Is NOT Talking About our Impact on Others Harmful?

Adrian Schröter
Univeristy of Victoria, Canada
schadr@uvic.ca

Daniela Damian
University of Victoria, Canada
danielad@cs.uvic.ca

ABSTRACT

Investigating the human aspect of software development becomes more and more prominent in current research. We study the communication and technical dependencies between developers, because developers are introducing failures into the product they develop. Observing the social networks constructed from the communication and dependencies can reveal harmful patterns that increase the chance of introducing errors. We build social networks for each software build in the IBM Jazz™ project using all discussions and changes related to the build. The Jazz™ project contains 21 pairs of developers that are technically dependent on each other but did not communicate. If any of the aforementioned pairs exists in a build, the build has an 80% chance of failure.

Categories and Subject Descriptors

D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*; D.2.9 [**Software Engineering**]: Management—*Programming Teams*; K.6.1 [**Management of Computing and Information Systems**]: Project and People Management—*Systems development*; K.6.3 [**Management of Computing and Information Systems**]: Software Management—*Software development*

General Terms

Human Factors, Measurement, Management

Keywords

Social Networks, Technical Networks, Socio-Technical Networks, Builds, Failures, Socio-Technical Congruence

1. INTRODUCTION

Ensuring a smooth progress during software development is key for a project to stay within budget and on schedule. Failures introduced into the source code often require an extensive amount of time to fix, especially if caught only at integration time. Time spent on fixing bugs uses up project budget and hinders development progress.

In the last decade, research has documented multiple reasons for software failures, both on the technical and the human side of software development. On the technical side, studies showed that technical dependencies in the code (e.g. [19, 50]) are powerful predictors of error. On the human side, human and organizational factors have been found to strongly affect how these technical dependencies are handled [13, 24] and thus affected software quality [6, 23]. Coordinating to handle technical dependencies in a project becomes ever more challenging as the level of interdependencies between tasks increases [18], especially in large [11] and distributed projects [12, 24].

Complementary to studies that relate coordinatioon to software defects (e.g. [6]), we investigate the relationship between team coordination and the success of its code integration activity. In our previous work [44] we found that properties of the social networks representing the communication behavior around software integrations can predict integration failure. Here we seek to further our understanding on the influence of communication by studying the misalignment between technical and social dependencies.

Therefore, we conduct a finer grain investigation at the level of developer-developer dependency in these work groups. Seeking to identify to what extent the misalignment of technical and social dimensions is linked to coordination failure, we pose the question "*Is NOT talking about our impact on others really harmful?*". It is important to gain more insights into the communication at the level of developers and not the entire team. Onlythese insights can be used to enhance coordination among team members before the integration fails and thus prevent a project slow down.

We study technical dependencies and communication in IBM's Jazz™ project in relation to software builds. Jazz™ is a development environment that focuses on collaboration support and tightly integrates programming, communication, and project management (http://www.jazz.net). One insight from our study is, for example, that out of 16 builds where developers Adam and Bart changed the same file without communicating, 13 builds failed while 3 succeeded, and that this developer pair significantly increased the risk of a build to fail.

In our methodology we investigated social networks that represent communication and technical dependencies among developers, extracted from several points in time, to unveil pairs of developers that repeatedly occur in networks that can be related to failure. Using the repository of the Jazz™ team, we explore the social networks that capture the discussions and changes impacting a software build. The outcome of a build can either be a working program or an error that either occurred during compiling or testing.

Overall, we found that a small number of developer pairs that did not communicate are statistically related to build failure. Moreover, if one of those pairs is present in a social network of a build, the build has at least an 80% chance to fail.

2. RESEARCH QUESTIONS

Recent research in socio-technical congruence [7], the study of the effects of alignment between social and technical elements on a development project, found evidence that this alignment influences the productivity of development teams [7]. The idea behind socio-technical congruence (STC) is that if people are technically dependent (e.g. working on interdependent tasks) they should coordinate [10]. If they do not coordinate appropriately, they will slow down progress of others dependent on their tasks. The slow down occurs when developers need to wait on others' tasks to complete or to make corrections, which in turn, requires more changes [16].

Recent findings show a relation between high socio-technical congruence and high productivity. To add to those findings, we study integration failure to determine whether STC has a similar relationship to the coordination outcome of developers If two developers work on interdependent tasks and their changes impact one another, they should coordinate. In case they do not coordinate, they may introduce failures into the software that make the upcoming integration fail. Therefore, our first research question:

RQ1: Can socio-technical congruence predict integration failure?

Socio-technical congruence implies the underlying concept of socio-technical *gaps* between developers. When the coordination need of two developers is not met by social interaction, they are said to form a gap. Research has generally assumed that these gaps are problematic (e.g. [16]). They are responsible for a weak socio-technical congruence and have been said to be responsible for lowering productivity [7]. Gaps may also be responsible for developers introducing bugs into the source code, for instance if a develoepr changes the behavior of a method a co-worker uses, the co-workers code might break during integration. Hence, we investigate if gaps in STC can generally be related to integration failures.

RQ2: Do socio-technical gaps lead to integration failure?

If we can relate socio-technical gaps to integration failure, we seek to provide explanation as to why they may be failure-related. For example, research suggests that different factors, such as team distribution [3] and problem domain [40], influence software quality.

The answer to our two research questions and their additional explanation enable us to devise strategies to fill socio-technical gaps. Those strategies leverage the inter-personal communication that are most important for the coordination outcome and are useful for both developers and managers.

3. RELATED WORK

Since we are building on the notion of socio-technical congruence we compare technical and social dependencies among developers. To represent such dependencies among developers a network with the respective is most appropriate. This leads us to three different types of developer networks: (1) social networks that capture ongoing coordination, such as communication, (2) technical networks that use source code dependencies to code owners, and (3) socio-technical networks, which combine social and technical networks. We use those networks to observe reoccurring patterns across those networks.

3.1 Networks in Software Engineering

Following, we will discuss how the three network types have been used in software engineering research to study software development.

3.1.1 Social Networks

Software engineering research shows an increasing interest in the human part of software development. To study developer interactions in a software project several techniques have been borrowed from social sciences. A number of studies uses social network analysis techniques to investigate the relation between developer social networks and different success measures, such as project success. These measures range from software quality measures over productivity to project success.

The mining software repository community described different approaches to mine social networks from software repositories, like email lists (e.g. [2]). Gonzales-Barahona et al. [29] used social networks to characterize whole projects, in contrast to Yu and Ramaswamy [47] who investigated different roles developers take on in software projects. Huang and Liu [28] study used a similar granularity level to draw conclusions about the learning processes in projects.

Wolf et al. showed how to mine social networks from repositories [45] and used their properties to predict the outcome integrating the software parts within teams [44]. Meneely et al. [31] found similar evidence by extracting developer networks on file level by using code churn information. Several studies at Microsoft [3, 34] showed that different kinds of distance between people that work together on a binary determine failure likelihood.

Ehrlich et al. [15] looked into how social networks can be used to leverage knowledge in distributed teams. Backstrom et al. [1] took a more general approach and investigated the evolution of large social network and the information they hold. Chung et al. [8] reported in recent work about behavior of individuals while performing knowledge intensive tasks. There have been a number of studies that investigated communication structures to identify good practices (e.g. [4, 25–27, 46]). In contrast to study the general development process Marczak studied social networks to idenify best practices for requirements management processes [30].

We use social networks to describe the communication between developers related to a build.

3.1.2 Technical Networks

Much research was concerned with the technical side of software development. This technical side is often concerned with the source code. Using code ownership we can use source code to connect developers constructing a technical network. In technical networks connections between people are derived from dependencies often extracted from source code. There are two major ways we observed to build technical networks: (1) Using explicit source code dependencies and (2) using implicit source code dependencies:

Explicit code dependencies have been used to construct dependency graphs between source code entities such as classes or methods. These dependency graphs can be constructed either for a complete project or per change made to the source code [21]. For instance, Nagappan et al. used several code complexity metrics to build failure prediction models [33].

Implicit code dependencies are often not visible in the source code itself. Those implicit dependencies can be aspects that connect different source code entities [42]. Source code management systems can make aspects or other implicit relationships visible by inspecting which files have been changed together [32].

Zimmermann et al. [49,50] used those technical networks to predict the failure probability of files. Similarly Pinzger et al. [36] build networks of developers connected via code artifacts to predict failures. Previous research was using technical networks for failure prediction by extraction complexity metrics, such as cyclomatic complexity or object oriented metrics, that are derived from technical networks [33].

We record technical networks describing relations between developers for each build in Jazz™ derived from co-changed files.

3.1.3 Socio-Technical Networks

In recent years research has started to investigate the effect of social and technical relations of software developers. Socio-technical networks focus on developers and connect them with two kinds of edges, social and technical. The initial idea of investigating the alignment between the communication and technical dependency between developers was formulated by Conway [10].

Expanding on this idea Cataldo et al. [7] formulated a coefficient that measures the alignment of the social and technical networks defining the term of socio-technical congruence. Moreover they observed that higher socio-technical congruence leads to higher developer productivity [7]. Others picked up on that notion and coefficient to further investigate the effect of congruence (e.g. [43]). Ducheneaut [14] investiagted the evolution of the social and technical relationships of open source project participants to see how those participants become a part of the comunity.

From research on socio-technical congruence emerges the question about what role gaps play. A gap in STC exists if two developer have a coordination need they do not meet. Ehrlich et al. [16] investigated gaps and found that files that are changed by developers which form a gap are more prone to change.

To leverage the relation of socio-technical congruence and optimizing task completion times Sarma et al. [37] developed TESERACT to visualize and explore the socio technical networks in a project. Besides software engineering research we found studies that look into socio-technical relationships in management science (e.g. [41]).

We pick up on the idea on making STC knowledge actionable and investigate congruence on the build level to give recommendations to prevent failures [39].

3.2 Pattern Mining in Software Engineering

Patterns in software engineering can either project specific or more general. In both cases a pattern describes a reoccurring event, such as after a project deadline people update source code documentation [38]. Good patterns are then used to form templates that can be used in the future. Bad patterns on the other hand can be used to identify harmful events that might cause problems. Note that good and bad can be defined in many ways.

Project Specific. Schröter et al. [40] extracted package usage information and found that using certain packages increases the chance of a file containing a failure. Neuhaus et al. [35] extended on that approach and investigated used packages in relation to vulnerabilities in Mozilla Firefox. Zimmermann er al. [48] developed eRose, an Eclipse plug-in that scans a source code repository for co-changed lines and makes recommendations for future changes.

General. Programs such as FindBugs [9] isolated anti patterns in source code, such as code smells, that have often been observed with failures. The book "Design Patterns" [20] gives general guidelines to construct better software by giving examples on working designs.

We look for patterns in the project history that concern social and technical relations between developers and their relation to build outcome. In our approach we focus on simple patterns that are comprised only of a pair of developers that are connected via a technical dependency.

4. METHODOLOGY

Our methodology to answer our research questions explains how we construct socio-technical networks. We use those networks to analyze socio-technical congruence and socio-technical gaps both in relation to integration outcome in software projects. Below we describe our methods we used to collect data on coordination and integration from the Jazz™ repository. Subsequent, we describe the methods we use to construct and analyze social networks associated with these integrations.

4.1 Data Collection

In the following we describe what data we use to extract social networks that we extend to socio-technical network.

4.1.1 Coordination and Integrations in Jazz

We analyze builds in the Jazz™ repository to study coordination and integrations in Jazz. The Jazz™ team integrates on different levels and in different intervals, for instance on the team or project level in a nightly and weekly interval. Each build and therefor integration includes a number of changesets. A *changeset* consists of changes to one or more files in a project, comparable to a transaction in the source code management system Subversion (http://subversion.tigris.org). Furthermore, information about a build is stored in the Jazz™ repository. This includes the time the building process started, if the build succeeded and passed its test cases, and the built product. But if we refer to the build outcome we are talking about whether it could be built and if it passed all test cases.

We investigate the Jazz™ builds between April and July 2008. We choose this time interval because this represents the interval with the most complete history of builds. The Jazz™ development team deletes builds that are less important due to space reasons. Thus older builds besides builds that represent important milestones have been deleted.

From this time interval we extracted a total of 244 builds (see Table 1 for details), specifically 70 failed builds and 174 successful builds. Each build has on average 32 changesets, with a changeset touching 29 files on average. Note that there are some builds that have only one changeset associated with them. These are project wide builds that accumulate all changes made by all teams into one changeset.

4.1.2 Extracting Social Networks

We first construct *social networks* to capture the coordination behavior of developers invovled in a build. We use the information contained in the Jazz™ workitems for the construction. A *workitem* in Jazz™ is the basic unit of work. It describes a general task which can be, but is not restricted to, a bug fix or feature request. Developers coordinate about work on workitems by posting comments in a discussion board style which we use as conceptualization of their coordination behavior.

We are interested in constructing a social network for each build in Jazz™. To create a social network for a given build we proceed in six steps:

	Successful	Failed	Total
min #WorkItem	1	1	1
avg #WorkItem	16.68	26.52	19.63
max #WorkItem	111	109	111
min #ChangeSet	1	1	1
avg #ChangeSet	26.71	46.27	32.57
max #ChangeSet	227	194	227
min #Developers	1	1	1
avg #Developers	19.62	28	22.16
max #Developers	64	71	71

Table 1: Statistics on Jazz data: builds, changesets, workitems, and developers.

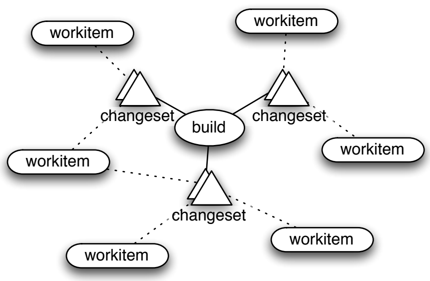


Figure 1: Linking workitems to builds using changesets.

1. Select the build of interest.
2. Extracting changesets that are part of the build.
3. Extracting workitems linked to the retrieved changesets.
4. Extracting developers commenting on a workitem before the build's built time.
5. Connect all developers commenting on the same workitem.

These steps take us as illustrated in Figure 1 from a build through a changeset to a workitem. From the workitem we are able to see who contributed to the workitem discussion (see Figure 2). These developers become part of the social network and share a *social edge* if they made a comment on the same workitem. Note that all links we use to get from a build to a developer are explicitly contained in the Jazz™ repository.

4.1.3 Extending to Socio-Technical Networks

To construct *socio-technical networks* we use the steps described below (see Figure 4). We essentially add technical edges to the build's already constructed social network. In our conceptualization a *technical edge* is a source code dependency between two developers. A technical dependency between two developers exists if they changed the same source code file in the build of interest.

1. Extract the changesets that are part the build (Figure 4(a)).
2. Determine changeset owners and add those that are not already part of the social network (Figure 4(b)).
3. Add a technical edge between changeset owners that changed the same file (see Figure 3).

We thus call a network that contains both social and technical edges a *socio-technical network*. The developers in the socio-technical network that share both a technical and social edge are said to share a *socio-technical edge*.

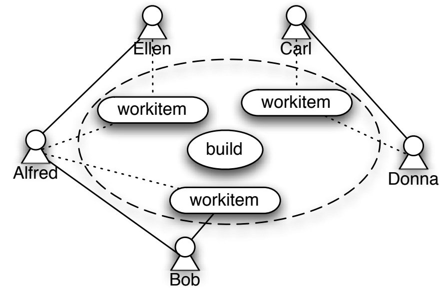


Figure 2: Social network connecting developers through workitem discussions linked to a build

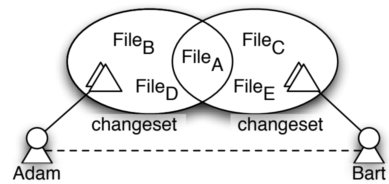


Figure 3: Conceptualization of technical relation using co-changed files.

4.2 Data Analysis

We perform two analyses on the networks we collected, starting with comparing the socio-technical congruence index for successful and failed builds, followed by a more detailed investigation of socio-technical gaps in relation to build outcome.

4.2.1 Build Outcome and STC Predictive power

To answer our first research question, we investigate the build outcome and the socio-technical congruence for all builds. Socio-technical congruence (STC) describes the match between the coordination needs in a development team as demanded by technical interdependencies and the ongoing coordination among developers.

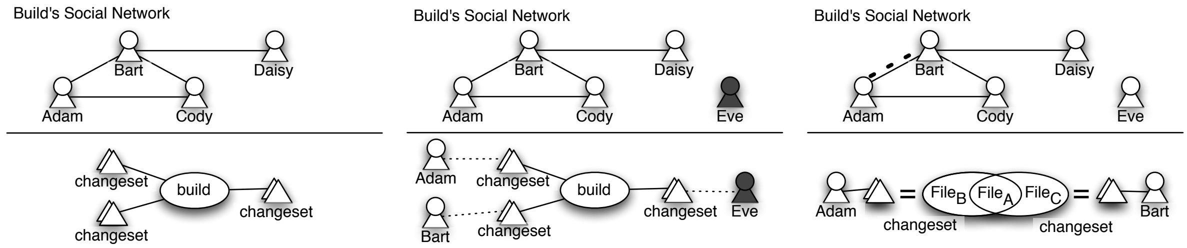
In calculating the STC index for each build's socio-technical network, we use the measure defined by Cataldo et al. [7], which is the ratio between the number of coordination needs that are met and the number of all coordination needs. The index ranges from 0 (no congruencet) to 1 (perfect congruence).

We conceptualize the coordination needs with technical edges and the ongoing coordination with social edges. Thus the socio-technical congruence index is determined by the number of socio-technical edges (number of met coordination needs) over the number of technical-edges (number of coordination needs). We compute this index for all socio-technical networks.

Since each build has an assigned build outcome (successful or failed), we split each build's socio-technical congruence index into two bins. To determine whether socio-technical congruence can be used to distinguish between successful and failed builds we perform a Wilcoxon signed rank test.

4.2.2 Analysis of Socio-Technical Gaps

Socio-technical gaps occur when coordination needs are not met by ongoing coordination. As such, we are interested in analyzing pairs of developers that share a technical edge (implying coordination need) but no social edge (implying unmet coordination need) in socio-technical networks. We refer to these pairs of developers as *technical pairs*, and to those that do share a socio-technical edge



(a) Identify all changesets related to the social network's build.

(b) Adding changeset owners that are not part of the social network.

(c) Connect Adam and Bart with a technical edge via the co-changed File$_A$.

Figure 4: Creating a socio-technical network by adding technical dependencies to a build's social-network.

(there is no gap) as *socio-technical pairs*.

To answer our second research question, we are interested in whether the technical pairs are related to build failure. Our analysis proceeds in four steps:

1. Identify all technical pairs from the socio-technical networks.

2. For each technical pair count occurrences in socio-technical networks of failed builds.

3. For each technical pair count occurrences in socio-technical networks of successful builds.

4. Determine if the pair is significantly related to success or failure.

For example, in Table 2 we illustrate the analysis of the technical pair (Adam, Bart). This pair appears in 3 successful builds and in 13 failed builds. Thus it does not appear in 171 successful builds, which is the total number of successful builds minus the number of successful builds the pair appeared in, and it is absent in 57 failed builds. A Fisher Exact Value test yields significance at a confidence level of α = .05 with a p-value of $4.273 \cdot 10^{-5}$.

Note that we adjust the p-values of the Fisher Exact Value test to account for multiple hypothesis testing using the Bonferroni adjustment. The adjustment is necessary because we deal with 961 technical pairs that need to be tested.

To enable us to discuss the findings as to whether closing socio-technical gaps are needed to avoid build failure, or which of these gaps are more important to close, we peform a two additional analyses. First we analyze whether the socio-technical pairs also appear to be build failure-related or not, by following the same steps as above for socio-technical pairs. Secondly, we prioritize the developer pairs using the coefficient p_x, which represents the normalizd likelihood of a build to fail in the presence of the specific pair:

$$p_x = \frac{\text{pair}_{failed}/\text{total}_{failed}}{\text{pair}_{failed}/\text{total}_{failed} + \text{pair}_{success}/\text{total}_{successs}}$$

The coefficient is comprised of four things: (1) pair$_{failed}$, the number of failed builds where the pair occurred; (2) total$_{failed}$, the number of failed builds; (3) pair$_{success}$, the number of successful builds where the pair occurred; (4) total$_{success}$, the number of successful builds. This coefficient is normalized with the number of failed and successful builds. A value closer to one means that the developer pair is strongly related to build failure. Additionally it describes a probability of failure likelihood that accounts for the imbalance in the data.

	success	failure
(Adam, Bart)	3	13
¬ (Adam, Bart)	171	57

Table 2: Contingency table for technical pair (Adam, Bart) in relation to build success or failure

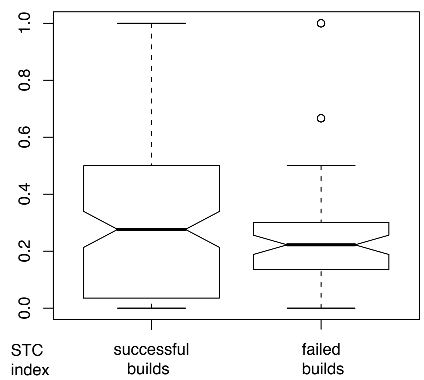


Figure 5: Boxplot of the STC index associated with successful (left) and failed (right) builds.

5. RESULTS

In this section we present our findings, starting with the investigation of the relation between socio-technical congruence and build success. Next we show the results we obtained from analyzing technical pairs.

5.1 STC and Build Outcome

We divide the socio-tecnical networks according to the respective build outcome, to see whether the socio-technical index [7] can be used to determine build success. After performing a Wilcoxon Signed Rank test with the hypothesis that the two populations are different at a confidence value of α = .05, we rejected the hypothesis (p = 0.2135). This implies that socio-technical congruence cannot differentiate between successful and failed builds and thus we cannot answer our first research question with yes.

The box plot in Figure 5 shows the two distributions of the networks according to build outcome. The medians of both categories (middle line) indicate a STC index of 0.27 and 0.22 for successful and failed builds respectively. The upper and lower boundaries of a box represent the 75% and 25% percentile respectively and the wiskers denote the 90% and 10% percentiles. All data points outside the 10-90% interval are shown as outliers.

Technical Pair	#successful	#failed	coefficient p_x
Cody-Daisy	0	12	1.0000
Adam-Ina	0	8	1.0000
Adam-Kim	0	8	1.0000
Adam-Nina	0	6	1.0000
Fred-Gina	0	6	1.0000
Gina-Oliver	0	6	1.0000
Adam-Daisy	1	14	0.9720
Bart-Daisy	1	9	0.9572
Adam-Lisa	1	8	0.9521
Bart-Eve	2	11	0.9318
Adam-Bart	**3**	**13**	**0.9150**
Bart-Cody	3	13	0.9150
Adam-Eve	4	16	0.9086
Daisy-Ina	3	12	0.9086
Cody-Fred	3	10	0.8923
Bart-Herb	3	10	0.8923
Cody-Eve	5	15	0.8817
Adam-Jim	4	11	0.8723
Herb-Paul	5	12	0.8564
Mike-Rob	6	13	0.8434
Adam-Fred	6	13	0.8434

Table 3: Twenty-one *technical pairs* that are failure-related

Socio-technical Pair	#successful	#failed	coefficient p_x
Adam-Cody	0	9	1.0000
Lisa-Sarah	0	8	1.0000
Bart-Ina	0	7	1.0000
Tom-Xavier	0	6	1.0000
Vince-Xavier	0	6	1.0000
Bart-Will	3	13	0.9150
Zac-Eve	**3**	**10**	**0.8923**

Table 4: Seven *socio-technical pairs* that are failure-related

5.2 Socio-technical Gaps and Build Outcome

We found a total of 961 technical pairs. While only 21 pairs are significantly correlated with build failure (see Table 3), none are correlated with successful builds. Similarly, we investigated whether specific socio-technical pairs influence build outcome and found that 7 pairs significantly correlated with build failure (see Table 4) while none correlated with successful builds. Note that we use fictitious names for confidentiality reasons.

We rank the the 28 identified technical and socio-technical pairs (see Tables 3 and 4) by the coefficient p_x. This coefficient indicates the strength of relationship between the developer pair and build failure. In other words p_x represents the normalized likelihood that a build that has the respective pair will fail. Note that all p_x values are above 84%. Below we describe how to read Tables 3 and 4:

Technical Pairs. Table 3 lists all 21 technical pairs that are significant according to the Fisher Exact Value test and ranks them according to the coefficient p_x. For instance, the developer pair (Adam, Bart), appears in 13 failed builds and in 3 successful builds. This means that pair$_{failed}$ = 13 and pair$_{success}$ = 3 with total$_{failed}$= 70 and total$_{success}$= 174 result in p_x= 0.9150.

Socio-Technical Pairs. Table 4 lists all 7 socio-technical pairs are significantly related to build failure. For instance, the developer pair (Zac, Eve), appears in 10 failed builds and in 3 successful builds. This means that pair$_{failed}$ = 10 and pair$_{success}$=3 with total$_{failed}$ =70 and total$_{success}$=174 result in p_x = 0.8923.

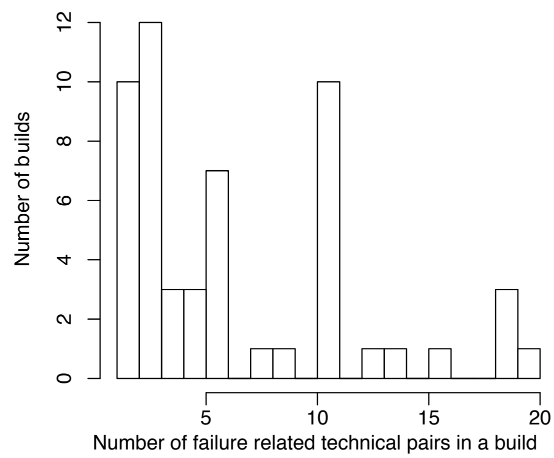


Figure 6: Histogram plotting how many builds have a certain number of failure-reated technical pairs.

The failure-related technical pairs span 55 out of the total 70 failed builds in the project. Figure 6 shows their distribution across the 55 failed builds. The histogram illustrates that there are few builds that have a large number of failure related builds, e.g. 4 with 18 or more pairs, but most builds only show a small number of pairs (22 out of 54 failed builds have 2 or less). This distribution of technical pairs indicate that the developer pairs we found did not concentrate in a small number of builds. In addition, it validates the assumption that it is worthwhile seeking insights about developer coordination in failed builds. Moreover, this enables us to explain why two thirds of the builds failed.

6. DISCUSSION

We first discuss the results that directly relate to our research questions and provide some explanations from our knowledge of the development process and developers in the Jazz™ project. Then we discuss some interesting insights about the failure related developer pairs that we found. We outline a number of implications for practice based on insights gained from socio-technical gaps to design collaborative tools.

6.1 STC and Build Outcome

Our analysis found that in Jazz, the socio-technical congruence index does not influence build outcome. Similarly, only a small number (21 out of 961, 2%) of technical pairs could be related to build failure. This indicates that those developer pairs that did not talk to each other although they shared a technical dependency were generally not harmful in the Jazz™ project. Below we give two reasons we believe might be responsible for why our results are different from existing literature:

- *Development process.* Many processes focus on reducing the amount of unnecessary coordination between developers. For example, a process might demand the generation of component specifications. Developers working with the specified components may not explicitly coordinate their work but use these specifications. Thus, the process reduces socio-

Developer	#Harmful Pairs	Team	Role
Adam	9	TeamA	Contributor
Bart	5	TeamB	Contributor
Cody	4	TeamA	Contributor
Daisy	4	TeamC	Contributor
Eve	3	TeamB	Contributor
Fred	3	TeamB	Contributor
Gina	2	TeamC	Contributor
Herb	2	TeamA	TeamLead
Ina	2	TeamB	Contributor
Jim	1	TeamA	Contributor
Kim	1	TeamC	Contributor
Lisa	1	TeamD	Contributor
Mike	1	TeamE	Contributor
Nina	1	—	—
Oliver	1	TeamC	Contributor
Paul	1	TeamB	Contributor
Rob	1	TeamF	Contributor

Table 5: List of developers with number of failure related technical pairs they appear in as well as their team and role.

technical congruence by removing the need to talk about certain technical dependencies.

- *Developer experience.* Experienced developers are capable of assessing the impact of a technical dependency and thus the need to talk about it. If a developer knows how technical dependencies affect others work, by for example reading others code [5], then he can act without the need to talk to the respective other developer. This, in turn, lowers the socio-technical congruence because developers do not need to talk about as many technical dependencies.

The IBM Jazz™ development team mostly consists of experienced developers that were part of the Eclipse development or part of IBM Rational™. Establishing communication channels and communicating itself is easy in Jazz™, which is additionally supported by the Eclipse Way of development [17]. Similar to other mature development processes, the Eclipse Way produces specifications of software components that others can rely on, thus reducing the need to explicitly coordinate.

6.2 Investigating Failure-Related Pairs

Our analysis revealed 21 technical pairs that significantly correlate to builds failure. Although this number as compared to the overall number of technical pairs is low, their high p_x values (all above 84%) indicate a strong likelihood that their presence in a build will result in failure. Moreover, their distribution across all failed builds indicates that they were not located in only a few builds but actually spanned the majority of builds. But what makes those pairs so dangerous? We discuss below our investigation of four characteristics of these pairs:

Developer characteristics. We present the distinct developers that appear in the failure related pairs in Table 5. The table contains the number of failure related technical pairs the respective developer was part of. We see that Adam appears in 9 out of the 21 harmful pairs. After performing a similar Fisher Exact Value test to determine if the developer is an influencing factor whether a pair is failure related or not we found that the developer has significant influence.

To perform this Fisher Exact Value test we counted in how many harmful pairs and in how many not harmful pairs the developer appears. Together with the number of total harmful and not harmful pairs, we can use the Fisher Exact Value test to see if the developer make it more likely if a pair is harmful.

In addition we also tested the presence of a developer in a build already suffices to make it more likely that a build fails. The results of the corrected Fisher Exact Value tests all turned out to be significant at an $\alpha = .05$ level. This implies that there might be skill or habits that a developer exhibits, that may be harmful to the build outcome.

Developer Roles. Similar to the analysis of the individual developer it makes sense to investigate individuals at a more abastract level. We see that according to Table 5 the most harmful role is of *contributor*. To ensure the validity of this claim we performed a Fisher Exact Value test to see if the role influences the likelihood that a pair is associated with build failure.

The Fisher Exact Value tests did not yield any significant findings. The two roles we looked at, contributor and leader, are very common and especially the concept of role is very coarse. This means that in the Jazz™ project the explicit assigned roles at this granularity level do not make any difference with respect to build failure.

Membership to Teams. Usually people work in teams rather than on their own, where each team is entrusted with developing a specific part of the software project. Table 5 also contains the teams to which developers belong to. TeamA spans more failure related technical pairs mostly due to the fact that Adam is part of 9 failure related technical pairs. But to be able to give a reasonable explanation why it seems that working with TeamA is more harmful, we need to investigate the teams in the future in more detail.

We observe that most of the harmful pairs do not have developers from the same team. We found only three pairs where both developers are from the same team. This is in accordance with other research that suggests coordination across distance is problematic (e.g. [11, 22]).

Developers Geographical location. We planned to investigate the influence of geographical location on the different pairs. But in the data we are analyzing, the pairs found in the Jazz™ project, geographical location and team coincide. Thus the analysis of location and team yield the same results.

Now that we have more insights into the developer pairs that are related to build failure, the next step would be to advise strategies to break those patterns.

6.3 Practical Implications

Our findings have several implications for the design of collaborative systems. We can incorporate the knowledge about developer pairs that tend to be failure related in a real-time recommender system. Not only do we provide the recommendations that matter, we also provide incentives to motivate developers to talk about their technical dependencies.

Project historical data can be used to calculate the likelihood that the builds fails given a particular developer pair that worked on that build without talking to each other. In the case of the pair (Adam, Bart) we would recommend that these developers should talk about their technical dependencies. Thus, we inform them that the next build will fail with a probability of 91% if they do not follow the recommendation. This probability does not only serve as way to rank importance of a socio-technical gap but also as an incentive to act upon.

For management, such a recommender system can provide details about the individual developers in, and properties of, these potentially problematic developer pairs. Individual developers may be an explanation for the behavior of the pairs we found in Jazz™. This may indicate developers that are harder to work with or too busy to coordinate appropriately, prompting management to reorganize teams and workloads. This would minimize the likelihood of a build to fail, by removing the underlying cause of a pair to be failure related.

Similarly, all but two developer pairs consist of developers that were part of different teams. Management may decide to investigate reasons for coordination problems that include factors such as geographical or functional distance in the project.

7. THREATS TO VALIDITY

During our study we identified three main threats. One threat covers issues that arise from the underlying data we used. The second threat deals with possible problems from our conceptualization and the third is concerned with the influence of confounding variables.

7.1 Data

We performed all our analysis on one set of data, the Jazz™ repository. This limits our generalizability due to the fact that we only made the observations within one project. Due to the reasonable project size and the project properties, reaching from incorporating open source practices, such as open development and encouraging community involvement, assures that the results still hold value.

Furthermore we only investigated three months of the projects lifetime. This might lead to smaller significance of our results. Since the three months are directly before a major release of the project we think that it contains the most viable data for our analysis. In those three months a lack of necessary coordination is the most harmful to the project.

Another threat that arises from the data we gathered is the possible lack of recorded communication. This and the possibility of people coordinating without communicating, such as reading each others source code [5], are mitigated by the development process. In Jazz™ the development process demands that the developers need to coordinate using workitem discussion. Moreover, our mining approach tries to account for that by ensuring that we only retrieve technical pairs that are statistically related to build failure.

7.2 Conceptualization

Our conceptualization of the three edges we are using in the socio-technical network might introduce inaccuracy into our findings. Social edges are extracted from workitem discussions. We assumed that every developer commenting on or subscribed to a work item reads all comments of that work item. This assumption might not always be correct. By manual inspection of a selected number of work items, we found that developers who commented on a work item are aware of the other comments, confirming our assumption.

The technical edges are not problematic by themselves, but they are not complete, since there are more technical relationships between developers that can be examined. For example, two developers can be connected if one developer changes someone else's code. This however does not invalidate our findings it just suggests that there is room for improvement we should address next.

Socio-technical edges on the other hand may suffer from the combination of social and technical edges. For example, it is not necessarily true that if she communicated with a developer she is dependent that they communicated about their dependency. Since the changes to source code files we use to extract technical dependencies are attached to workitem discussion, we are confident that they addressed the changes at least indirectly.

8. CONCLUSION AND CONSEQUENCES

Identifying ways to guarantee smooth progress in developing software is a major concern of software engineering research. Failing to build or having failing tests cause trouble and mean that developers need to spend time on fixing those issues to progress in the development. We think that one of the sources for failures is lack of coordination.

To investigate the relation between the lack of coordination and build outcome we represent each build by its socio-technical network, combining communication as social edges, and co-changed files as technical edges. Analyzing the developer pairs that only share a technical edge in at least one build we found that only 21 out 961 of such pairs are statistically related to build failure. This suggests two things: (1) In general it is not necessary to talk about changes that effect others and (2) that there are a selected few developer that should talk.

As a next step we plan to expand the research into two directions:

Finer edges. We plan to refine all three edge types social, technical and socio-technical. For the social edges we plan on identifying who people are talking to and exactly about what. Technical edges can be refined by examining other source code relations, such as call graphs, or changes made to others' source code. To combine social and technical edges to socio-technical edges we plan to use content analysis techniques on communication to match it to the appropriate technical edge.

Different edges. In this study we focused on technical pairs with only briefly touching on socio-technical pairs. In the future we plan to extend this focus to include a detailed analysis of socio-technical pairs and also developer pairs that talked without sharing a technical dependency. and extending our analysis to include social and socio-technical pairs.

Finer failures. Build failure is compared to bugs on file very corse. Hence we plan on investigating single bugs. This additionally enables us to investigate pre-release and post-relase failures separately.

In addition to the future research directions we plan on repeating this study on more data sets to ensure a better generalizability.

9. ACKNOWLEDGEMENTS

This project is funded by an IBM Jazz Inovation Award and a Univeristy fellowship of the University of Victoria. Thanks for continuous feedback goes to the SEGAL Groups especially to Irwin Kwan, Sarbina Marczak, and Mattew Richards.

10. REFERENCES

[1] L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan. Group Formation in Large Social Networks: Membership, Growth, and Evolution. In *Proceedings of the 12th*

International Conference on Knowledge Discovery and Data Mining, pages 44–54, New York, NY, USA, 2006. ACM.

[2] C. Bird, A. Gourley, P. Devanbu, M. Gertz, and A. Swaminathan. Mining Email Social Networks. In *Proceedings of the Third International Workshop on Mining Software Repositories*, pages 137–143, New York, NY, USA, 2006. ACM.

[3] C. Bird, N. Nagappan, P. Devanbu, H. Gall, and B. Murphy. Does Distributed Development Affect Software Quality?: An Empirical Case Study of Windows Vista. *Communication of the ACM*, 52(8):85–93, 2009.

[4] C. Bird, D. Pattison, R. D'Souza, V. Filkov, and P. Devanbu. Latent Social Structure in Open Source Projects. In *Proceedings of the 16th International Symposium on Foundations of Software Engineering*, pages 24–35, New York, NY, USA, 2008. ACM.

[5] F. Bolici, J. Howison, and K. Crowston. Coordination without Discussion? Socio-Technical Congruence and Stigmergy in Free and Open Source Software Projects. In *Proceedings of the Second International Workshop on Socio-Technical Congruence*, 2009.

[6] M. Cataldo, A. Mockus, J. A. Roberts, and J. D. Herbsleb. Software Dependencies, Work Dependencies, and Their Impact on Failures. *IEEE Transactions on Software Engineering*, 99(1), 2009.

[7] M. Cataldo, P. A. Wagstrom, J. D. Herbsleb, and K. M. Carley. Identification of Coordination Requirements: Implications for the Design of Collaboration and Awareness Tools. In *Proceedings of the 20th Anniversary Conference on Computer Supported Cooperative Work*, pages 353–362, New York, NY, USA, 2006. ACM.

[8] K. S. K. Chung, L. Hossain, and J. Davis. Individual Performance in Knowledge Intensive Work through Social Networks. In *Proceedings of the 45th Conference on Computer Personnel Research*, pages 159–167, New York, NY, USA, 2007. ACM.

[9] B. Cole, D. Hakim, D. Hovemeyer, R. Lazarus, W. Pugh, and K. Stephens. Improving Your Software Using Static Analysis to Find Bugs. In *Companion to the 21st Symposium on Object-Oriented Programming Systems, Languages, and Applications*, pages 673–674, New York, NY, USA, 2006. ACM.

[10] M. E. Conway. How do Comittees Invent? *Datamation*, 14(4):28–31, 1968.

[11] B. Curtis, H. Krasner, and N. Iscoe. A Field Study of the Software Design Process for Large Systems. *Communincation of the ACM*, 31(11):1268–1287, 1988.

[12] D. Damian, L. Izquierdo, J. Singer, and I. Kwan. Awareness in the Wild: Why Communication Breakdowns Occur. In *Proceedings of the Second International Conference on Global Software Engineering*, pages 81–90, Washington, DC, USA, 2007. IEEE Computer Society.

[13] C. R. B. de Souza, D. Redmiles, L.-T. Cheng, D. Millen, and J. Patterson. Sometimes You Need to See Through Walls: A Field Study of Application Programming Interfaces. In *Proceedings of the 18th Conference on Computer Supported Cooperative Work*, pages 63–71, New York, NY, USA, 2004. ACM.

[14] N. Ducheneaut. Socialization in an Open Source Software Community: A Socio-Technical Analysis. *Computer Supported Cooperative Work*, 14(4):323–368, 2005.

[15] K. Ehrlich and K. Chang. Leveraging Expertise in Global Software Teams: Going Outside Boundaries. In *Proceedings of the First International Conference on Global Software Engineering*, pages 149–158, Washington, DC, USA, 2006. IEEE Computer Society.

[16] K. Ehrlich, M. Helander, G. Valetto, S. Davies, and C. Williams. An Analysis of Congruence Gaps and Their Effect on Distributed Software Development. In *Proceedings of the First International Workshop on Socio-Technical Congruence*, 2008.

[17] R. Frost. Jazz and the Eclipse Way of Collaboration. *IEEE Software*, 24(06):114–117, 2007.

[18] J. R. Galbraith. *Designing Complex Organizations*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1973.

[19] H. Gall, K. Hajek, and M. Jazayeri. Detection of Logical Coupling Based on Product Release History. In *Proceedings of the Fourteenth International Conference on Software Maintenance*, page 190, Washington, DC, USA, 1998. IEEE Computer Society.

[20] E. Gamma, R. Helm, R. Johnson, and J. Vlissides. *Design Patterns*. Addison-Wesley, Boston, MA, 1995.

[21] D. M. German, A. E. Hassan, and G. Robles. Change Impact Graphs: Determining the Impact of Prior Codechanges. *Information and Software Technology*, 51(10):1394–1408, 2009.

[22] R. E. Grinter, J. D. Herbsleb, and D. E. Perry. The Geography of Coordination: Dealing with Distance in R&D Work. In *Proceedings of the International Conference on Supporting Group Work*, pages 306–315, New York, NY, USA, 1999. ACM.

[23] J. Herbsleb, A. Mockus, and J. Roberts. Collaboration in Software Engineering Projects: A Theory of Coordination. In *Proceedings of 27th International Conference on Information Systems*, 2006.

[24] J. D. Herbsleb and R. E. Grinter. Splitting the Organization and Integrating the Code: Conway's Law Revisited. In *Proceedings of the 21st International Conference on Software Engineering*, pages 85–95, New York, NY, USA, 1999. ACM.

[25] D. Hinds and R. M. Lee. Social Network Structure as a Critical Success Condition for Virtual Communities. In *Proceedings of the 41st Annual Hawaii International Conference on System Sciences*, page 323, Washington, DC, USA, 2008. IEEE Computer Society.

[26] P. Hinds and C. McGrath. Structures that Work: Social Structure, Work Structure and Coordination Ease in Geographically Distributed Teams. In *Proceedings of the 20th Anniversary Conference on Computer Supported Cooperative Work*, pages 343–352, New York, NY, USA, 2006. ACM.

[27] L. Hossain, A. Wu, and K. K. S. Chung. Actor Centrality Correlates to Project Based Coordination. In *Proceedings of the 20th Anniversary Conference on Computer Supported Cooperative Work*, pages 363–372, New York, NY, USA, 2006. ACM.

[28] S.-K. Huang and K.-m. Liu. Mining Version Histories to Verify the Learning Process of Legitimate Peripheral Participants. In *Proceedings of the Second International Workshop on Mining Software Repositories*, pages 1–5, New York, NY, USA, 2005. ACM.

[29] Luis, G. Barahona, and G. Robles. Applying Social Network Analysis to the Information in CVS Repositories. In

Proceedings of the First International Workshop on Mining Software Repositories, 2004.

[30] S. Marczak, D. Damian, U. Stege, and A. Schröter. Information Brokers in Requirement-Dependency Social Networks. In *Proceedings of the 16th International Conference on Requirements Engineering*, volume 0, pages 53–62, Los Alamitos, CA, USA, 2008. IEEE Computer Society.

[31] A. Meneely, L. Williams, W. Snipes, and J. Osborne. Predicting Failures with Developer Networks and Social Network Analysis. In *Proceedings of the 16th International Symposium on Foundations of Software Engineering*, pages 13–23, New York, NY, USA, 2008. ACM.

[32] N. Nagappan and T. Ball. Use of Relative Code Churn Measures to Predict System Defect Density. In *Proceedings of the 27th International Conference on Software Engineering*, pages 284–292, New York, NY, USA, 2005. ACM.

[33] N. Nagappan, T. Ball, and A. Zeller. Mining Metrics to Predict Component Failures. In *Proceedings of the 28th International Conference on Software engineering*, pages 452–461, New York, NY, USA, 2006. ACM.

[34] N. Nagappan, B. Murphy, and V. Basili. The Influence of Organizational Structure on Software Quality: An Empirical Case Study. In *Proceedings of the 30th International Conference on Software Engineering*, pages 521–530, New York, NY, USA, 2008. ACM.

[35] S. Neuhaus, T. Zimmermann, C. Holler, and A. Zeller. Predicting Vulnerable Software Components. In *Proceedings of the 14th Conference on Computer and Communications Security*, pages 529–540, New York, NY, USA, 2007. ACM.

[36] M. Pinzger, N. Nagappan, and B. Murphy. Can Developer-Module Networks Predict Failures? In *Proceedings of the 16th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, pages 2–12, New York, NY, USA, 2008. ACM.

[37] A. Sarma, L. Maccherone, P. Wagstrom, and J. Herbsleb. Tesseract: Interactive Visual Exploration of Socio-Technical Relationships in Software Development. In *Proceedings of the 31st International Conference on Software Engineering*, pages 23–33, Washington, DC, USA, 2009. IEEE Computer Society.

[38] D. Schreck, V. Dallmeier, and T. Zimmermann. How Documentation Evolves over Time. In *IWPSE '07: Proceedings of Ninth International Workshop on Principles of Software Evolution*, pages 4–10, New York, NY, USA, 2007. ACM.

[39] A. Schröter, I. Kwan, L. D. Panjer, and D. Damian. Chat to Succeed. In *Proceedings of the First International Workshop on Recommendation Systems for Software Engineering*, pages 43–44, New York, NY, USA, 2008. ACM.

[40] A. Schröter, T. Zimmermann, and A. Zeller. Predicting Component Failures at Design Time. In *Proceedings of the Fifth International Symposium on Empirical Software Engineering*, pages 18–27, New York, NY, USA, 2006. ACM.

[41] M. E. Sosa, S. D. Eppinger, and C. M. Rowles. The Misalignment of Product Architecture and Organizational Structure in Complex Product Development. *Management Science*, 50(12):1674–1689, 2004.

[42] P. Tarr, H. Ossher, W. Harrison, and S. M. Sutton, Jr. N Degrees of Separation: Multi-Dimensional Separation of Concerns. In *Proceedings of the 21st International Conference on Software Engineering*, pages 107–119, New York, NY, USA, 1999. ACM.

[43] G. Valetto, M. Helander, K. Ehrlich, S. Chulani, M. Wegman, and C. Williams. Using Software Repositories to Investigate Socio-technical Congruence in Development Projects. In *Proceedings of the Fourth International Workshop on Mining Software Repositories*, page 25, Washington, DC, USA, 2007. IEEE Computer Society.

[44] T. Wolf, A. Schröter, D. Damian, and T. Nguyen. Predicting Build Failures Using Social Network Analysis on Developer Communication. In *Proceedings of the 31st International Conference on Software Engineering*, pages 1–11, Washington, DC, USA, 2009. IEEE Computer Society.

[45] T. Wolf, A. Schröter, D. Damian, L. D. Panjer, and T. H. D. Nguyen. Mining Task-Based Social Networks to Explore Collaboration in Software Teams. *IEEE Software*, 26(1):58–66, 2009.

[46] J. Xu, Y. Gao, S. Christley, and G. Madey. A Topological Analysis of the Open Souce Software Development Community. In *Proceedings of the Proceedings of the 38th Annual Hawaii International Conference on System Sciences*, page 198.1, Washington, DC, USA, 2005. IEEE Computer Society.

[47] L. Yu and S. Ramaswamy. Mining CVS Repositories to Understand Open-Source Project Developer Roles. In *Proceedings of the Fourth International Workshop on Mining Software Repositories*, page 8, Washington, DC, USA, 2007. IEEE Computer Society.

[48] T. Zimmermann, V. Dallmeier, K. Halachev, and A. Zeller. eROSE: guiding programmers in eclipse. In *Proceedings of the 20th Conference on Object-Priented Programming, Systems, Languages, and Applications*, pages 186–187, New York, NY, USA, 2005. ACM.

[49] T. Zimmermann and N. Nagappan. Predicting Subsystem Failures using Dependency Graph Complexities. In *Proceedings of the 18th International Symposium on Software Reliability*, pages 227–236, Washington, DC, USA, 2007. IEEE Computer Society.

[50] T. Zimmermann and N. Nagappan. Predicting Defects Using Network Analysis on Dependency Graphs. In *Proceedings of the 30th International Conference on Software Engineering*, pages 531–540, New York, NY, USA, 2008. ACM.