbrella, hence defined human capital as a combined form of social and organization capital. Similarly, we do not distinguish other forms of intellectual capital, but instead use human-aspects to map into human capital.

A practical implementation of human capital is the Global Human Capital Index (GHCI) as proposed and reported by the World Economic Forum. In 2017, the GHCI 2017 ranked 130 countries on how well they are developing their human capital on a scale from 0 (worst) to 100 (best) across four thematic dimensions and five distinct age groups to capture the full human capital potential profile of a country. Our intention is to reconceptualize human aspects in software engineering (SE), hence, building a framework of software engineering human capital (SE human capital) which is similar to GHCI.

This paper is an investigation into how human aspects can be reconceptualized into SE human capital. We carried out a systematic mapping from five top journal articles and four top international conferences published between 2013 to 2017. Based on the GHCI framework, we then classified the 78 studies into four dimensions: capacity for skill attainment, deployment for a workforce, development for upskilling and reskilling, and know-how for specialized skills.

1 Capital covers people (i.e., human capital), the value inherent in its relationships (i.e., relational capital), and everything that is left when the employees go home (i.e., structural capital).
2 http://reports.weforum.org/global-human-capital-report-2017/
3 https://www.weforum.org
Table 1: Our proposed reconceptualization of human aspects classified into four human capital dimensions

| Dimensions | GHCI (Samans et al, 2017) | SE Human Capital (proposed) |
|------------|---------------------------|----------------------------|
| Capacity   | Formal educational attainment as a result of past education investment. | **Skill** attainment as a result of the past experiences in software ecosystems. |
| Deployment | Active participation in the workforce. | Active participation in the community. |
| Development| Formal education of the next-generation workforce and continued upskilling and reskilling of the current workforce. | Potential contributor involvement and upskilling and reskilling of contributors in the community. |
| Know-how   | Breadth and depth of specialized skills used in the workforce. | Breadth and depth of specialized skills (i.e., work practices) used in the community. |

The mapping study addresses three areas of SE human capital, which is (a) topics, (b) theories and (c) data origins. Results show that there are specific topics in each dimension. Regarding theories, we find that 18 papers described theories in their studies: 10 theories are identified including game theory, organization theory, signaling theory, and so on. In terms of the data, half of the papers tend to use multiple sources of data, often combining code and other assets. We also found that most papers studied OSS projects (83%), although some analyzed company data.

Our main contribution is a listing of *indicators* derived from summarizing the mapped studies. This listing is useful for constructing a SE Human Capital Index (SE-HCI) in the future. Much like the GHCI, the SE-HCI has potential to reveal insights into how projects develop their human capital and will be used as an important determinant of their long-term success.

The rest of the paper is outlined as follows. Section 2 presents a translation of the four dimensions in the GHCI to SE human capital. The systematic mapping methodology is then presented in Section 3, with the results to the research questions are presented in Section 4. Section 5 presents our indicators for the SE human capital. Finally, we conclude the study in Section 7.

2 A Reconceptualization of Human Aspects in SE

Inspired by the GHCI classification schema, Table 1 presents a summarized reconceptualization of the four dimensions into a SE context. We now describe the rationale for each translated dimension from GHCI into SE human capital.

*Capacity:* A more educated population is better prepared to adapt to new technologies, innovate and compete on a global level. Thus, GHCI defines ca-
pacity as formal education such as primary, secondary and tertiary levels of attainment (Samans et al, 2017). For open source software development, there is no formal education in general. Instead, skills from experience is key. A previous replication study reported that having a computer science or a software engineering background is not helpful during a requirement inspection, but having high experiences is significantly more effective (Albayrak and Carver, 2014). Considering these differences, we define capacity in SE human capital as the skill attainment of individuals from the past development experiences.

**Deployment:** Beyond formal learning, global human capital is enhanced in the workplace through learning-by-doing, tacit knowledge, exchange with colleagues and formal on-the-job learning. For GHCI, the deployment dimension measures how many people are able to participate actively in the workforce as well as how successfully particular segments of the population are able to contribute (Samans et al, 2017). The labor force participation of a country (i.e., employment rates) is the broadest measure of the share of its people participating in the labor market. In the SE context, abstraction is where the community involves developers that belong to a single project. However, there are cases where the community covers a larger set of developers that contribute to an ecosystem of dependent projects. We define the deployment dimension as understanding community structure or social interaction and measures how many contributors actively participate in the community.

**Development:** The development dimension in GHCI concerns current efforts to educate the next-generation workforce and continued upskilling and reskilling of the current workforce (Samans et al, 2017). Similarly, in our definition, the development dimension is potential contributor involvement, upskilling and reskilling of current contributors in the community.

**Know-how:** Know-how is concerned with the breadth and depth of specialized skills used in the workplace. In GHCI, the economic complexity is a measure of the degree of sophistication of a country’s “productive knowledge” as can be empirically observed in the quality of its export products. In addition, the GHCI measures the current level availability of high- and mid-skilled opportunities and, in parallel, employer’s perceptions of the ease or difficulty of filling vacancies (Samans et al, 2017). In the SE context, we define the know-how dimensions as breadth and depth of specialized skill (i.e., work practices) used in the community, for example, the proportion of core or peripheral contributors’ performance and knowledge loss caused by contributors’ leaving the community.

3 A Systematic Mapping of Human Capital in SE

To realize SE human capital, we carried out a detailed systematic mapping to classify related studies into the four dimensions (i.e., presented in Section 2).
A systematic mapping is more appropriate over a system literature review as (i) it is a repeatable method for identifying relevant studies to answer specific research questions ([MacDonell et al., 2010]) and (ii) it is designed to give an overview of a research area through classification and counting contributions in relation to the categories of that classification ([Kitchenham and Charters, 2007]; [Petersen et al., 2008, 2015]; [Kitchenham et al., 2010]) and (iii) it does not have strict rules compared to systematic literature reviews; therefore, various types of papers can be covered.

3.1 Research Questions

As part of the mapping study, we use the following research questions to describe and validate our reconceptualization of SE human capital:

**RQ1:** What SE topics relate to SE human capital?

Our intention is to investigate what human aspect topics and common SE terminology are often used to describe SE human capital.

**RQ2:** What theories have been analyzed for SE human capital studies?

We conjecture that there are different kinds of theories being analyzed and adapted for human aspect studies. Those theories indicate previous study interests in various human aspects from interrelated concepts, definitions, and propositions to explain or predict events or situations related to specific dimensions of human capital.

**RQ3:** Where does the data originate from for studies related to SE human capital?

We would like to understand what kind of different data sources are used to uncover evidence of human capital. In detail, we extract data characteristics, such as data sizes, durations and diversities related to each dimension.

3.2 Systematic Mapping Overview

Similar to the systematic mapping study performed by [Abelein et al., 2015], we consider the following characteristics recommended by [Kitchenham and Charters, 2007]:

- (C₁) a defined search strategy
- (C₂) a defined search string, based on a list of synonyms combined by ANDs and ORs
- (C₃) a broad collection of search sources
- (C₄) a strict documentation of the search
- (C₅) quantitative and qualitative papers should be analyzed separately
- (C₆) explicit inclusion and exclusion criteria
- (C₇) paper selection should be checked by two researchers

Figure 1 presents an overview of the mapping study design, which follows (C₁) a defined search strategy. Our method is comprised of two parts, the
3.2.1 Step 1: Collection of Papers

Table 2 shows the sources of papers for our mapping, along with their impact factors (IF) and conference rankings (the CORE Conference Ranking of 2017). To ensure a high quality of papers and to understand the state-of-the-art in the field, we specifically searched for papers in the top journals and conferences from the software engineering domain. To reduce its selection bias, we selected from a range of digital resources to follow (C3) a broad collection

\[\text{http://www.core.edu.au}\]
Table 2: Targeted SE journals and conferences with rankings and impact factors (IF) as of 2017

| Journal (TSE) | IEEE Transaction on Software Engineering | IF: 2.63 |
|---------------|------------------------------------------|----------|
| (EMSE)        | Empirical Software Engineering            | IF: 3.28 |
| (ASEJ)        | Automated Software Engineering Journal    | IF: 3.27 |
| (TOSEM)       | ACM Transactions on Software Engineering  | IF: 2.87 |
|               | and Methodology                           |          |
| (IST)         | Information and Software Technology       | IF: 2.69 |
| (ICSE)        | International Conference on Software Engineering | Rank: A* |
| (ESEC/FSE)    | ACM Join European Software Engineering and Symposium on Foundation of Software Engineering | Rank: A* |
| (ICSME)       | International Conference on Software Maintenance | Rank: A |
| (MSR)         | Working Conference on Mining Software Repositories and Evolution | Rank: A |

As shown in Figure 1, we extracted 2,698 papers from the four search sources, which map to the top ten publication venues for software engineering. Additionally, we only included technical papers, hence filtering out short papers, editorials, tutorials, panels, poster sessions and prefaces and opinions (i.e., we automatically filtered out any papers that was shorter than 8 pages). Since our intention is to understand the current trends of human-related research, we collected papers that were published in the last five years (i.e., 2013 – 2017).

3.2.2 Step 2: Identification of Research

To provide a comprehensive picture of recent research related to human capital, we used \( C_2 \) a defined search string to identify the research area. In this step, we conducted the first automated \( C_6 \) explicit inclusion and exclusion criteria based on the search results.

Figure 2 shows the two terms (term 1 and term 2) used in our search string. To understand human-related areas in SE, we formulate term 1 to include developer, human, social, collaboration, population, and so on. To capture synonyms and other extensions, as shown in Table 3, we stem and use the keywords contribu*, activit* and communi* to expand the search space. Since, we are interesting in more generic human-related research from the SE domain, our search string also includes a exclusion list (i.e., term 2). We exclude words in term 2 to avoid papers that are specific to particular research topics in SE.

5 https://dl.acm.org/
6 http://ieeexplore.ieee.org/Xplore/home.jsp
7 http://www.sciencedirect.com/
8 https://link.springer.com/
Search Terms in title, abstract, keywords

Term 1
(developer) OR (contribut*) OR (human) OR (activit*) OR (communi*) OR (social) OR (collaboration) OR (population)

NOT

Term 2
(agile) OR (cloud) OR (visualization) OR (mobile) OR (refactoring) OR (framework) OR (api) OR (design) OR (testing) OR (embed) OR (reverse engineering) OR (specification) OR (tool) OR (debug)

Fig. 2: Defined search strings

Table 3: Synonyms of Keywords used in the search.

| Base Term  | Synonyms                     |
|------------|------------------------------|
| contribut* | contributor, contribution    |
| activit*   | activity, activities         |
| communi*   | community, communities, communication(s) |

Fig. 3: The process flow of the strict documentation procedure followed \((C_4)\) to obtain 340 papers.

such as agile, cloud, reverse engineering, and so on. We apply these search strings to the title, abstract and keywords sections of targeted papers.

As shown in Figure 1, we end with 340 papers after our automatic search execution. For ICSE and MSR conferences, we found that special editions of ICSE14 and MSR14 were only published in the ACM Digital Library and not the Xplore. Figure 3 shows the details of remaining papers from the original 2,698 papers collected in Step 1.
3.2.3 Step 3: First Manual Exclusion

To complete the initial phase, Step 3 involves the manual exclusions from the collected 340 papers. This step involves (C6) an explicit inclusion and exclusion criteria to remove papers that have a different context and focus to our research area.

For this manual exclusion, the following inclusion and exclusion criteria were applied to the abstract of each paper.

**Inclusion criteria:** Only a single inclusion criterion is defined, namely, (IC1), the paper should focus on humans (i.e., software developers and contributors in a project).

**Exclusion criteria:** Three exclusion criteria were defined that cover the datasets, purposes, and the evaluation of the studies. The following papers were excluded.

- (EC1) the paper does not analyze any activity data
- (EC2) the purpose of the paper is collecting activity data
- (EC3) the paper intends to evaluate their proposed methods

Papers of survey and meta studies (in the qualitative category) were excluded if their primary studies meet the above exclusion criteria. To reduce bias and follow (C7), this manual paper selection was performed by the first and the second authors. As a result of Step 3, we were able to reduce the collected 340 papers to 101 papers.

3.2.4 Step 4: Second Manual Exclusion of Qualitative and Quantitative papers

Similar to Step 3, we use the same inclusion and exclusion criteria (i.e., IC1, EC1, EC2 and EC3) for the quantitative papers in Step B-4. However, Step 4 includes a full reading of all contents of the paper. Finally two exclusion criteria have been added to Step B-4:

- (EC4) the paper focuses on software artifacts (i.e., products)
- (EC5) the paper proposes human recommendation techniques

For the qualitative papers in Step 4-A, we add another criterion for exclusion (EC6) the paper focuses on specific techniques, systems, or phenomena which differs from the theme of human aspects. In this manual analysis, we added the third author (i.e., making the total number of reviewers to three) to increase the confidence and the quality of our survey. As a result of Step 4, we were able to reduce the initial 101 papers to 69 papers (26 qualitative and 43 quantitative papers).

3.2.5 Step 5: Consolidation of Results

In this step, three processes are performed. First, we conduct a review of excluded papers, as recommended by [Petersen et al. 2015](#). Some papers (i.e.,
two qualitative and seven quantitative papers) were included that were excluded in the initial phase, bringing the final papers to 78 in total (29 qualitative and 49 quantitative papers).

Figure 4 shows the number of papers identified within the years 2013–2017 to each research category (qualitative and quantitative). We see that from 2014 both qualitative and quantitative papers have been consistently published. Figure 5 shows a heat map of the number of paper publications in
Table 4: Summary of the paper classification into each dimension and quantitative and qualitative categories. Underlines indicate papers mutually inclusive in one or more dimensions.

| Dimension   | Paper         | Quantitative | Qualitative |
|-------------|---------------|--------------|-------------|
| Capacity    | S09, S16, S18, S26, S39, S74 |              | S47, S65    |
| Deployment  | S01, S02, S08, S12, S14, S17, S19, S27, S29, S34, S42, S43, S44, S50, S53, S66, S67, S69, S70, S71, S76, S78 | S07, S24, S28, S36, S38, S45, S48, S59, S63 | |
| Development | S22, S31, S33, S49, S55, S72 | S03, S11, S46, S56, S57, S68 | |
| Know-how    | S05, S10, S15, S20, S21, S23, S30, S32, S35, S40, S50, S54, S58, S64, S73, S74, S75 | S04, S06, S13, S25, S37, S41, S51, S52, S60, S61, S62, S77 | |

Each conference or journal in each year. This shows that many papers related to human aspects have been presented in IST, ICSE and EMSE.

Next, three reviewers classified all collected papers into the dimensions. A consensus was reached among all the reviewers on which dimension best described the paper. Our classifications allow for mutually inclusive, thus papers can belong to multiple dimensions. We used the following rationales used to classify each paper, which were based on the rationales presented in Section 2.

- **Capacity** - Papers that discuss learning experiences of contributors.
- **Deployment** - Papers that discuss contributor participation.
- **Development** - Papers that discuss potential contributor involvement and learning within their community.
- **Know-how** - Papers that discuss work practices in their community.

Table 4 shows the results of the classifications of the collected papers (the papers are presented in Appendix A). Results indicate that much research has been carried out on the deployment and know-how dimensions.

### 4 Results of the Mapping

In this section, we present and discuss results of the systematic mapping in terms of human aspect topics (i.e., RQ1), theories (i.e., RQ2) and data (i.e., RQ3) that were classified into SE human capital. For each research question, we first introduce the approach to answer before we present each result.
Fig. 6: Topic co-occurrence networks for each dimension. The size of nodes represent the frequencies of topics, and the width of edges represent the frequencies of topics co-occurrences. GSD represents ‘global software development’ and SLR is ‘systematic literature review’.

4.1 RQ$_1$: Topics Discussed in SE Human Capital

**Approach to answer RQ$_1$**: Our approach includes a visualization and n-gram modeling to show what topics are discussed for the different dimensions. Kuhrmann et al (2017) reported the usefulness of word clouds (tag clouds) for dataset cleaning in their systematic literature study experiences. Word clouds visualize the occurrences of words or terms in documents. Similar to their ideas of automatically extracting keywords as references, we extract n-gram
Table 5: Topic pairs with high co-occurrence.

| Dimension   | Topic pair                        | # co-occurrence |
|-------------|-----------------------------------|-----------------|
| Capacity    | personality & team                | 2               |
|             | personality & success             | 2               |
|             | performance & success             | 2               |
| Deployment  | OSS & community                   | 4               |
|             | OSS & communication               | 4               |
|             | OSS & productivity                | 4               |
| Development | popularity & user                 | 3               |
|             | popularity & OSS                  | 3               |
| Deployment  | practice & challenge              | 6               |
|             | practice & OSS                    | 6               |
|             | pull request & GitHub              | 5               |

terms in a paper as topics by applying \textit{n-gram} IDF \cite{shirakawa2015,shirakawa2017}. N-gram IDF is a theoretical extension of Inverse Document Frequency (IDF) for handling multiple terms and phrases by bridging the theoretical gap between term weighting and multi-word expression extraction \cite{shirakawa2015,shirakawa2017}. Terdchanakul et al. \cite{terdchanakul2017} reported that n-gram keywords detected with n-gram IDF were useful for bug report classification. N-gram Weighting Scheme tool\footnote{https://github.com/iwnsew/ngweight} is used to extract n-gram topic keywords from title, abstract, and keywords in the collected papers. Using a list of obtained n-gram keywords as a reference, we identified two to five keywords as topics for each paper. After integrating different expressions into the same terms (‘open source software’ is replaced with OSS, for example), co-occurrences of topics are analyzed.

For the analysis results, we display topics within a dimension as connected networks, with the nodes representing the frequencies of topics and the width of the edges representing the frequency of topic co-occurrences. Sets of topics (keywords) for the collected papers are presented in Appendix \ref{appendix:a}.

\textbf{Results}. Findings show that the extracted topic keywords correspond to the definitions of SE human capital (see Table \ref{table:human_capital}), thus providing a validation as well as insights into each dimension. Figure \ref{fig:network} presents topic co-occurrence networks for each dimension. These networks provide insights into frequently studied topics. We can see individual frequent keywords in each dimension and their relations in the networks. Furthermore, Table \ref{table:topic_pairs} summarizes frequently appeared topic keyword pairs in the same papers for the four human capital dimensions. In capacity, individual personality linking to team or success, or performance and overall success have been mainly studied. In terms of deployment, community, communication, and productivity in OSS have been widely targeted for the studies. For development, popularity among users, and popularity of OSS projects have been major interests. Finally, in know-how, much of the topics are related to practices as seen in Figure \ref{fig:network}. The topics of
Table 6: Percentages of the collected papers discussing theories

| Dimension   | Percentage | Paper                                      |
|-------------|------------|--------------------------------------------|
| Capacity    | 75% (6/8)  | S09, S16, S18, S26, S39, S65               |
| Deployment  | 16% (5/31) | S01, S14, S34, S67, S71                    |
| Development | 0% (0/12)  |                                            |
| Know-how    | 24% (7/29) | S06, S23, S32, S40, S52, S54, S58         |

Table 7: Theories in the selected papers. Underlines indicate papers mutually inclusive, showing that multiple theories are employed.

| Theory                                      | Paper                                      |
|---------------------------------------------|--------------------------------------------|
| Psychology/Psycholinguistics                | S01, S06, S09, S16, S18, S39, S54, S65, S71 |
| Game theory                                | S14, S67                                   |
| Group dynamics                             | S52, S67                                   |
| Organization theory                        | S23, S71                                   |
| Demography                                 | S34                                        |
| Food web (ecology)                         | S23                                        |
| Financial risk management                  | S40                                        |
| Information field theory                   | S26                                        |
| Knowledge-based theory of the firm          | S58                                        |
| Signaling theory                           | S32                                        |

practices in OSS and their challenges have been mainly studied. In addition, GitHub-related research have been popular, with links to pull requests.

4.2 RQ2: Theories Analyzed in SE Human Capital

Approach to answer RQ2. Our approach includes a manual reading of all 78 collected papers, extracting each theory and grouping them into common types. Similar to the mapping study, the first author manually extracts the type of theory used, looking for explicit keywords or a clear description of the theory in each paper. Later, the results are validated with a consensus by the other co-authors. Note that papers can contain multiple theories. This is common, especially for empirical studies, that may employ mixed methods and various techniques and test several theories in a large study. Analysis of the results includes a frequency count of each type of theory as well as their groupings into their respective dimensions.

Results. Findings show that although a variety of theories are employed in SE research, many SE human aspect studies do not explicitly state their underlying theories. Out of the 78 collected papers, only 18 papers described theories in their studies. Grounded theory is excluded because it is a systematic methodology rather than a specific theory. We see in Table 6 that most papers categorized in capacity discussed theories, and no paper in development refers any theories.
Table 8: Summary of data sources of SE human capital into the four dimensions. Underlines indicate papers mutually inclusive, showing that multiple data sources where used in the papers. Note that VCS includes other version control system other than git. Other abbreviations are Bug Tracking System (BTS) and Issue Tracking System (ITS).

| Dimension     | Percentage | Source | Paper |
|---------------|------------|--------|-------|
| Capacity      | 13% (1/8)  | Jazz   | S16   |
| Deployment    | 68% (21/31)| VCS    | S12, S27, S42, S66, S69, S70, S76 |
|               |            | ML/Chat| S12, S17, S19, S22, S42, S64, S66, S67, S69 |
|               |            | GitHub | S02, S14, S34, S53, S71 |
|               |            | BTS/ITS| S08, S19, S29, S69 |
|               |            | Other  | S02, S19, S43, S50, S78 |
| Development   | 50% (6/12) | VCS    | S31, S49 |
|               |            | ML/Chat| S33 |
|               |            | GitHub | S55 |
|               |            | BTS/ITS| S72 |
|               |            | Other  | S22, S72 |
| Know-how      | 55% (16/29)| VCS    | S15, S28, S40, S63, S75 |
|               |            | ML/Chat| S15, S44, S75 |
|               |            | GitHub | S05, S21, S30, S32, S35 |
|               |            | BTS/ITS| S20, S23, S32, S64, S73 |
|               |            | Jazz   | S54 |
|               |            | Other  | S10, S50, S58, S73, S75 |

Table 8 summarizes theories analyzed in the identified 18 papers. We found 10 theories including game theory, organization theory, signaling theory, and so on. Psychology/psycholinguistics is the most popular; it was referred in nine papers. For instance, there were several papers that borrowed concepts from various aspects of the human psychology (i.e., S01 – creation of models for team leader roles with personality types and gender classifications, S06 – the success factors in global software development studied with a questionnaire, and S09 – an experiment of personality factors and group processes). Although some theories were adopted in multiple papers, six theories appeared only in single papers.

4.3 \textbf{RQ}_3: Data Sources Used in SE Human Capital

\textbf{Approach to answer} \textit{RQ}_3. Similar to \textit{RQ}_2, our approach includes a manual reading of the 49 quantitative collected papers, extracting each data source and grouping them. Similarly, the first author manually extracts the data-source related information, then later reports to other co-authors for a validated consensus. Firstly, we extract the type of data management system (source) from which the data originated from (i.e., GitHub, version control system (VCS), Bug Traking System (BTS), Issue Tracking System (ITS) and so on.) Note that papers can originate from multiple data sources. Furthermore, we would like to understand other useful data information such as (a) the number of projects
where analyzed in each paper, (b) the time period of the data collection, (c)
whether the data is Open Source or company data and (d) whether the data is
taken from multiple sources. Analysis of the results includes a frequency count
of each type of data source as well as their groupings into their respective
dimensions.

Results. Findings show that although a variety of data sources are be-
ing employed in SE research, that analyze multiple project over a five to six
year period. Data sources are investigated from 49 quantitative papers. For reproducibility of measurement, we focus on archived data sources and exclude seven papers of experimentation studies (S01, S09, S18, S26, S39, S44, and S74). Table 8 summarizes data sources used in 42 quantitative papers. Note that others refers to rarely used data sources in the collected papers, such as closed company data, stack overflow, code review, web documents, gerrit code review and Ruby API systems. Compared to the percentages of theories used in Table 6, the percentage of capacity papers is the lowest, that is, most studies categorized in capacity did not analyzed archived data sources. We consider that capacity-related studies using archived data is a challenging research topic and currently missing. Papers belonging to the other three dimensions used various and common data sources, such as version control systems (VCS), mailing lists (ML) and chat data, GitHub archives, bug tracking systems (BTS) and issue tracking systems (ITS).

Figure 7 shows a detailed classifications of data sources (i.e., size as the number of analyzed projects, analyzed periods, data origins, and varieties of data sources) in 42 quantitative papers. Although only a small number of projects analyzed single projects for their studies, some papers used more than 100 projects. For example, the paper S21 used 58,092 projects in their study. Regarding analyzed periods, we found many papers analyzed more than five years data. Another interesting finding is that most papers used OSS projects (83%) compared to closed company data. In regards to data sources, about half of the papers used multiple sources, often combining code from other sources (i.e., as shown in Table 8) in their studies.

5 Indicators for SE Human Capital

The key outcome of this study is a set of indicators for the different dimensions of SE human capital. Based on the results of the mapping study and results of the three research questions, we were able to extract candidate indicators that map to each dimension. Table 9 describes our proposed indicators and the mapping to their respective inspired collected papers. This is another mapping of existing papers towards the future creation of a SE human capital index (SE-HCI); all 79 papers are categorized into 13 indicators. We now describe the rationale and definition of each indicator by dimension and related studies.

Capacity Dimension

1. **Contributer activity profiling** - This indicator captures the skill attainment based on individual contributor activities. One of related papers is a study about measuring team personality and climate (i.e., S09). This study measured the neuroticism, extroversion, conscientiousness and all that of developers from their experiment. Another study is related to personality profiles of developers (i.e., S16). This study analyzed message exchanges or developers’ tasks using code and assets data source.
Table 9: Proposed SE human capital indicators mapped to the collected papers. Underlines indicate papers mutually inclusive, showing that a papers can contain multiple indicators.

| Dimension       | Indicator                          | Quantitative                                                                 | Qualitative                                                                 |
|-----------------|------------------------------------|------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Capacity        | Contributor activity profiling     | $S09, S16, S18, S26, S39, $S74                                               | $S47, S65                                                                   |
| Deployment      | Community diversity                | $S01                                                                         | $S28, S38                                                                   |
|                 | Community social interaction       | $S02, S08, S12, S17, S19, S29, S42, S50, S66, S67, S69, S70, S71          |                                                                              |
|                 | Community structural complexity    | $S14, S27, S34, S63                                                        |                                                                              |
| Know-how        | Participation rates                | $S53, S78                                                                    | $S38, S63                                                                   |
|                 | Productivity rates                 | $S08, S12, S19, S27, S42, S44, S66                                          | $S24, S53, S63, S71                                                        |
|                 | Workload equality                  | $S76                                                                        |                                                                              |
| Development     | Developer learning-curve           | $S31, S49                                                                    | $S11, S56                                                                   |
|                 | End-user participation             | $S22, S33, S55, S72                                                         | $S03, S46, S57, S68                                                       |
| Know-how        | Core contributor knowledge         | $S15, S20, S54                                                              |                                                                              |
|                 | Knowledge loss rates               | $S40                                                                        |                                                                              |
|                 | Maturity of work practices         | $S05, S10, S23, S30, S32, S35, S50, S58, S64, S73, S74, S75                | $S04, S06, S13, S25, S37, S41, S51, S52, S60, S61, S62, S77               |
|                 | Onboarding rates                   | $S21                                                                        |                                                                              |

**Deployment Dimension**

1. **Community diversity** - This indicator measures the diversity within the community. For example, S01 studied team leadership roles with personality types and gender classification. It used experimental data to develop a model for software development team composition by keeping gender as a major effecting variable with personality. Furthermore, study S38 identified barriers for female participation on stack overflow by interviewing female contributors about contribution barriers in online communities.

2. **Community social iteration** - The social interaction indicator is a measure of contributor collaboration and communication within the community. Examples include a study about communication in open source software development mailing lists (i.e., S17) and a study about identification of contributors’ collaborations from different sources by analyzing source code co-changes (i.e., S29).
3. Community structural complexity - This indicator focuses on the complexity of the community. An example is studying about population structure in OSS projects (i.e., S34). This study created a population pyramid considering the contributors’ activity periods in the community. Another example is a study about the impacts of organizational factors on software quality (i.e., S59), where authors reported observations of an in-house software development project within a large telecommunications company.

4. Participation rate - This indicator describes contributor participation in a particular activity such as code review (i.e., S53, S78). S53 investigated the phenomena of inactive code review contributors from activities such as pull requests, while S78 is a study about review participation in code review, introducing several metrics such as purpose, history, and prior activities of reviewers and patch authors.

5. Productivity rate - This indicator measures the productivity of contributors. For instance, study S24 investigated performance measurement practices related to software product development activities by interviewing managers how they perceive and evaluate performance in large organizations from a managerial perspective. On the other hand, study S44 is about sensing developers’ emotions, progress and the use of biometric measures.

6. Workload equality - This indicator focuses on workload of contributors in the community. Example studies include observation of the variation and specialization of workload in an ecosystem community to identify developers’ activity types and comparing the number of files that developers modify (i.e., S76).

Development Dimension

1. Developer learning-curve - This indicator is a developer-centric measurement of skill development. For example, study S31 investigated the effect of the Google summer of code by comparing developers’ activities in OSS projects before and after participating the Google summer of code event. Another study conducted a questionnaire to investigate the impressions, motivations, and barriers of one time code contributors to FLOSS projects (i.e., S56).

2. End-user participation - This indicator is a user-centric measurement of skill development. For instance, previous study analyzed how end-users and their communities use public repositories (i.e., S22). Another study investigated factors that impact the popularity of GitHub repositories (i.e., S55). This work analyzed stars awarded to GitHub projects and analyzed the popularity growth of these repositories.

Know-how Dimension

1. Core contributor knowledge - This indicator explores the knowledge of core contributors (compared to peripheral contributors). For instance,
study S15 classified developers into core and peripheral by proposing network metrics. Another example is a study about determining developers’ expertise and roles (i.e., S20). This study analyzed bug tracker and source code repositories to characterize developers.

2. Knowledge loss rates - This indicator investigates the loss of knowledge because of contributors’ leaving from the community. For instance, study S40 quantified and investigated how to mitigate turnover-induced knowledge loss. In detail, it quantified the extent of abandoned source files using source code history and assessed knowledge loss.

3. Maturity of work practices - This indicator measures the degree of work practices used in contributors’ software development processes. For instance, study S05 is concerned with a pull-based software development model. It explored how pull-based software development worked by analyzing pull requests and comments history. On the other hand, study S10 explored the prior beliefs of developers at Microsoft, confirming beliefs to actual empirical data.

4. Onboarding rates - This indicator measures the retention of contributors in the community. Study S21 analyzed the technical factors of past experience and social factors of past connections to understand onboarding in software projects.

6 Threats to Validity

A key threat to the systematic mapping is the selection process, which was mostly carried out by the first author of this paper. The initial round was mostly done using the abstract and titles. To mitigate this bias, the next rounds of exclusions and inclusions were validated by two other co-authors. As shown in Figure 1, which follows the mapping guidelines [Kitchenham and Charters, 2007], five method papers and four survey papers that were initially discarded were later included in the final consolidation of the papers.

The second possible bias is the keywords that were used in the search string. An alternative method includes performing a snowballing of references to get papers [Jalali and Wohlin, 2012]. To mitigate this threat, we used reliable sources of only the premium conferences and recognized journals in software engineering (i.e., ranked as A to A++ only with impact factors higher than 2.63)\(^{10}\).

The final threat to the study is the scope of exclusion and inclusion of the papers collected. First, our scope does not include any papers published before 2013. In line with our main goal, we would like to understand the more recent and applicable metrics that measure modern OSS projects. Hence, the study of older papers is prone to reveal obsolete metrics that cannot be applied to current technology platforms (i.e., GitHub). Second, as shown in Figure 2, our search terms revolves around the eight inclusion keywords and fourteen exclusion terms. A threat is that there could be other papers that were excluded.

\(^{10}\) taken from [http://www.core.edu.au](http://www.core.edu.au) rankings
due to this exclusion. We are confident that this case is highly unlikely, as those papers would have a more narrow focus (i.e., human aspects in cloud technologies). Furthermore, since the SE human capital is a generalized abstract of human capital, we assume that the metrics used in those specialized papers would not be useful.

7 Conclusion

In this paper, we use a systematic mapping to understand human capital, especially in the field of software engineering. We carried out a systematic mapping from five top journal articles and four top international conferences published between 2013 and 2017. Based on the economic Global Human Capital Index (GHCI) framework, we then identified and classified 78 studies into four dimensions: capacity for skill attainment, deployment for a workforce, development for upskilling and reskilling, and know-how for specialized skills.

The key outcome of this mapping study is a set of indicators for future constructing a software engineering (SE) HCI. Much like the GHCI, the SE-HCI can be used to understand how projects develop their human capital and be used as an important determinant of their long-term success than virtually any other factors. We envision that HCI as a ranking of software projects to capture the full human capital potential profile. For future work, we aim to implement the SE-HCI as a tool to assess progress within projects and point to opportunities for cross-project learning and exchange across projects.

A References of Collected Papers

S01 Gilal et al (2016) Abdul Rehman Gilal, Jafreezal Jaafar, Mazni Omar, Shuib Basri, and Ahmad Waqas. A rule-based model for software development team composition: Team leader role with personality types and gender classification. Information and Software Technology, 74:105–113, 2016.
Topics: team, personality, performance, gender

S02 Palyart et al (2017) Marc Palyart, Gail C. Murphy, and Vaden Masrani. A Study of Social Interactions in Open Source Component Use. IEEE Transactions on Software Engineering, 5589(c):1–1, 2017.
Topics: social interaction, community, OSS

S03 Bano and Zowghi (2015) Muneera Bano and Didar Zowghi. A systematic review on the relationship between user involvement and system success. Information and Software Technology, 58:148–169, 2015.
Topics: user, success, challenge, SLR

S04 Bjarnason et al (2016) Elizabeth Bjarnason, Kari Smolander, Emelie Engström, and Per Runeson. A theory of distances in software engineering. Information and Software Technology, 70:204–219, 2016.
Topics: distance, challenge, practice
S05 Gousios et al. (2014) Georgios Gousios, Martin Pinzger, and Arie Van Deursen. An Exploratory Study of the Pull-Based Software Development Model. *Proceedings of the 36th International Conference on Software Engineering*, 345–355, 2014. 
Topics: GitHub, community, pull request

S06 Vizcaíno et al. (2013) Aurora Vizcaíno, Félix García, José Carlos Villar, Mario Piattini, and Javier Portillo. Applying Q-methodology to analyse the success factors in GSD. *Information and Software Technology*, 55:1200–1211, 2013. 
Topics: success, GSD, challenge, knowledge

S07 Schultis et al. (2014) Klaus-Benedikt Schultis, Christoph Eilsner, and Daniel Lohmann. Architecture Challenges for Internal Software Ecosystems: A Large-Scale Industry Case Study. *Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering*, 542–552, 2014. 
Topics: ecosystem, industry, challenge

S08 Ortu et al. (2015) Marco Ortu, Bram Adams, Giuseppe Destefanis, Parastou Tournari, Michele Marches, and Roberto Tonelli. Are Bullies more Productive? Empirical Study of Affectiveness vs. Issue Fixing Time. *Proceedings of the 12th IEEE/ACM Working Conference on Mining Software Repositories*, 303–313, 2015. 
Topics: emotion, productivity, developer

S09 Acuña et al. (2015) Silvia T Acuña, Marta N Gómez, Jo E Hannay, Natalia Juristo, and Dietmar Pfahl. Are team personality and climate related to satisfaction and software quality? Aggregating results from a twice replicated experiment. *Information and Software Technology*, 57:141–156, 2015. 
Topics: team, personality, software quality, satisfaction

S10 Devanbu et al. (2016) Prem Devanbu, Thomas Zimmermann, and Christian Bird. Belief & Evidence in Empirical Software Engineering. *Proceedings of the 38th IEEE/ACM International Conference on Software Engineering*, 108–119, 2016. 
Topics: developer, practice, evidence

S11 Wnuk et al. (2014) Krzysztof Wnuk, Per Runeson, Matilda Lantz, and Oskar Weijden. Bridges and barriers to hardware-dependent software ecosystem participation - A case study. *Information and Software Technology*, 56(11):1493–1507, 2014. 
Topics: barrier, ecosystem, communication

S12 Xuan and Filkov (2014) Qi Xuan and Vladimir Filkov. Building It Together: Synchronous Development in OSS. *Proceedings of the 36th International Conference on Software Engineering*, 222–233, 2014. 
Topics: OSS, productivity, communication

S13 Niazi et al. (2016) Mahmood Niazi, Sajjad Mahmood, Mohammad Alshayeb, Mohammed Rehan Riaz, Kanaan Faisal, Sifat Ullah Khan, and Ita Richardson. Challenges of project management in global software development: A client-vendor analysis. *Information and Software Technology*, 86:1–19, 2016. 
Topics: challenge, GSD, SLR

S14 Hata et al. (2015) Hideaki Hata, Taiki Todo, Saya Onoue, and Kenichi Matsumoto. Characteristics of Sustainable OSS Projects : A Theoretical and Empirical Study. *Proceedings of the 8th International Workshop on Cooperative and Human Aspects of Software Engineering*, 15–21, 2015. 
Topics: OSS, community, GitHub
S15 Joblin et al (2017a) Mitchell Joblin, Sven Apel, Claus Hunsen, and Wolfgang Mauerer. Classifying Developers into Core and Peripheral: An Empirical Study on Count and Network Metrics. Proceedings of the 39th IEEE/ACM International Conference on Software Engineering, 164–174, 2017.
Topics: developer, network, knowledge

S16 Licorish and Macdonell (2015) Sherlock A Licorish and Stephen G Macdonell. Communication and personality profiles of global software developers. Information and Software Technology, 64:113–131, 2015.
Topics: communication, personality, GSD

S17 Guzzi et al (2013) Anja Guzzi, Alberto Bacchelli, Michele Lanza, Martin Pinzger, and Arie Van Deursen. Communication in open source software development mailing lists. Proceedings of the 10th IEEE International Working Conference on Mining Software Repositories, 277–286, 2013.
Topics: communication, OSS, team

S18 Bergersen et al (2014) G R Bergersen, D I K Sjoberg, and T Dyba. Construction and Validation of an Instrument for Measuring Programming Skill. IEEE Transactions on Software Engineering, 40(12):1163–1184, 2014.
Topics: success, practice, knowledge, performance

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Topics: productivity, success, team, software quality

S20 Bhattacharya et al (2014) Pamela Bhattacharya, Iulian Neamtiu, and Michalis Faloutsos. Determining developers’ expertise and role: A graph hierarchy-based approach. Proceedings of the 30th International Conference on Software Maintenance and Evolution, 11–20, 2014.
Topics: developer, expertise, community

S21 Casalnuovo et al (2015) Casey Casalnuovo, Bogdan Vasilescu, Premkumar Devanbu, and Vladimir Filkov. Developer onboarding in github: The role of prior social links and language experience. Proceedings of the 10th Joint Meeting on Foundations of Software Engineering, 817–828, 2015.
Topics: GitHub, team, productivity

S22 Stolee et al (2013) Kathryn T Stolee, Sebastian Elbaum, and Anita Sarma. Discovering how end-user programmers and their communities use public repositories: A study on Yahoo! Pipes. Information and Software Technology, 55:1289–1303, 2013.
Topics: community, user, challenge, popularity

S23 Posnett et al (2013) Daryl Posnett, Raissa D’souza, Premkumar Devanbu, and Vladimir Filkov. Dual Ecological Measures of Focus in Software Development. Proceedings of the 35th International Conference on Software Engineering, 452–461, 2013.
Topics: practice, software quality, network

S24 Cedergren and Larsson (2014) Stefan Cedergren and Stig Larsson. Evaluating performance in the development of software-intensive products. Information and Software Technology, 56:516–526, 2014.
Topics: performance, practice, organization
S25 Baum et al. (2016) Tobias Baum, Olga Liskin, Kai Niklas, and Kurt Schneider. Factors Influencing Code Review Processes in Industry. Proceedings of the 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering, 85–96, 2016. Topics: code review, industry, OSS

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S27 Joblin et al. (2015) Mitchell Joblin, Wolfgang Mauerer, Sven Apel, Janet Siegmund, and Dirk Riehle. From Developer Networks to Verified Communities: A Fine-Grained Approach. Proceedings of the 37th IEEE/ACM International Conference on Software Engineering, 563–573, 2015. Topics: network, community, software quality, productivity

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S29 Panichella et al. (2014) Sebastiano Panichella, Gabriele Bavota, Massimiliano Di Penta, Gerardo Canfora, and Giuliano Antoniol. How developers’ collaborations identified from different sources tell us about code changes. Proceedings of the 30th International Conference on Software Maintenance and Evolution, 251–260, 2014. Topics: developer, network, communication, OSS

S30 Ma et al. (2017) Wanwangying Ma, Lin Chen, Xiangyu Zhang, Yuming Zhou, and Baowen Xu. How do Developers Fix Cross-project Correlated Bugs? A case study on the GitHub scientific Python ecosystem. Proceedings of the 39th IEEE/ACM International Conference on Software Engineering, 381–392, 2017. Topics: GitHub, ecosystem, challenge, practice

S31 Silva et al. (2017) Jefferson O. Silva, Igor Wiese, Daniel German, Igor Steinmacher, and Marco A Gerosa. How Long and How Much: What to Expect from Summer of Code Participants? Proceedings of the 33rd International Conference on Software Maintenance and Evolution, 69–79, 2017. Topics: OSS, community, success, participation, experience

S32 Tsay et al. (2014) Jason Tsay, Laura Dabbish, and James Herbsleb. Influence of Social and Technical Factors for Evaluating Contribution in GitHub. Proceedings of the 36th International Conference on Software Engineering, 356–366, 2014. Topics: GitHub, OSS, practice, pull request

S33 Gala-Prez et al. (2013) Santiago Gala-Pérez, Gregorio Robles, Jesús M González-Barahona, and Israel Herranz. Intensive Metrics for the Study of the Evolution of Open Source Projects: Case Studies from Apache Software Foundation Projects. Proceedings of the 10th Working Conference on Mining Software Repositories, 159–168, 2013. Topics: evolution, OSS, popularity
S34 Onoue et al (2016) Saya Onoue, Hideaki Hata, Akito Monden, and Kenichi Matsumoto. Investigating and projecting population structures in open source software projects: A case study of projects in GitHub. *IEICE Transactions on Information and Systems*, E99D(5):1304–1315, 2016.
Topics: OSS, GitHub, community, population

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Topics: GitHub, OSS, pull request, community

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Topics: OSS, practice, GitHub, popularity, pull request

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Topics: barrier, community, expertise

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Topics: personality, success, emotion

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Topics: risk, GSD, SLR

S42 Gharehyazie and Filkov (2017) Mohammad Gharehyazie and Vladimir Filkov. Tracing distributed collaborative development in apache software foundation projects. *Empirical Software Engineering*, 22(4):1795–1830, 2017.
Topics: developer, OSS, team, productivity

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Topics: emotion, productivity

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Topics: challenge, satisfaction, community

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Topics: success, practice, satisfaction, performance

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Topics: personality, performance, success, team

S48 Nguyen-Duc et al (2015) Anh Nguyen-Duc, Daniela S Cruzes, and Reidar Conradi. The impact of global dispersion on coordination, team performance and software quality – A systematic literature review. Information and Software Technology, 57:277–294, 2015.
Topics: GSD, SLR, performance, software quality

S49 Kim and Jiang (2014) Youngsoo Kim and Lingxiao Jiang. The Learning Curves in Open-Source Software (OSS) Development Network. Proceedings of the 6th International Conference on Electronic Commerce, 41–48, 2014.
Topics: OSS, network, developer, learning

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Topics: knowledge, communication, team

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Topics: team, challenge, knowledge, practice

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S60 Coelho and Valente (2017) Jailton Coelho and Marco Tulio Valente. Why Modern Open Source Projects Fail. *Proceedings of the 11th Joint Meeting on Foundations of Software Engineering*, 186–196, 2017. Topics: OSS, practice, success

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Topics: OSS, network, productivity

S67 Wang and Redmiles (2016) Yi Wang and David Redmiles. Cheap talk, cooperation, and trust in global software engineering. *Empirical Software Engineering*, 21(6):2233–2267, 2016.
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