How Social Distance of Process Designers Affects the Process of Process Modeling: Insights From a Controlled Experiment

Jens Kolb, Michael Zimoch
Ulm University, Germany
{jens.kolb, michael.
zimoch}@uni-ulm.de

Barbara Weber
Quality Engineering Research
Group, University of
Innsbruck, Austria
barbara.weber@uibk.ac.at

Manfred Reichert
Ulm University, Germany
manfred.reichert
@uni-ulm.de

ABSTRACT

The increasing adoption of process-aware information systems (PAISs) by enterprises has resulted in large process model collections. Usually, process models are created either by in-house domain experts or external consultants. Thereby, high model quality is crucial, i.e., process models should be syntactically correct and sound, and also reflect the real business processes properly. While numerous guidelines exist for creating correct and sound process models, there is only little work dealing with cognitive aspects affecting process modeling. This paper addresses this gap and presents a controlled experiment using construal level theory. We investigate the influence the social distance of a process designer to the modeled domain has on the creation of process models. In particular, we are able to show significant differences between high and low social distance in respect to model quality and granularity. The results may help enterprises to compose adequate teams for creating or optimizing business process models.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Software Psychology

Keywords

business process modeling, construal level theory

1. INTRODUCTION

Due to the increasing adoption of process-aware information systems (PAIS), more and more enterprise repositories comprise large process model collections [1]. Usually, process models vary in respect to their quality and level of granularity, and contain a wide range of problems that impede upon their understandability [2]. However, high quality of process models is crucial for enterprises to guarantee proper process execution in PAIS [3]. As a prerequisite for the latter, process models should reflect the real-world processes properly and at the right level of granularity [4]. To address this issue, considerable work on criteria that ensure process model quality and comprehensibility has been conducted [5, 6]. Further, different modeling guidelines (e.g., GoM, 7PMG) exist, supporting process designers in creating process models of high quality [7, 8]. However, there is only little work evaluating the influence of cognitive aspects on the *process of process modeling* [9] and their effects on the resulting process models [10, 11]. However, if we do not understand the cognitive aspects affecting process model quality, process modeling projects might not deliver the required results or even fail. This paper investigates a fundamental factor presumably influencing the *process of process modeling—social distance* [12]. The latter is addressed by the *Construal Level Theory (CLT)* [13] and constitutes an important part of *psychological distance*. In particular, studies have shown that human thinking and acting are both strongly influenced by psychological distance [14]. According to CLT, we experience only the *here and now*, and form an abstract mental construal of distant objects [12, 14]; e.g., when thinking about a concert we plan to visit, it is important to know which bands will be playing, but details about the trip are not in our mind set yet. In turn, just before the concert, it is important to know with whom to visit or how to get there, i.e., planning is at a more fine-grained level.

Similarly, in the process of process modeling, various actors having different distance to the modeled business process and its environment may be involved. While certain process models are directly designed by process participants, others are modeled by external consultants or in-house experts (e.g., from the quality assurance department) not involved in the process (i.e., people having a *high social distance* to the process). A relevant question in this context is how social distance influences resulting process models. Taking CLT as theoretical basis, we conduct a controlled experiment investigating the influence social distance has on the *process of process modeling* as well as the quality and granularity of the resulting process models. Our results show a significant influence of social distance on the granularity of process models. Regarding process model quality, significant effects can be observed as well. Respective insights allow companies when composing process modeling teams. In particular, our results indicate that it is advisable to involve process designers with low social distance in any process modeling team.

The experiment has been conducted and results are used in the context of the *proView* project[1], which utilizes experimental results aiming at user-centered business process support. In particular, proView provides techniques enabling personalized process models (i.e., process views [15, 16]) as well as user-friendly process model visualizations (e.g., diagrams and trees [17]) and interactions [18, 19].

Sect. 2 provides backgrounds on CLT. Sect. 3 introduces our research question and defines the experiment. Sect. 4 deals with experiment preparation and its execution. Results are presented and analyzed in Sect. 5. Finally, Sect. 6 discusses related work and Sect. 7 summarizes the paper.

2. FUNDAMENTALS ON CONSTRUAL LEVEL THEORY

Construal Level Theory (CLT) describes the effects *psychological distance* has on objects or events [12, 14]. Generally, CLT states that increasing psychological distance affects our mental representation of these objects or events. In turn, this influence on human perception has a strong impact on our actions and thoughts [13], i.e., everything being distant to us creates more abstract mental reflections. The reason behind this phenomenon is the *level of construal (LOC)*, which describes how individuals interpret and perceive objects and events. Increasing psychological distance affects the cognitive abilities of individuals and leads to a change in their perception of an object or event.

CLT describes two levels of thinking: *high-* and *low-level construal*. *High-level construals* are abstract, imprecise, coherent, and superordinate representations compared to *low-level construals*. If an object is further away, we think about it in terms of high-level construals. However, the smaller our distance to objects or events is, the more we think in low-level construals. Moreover, these two levels of construals are influenced by *psychological distance*. While *objective distance* describes the quantitative spatial distance in the real world, *psychological distance* describes our feelings, thoughts and emotions in relation to an object or event. In turn, an object or event is defined as *psychological distant*, if it is not experienced physically. For this case, a mental representation must be constructed. Psychological distance can be further subdivided into *social, spatial, temporal*, and *hypothetical distance. Social distance*, on which we focus in this paper, describes our relation to other individuals (cf. Fig. 1); e.g., whether choosing a more distant seat in a bus from another individual or not is directly reflected by social distance [20]. Other psychological distances included in our work, but not considered in this paper are *spatial, temporal*, and *hypothetical distance* [13, 21, 22, 23].
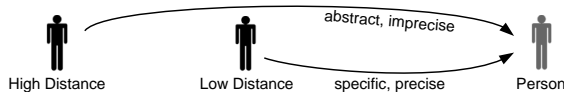

Figure 1: Construal Level Theory - Social Distance

3. RESEARCH QUESTION AND EXPERIMENT DEFINITION

This section deals with definition and planning of our experiment for measuring the influence of social distance on

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the *process of process modeling* and resulting artifacts. Sect. 3.1 explains the context of the experiment and defines its goal. Sect. 3.2 introduces the hypothesis considered for testing and Sect. 3.3 presents the experimental setup. Sect. 3.4 explains the design of our experiment. Finally, Sect. 3.5 discusses factors threatening the validity of results.

3.1 Context Selection and Goal Definition

In companies, processes are typically either modeled by in-house teams or external consultants. Respective process designers are responsible for interviewing process participants and capturing gathered knowledge in process models. However, these designers are often not directly involved in the process to be modeled; e.g., they may be member of the quality assurance department. In other cases, due to limited resources, companies assign such modeling tasks to external consultants. However, it is not well understood how such an increased social distance affects the quality and granularity of resulting process models. To close this gap, this paper investigates the following fundamental research question:

Is the process of process modeling, i.e., quality and granularity of the process models resulting from it, affected by the social distance process designers have on respective business processes?

Despite the large number of work on process model quality [2, 8, 24, 25, 26] and granularity of process modeling [27], there exists only little work dealing with cognitive aspects of process modeling [10, 11, 28, 29]. In particular, it is not well understood how these factors actually lead to minor process quality, i.e., deficiencies regarding syntactic, semantic, and perceived quality, and how they impact granularity of process models. What has not been considered so far, is the social distance process designers have to the process models created by them. According to CLT, however, existing social distance to objects influences the way we act and therefore presumably also impacts the way how process models are created. Based on a controlled software experiment, this paper investigates the influence social distance has on the *process of process modeling* and its outcomes. The experiment varies social distance to learn whether it has any influence on the quality and granularity of the resulting process models. The goal may be formulated as:

Analyze	*process models*
for the purpose of	*evaluating*
with respect to their	*level of construal*
from the point of view of	*the researchers*
in the context of	*students and research staff.*

3.2 Hypothesis Formulation

Based on the goal of our experiment, the following hypotheses are derived. The experiment investigates whether social distance influences the level of construal during the *process of process modeling*, and thus the quality and granularity of the resulting process model. In total, we have derived four hypotheses, one for the *level of granularity* and three for the quality dimensions, i.e., *syntactic, semantic*, and *perceived quality*:

Does social distance lead to an increase of the **level of granularity** *when modeling a process?*
$H_{0,1}$: There are no significant differences in the level of granularity when modeling processes with low social distance compared to high social distance. $H_{1,1}$: There are significant differences in the level of granularity when modeling processes with low social distance compared to high social distance.
Does social distance lead to an increase of the **syntactic quality** *when modeling a process?*
$H_{0,2}$: There are no significant differences in the syntactic quality when modeling processes with low social distance compared to high social distance. $H_{1,2}$: There are significant differences in the syntactic quality when modeling processes with low social distance compared to high social distance.
Does social distance lead to an increase of the **semantic quality** *when modeling a process?*
$H_{0,3}$: There are no significant differences in the semantic quality when modeling processes with low social distance compared to high social distance. $H_{1,3}$: There are significant differences in the semantic quality when modeling processes with low social distance compared to high social distance.
Does social distance lead to an increase of the **perceived quality** *when modeling a process?*
$H_{0,4}$: There are no significant differences in the perceived quality when modeling processes with low social distance compared to high social distance. $H_{1,4}$: There are significant differences in the perceived quality when modeling processes with low social distance compared to high social distance.

3.3 Experimental Setup

This section describes *subjects*, *object*, and *response variables* of our experiment as well as its *instrumentation* and *data collection procedure*.

Subjects. Ideally, process designers in enterprises are modeling experts. But, often they only obtain basic training and have limited process modeling skills [30]. Hence, from subjects we require that they are at least moderately familiar with process modeling, but we do not require expert level.

Object. The object is a process model using the *Business Process Model and Notation (BPMN)*. To ensure familiarity of subjects and that differences in quality and granularity are not caused due to a lack of familiarity, but rather due to differences in social distance, we choose a well-known scenario. More precisely, the modeling task deals with the process of *visiting the university canteen*. We created task descriptions in two versions reflecting different social distances (cf. Tab. 1). To ensure that the gap between the two distances is big enough, a pilot study is performed. In the context of low social distance, visiting the canteen with a good friend shall be modeled. Regarding high social distance, visiting the canteen with a foreign (i.e., unknown) student shall be modeled. Note that task description are rather abstract to give subjects the possibility to model as detailed as they like.

Low Social Distance: *A good friend of you starts to study at your university.* Since it is essential for students to know the canteen, model the process of a characteristic visit of the canteen. Start the process at the point, the student enters the canteen.
High Social Distance: *A foreign student visits your university.* Since it is essential for students to know the canteen, model the process of a characteristic visit of the canteen. Start the process at the point, the student enters the canteen.

Table 1: Task Descriptions

Factor and factor levels. The factor considered in our experiment is *social distance* with levels *high* and *low*. Accordingly, the task description is adjusted to vary social dis-

tance: i.e., modeling the canteen process either for a foreign student (i.e., high) or good friend (i.e., low social distance). **Response variable.** As response variable, we consider the level of construal which cannot be directly measured. Considering the level of construal, everything being distant from us is created more abstract (cf. Sect. 2). Hence, we assume that the level of construal impacts *quality* and *granularity* of the resulting process model. Therefore, high social distance may lead to course-grained, more abstract, and imprecise process models (i.e., reflecting a low quality/granularity), while low social distance may result in more fine-grained and precise process models (i.e., reflecting a high quality/granularity). Hence, *process model quality* is characterized by three dimensions, i.e., *syntactic*, *semantic*, and *perceived quality*, making use of semiotic theory [31].

Syntactic quality of a process model is measured by counting syntactical errors (i.e., syntactical rule violations) of the applied modeling language (i.e., BPMN) [32]. In turn, *semantic quality* covers *correctness, completeness, relevance*, and *authenticity* of a process model. *Correctness* expresses that all elements in a process model are correct and relevant. *Completeness* implies that relevant aspects about the domain are missing. Further, *relevance* signifies that all elements in the process model are relevant for the process (i.e., superfluous elements are considered as well). Finally, *authenticity* expresses that the chosen representation gives a true impression of the domain. All four dimensions of *semantic quality* are rated by two modeling experts in a consensus building process from each other and based on a 7-point Likert scale [33]: i.e., between 0 (strongly disagree) and 6 (strongly agree). Finally, *perceived quality* depends on the degree to which a subject agrees with the resulting model [34]. Perceived quality can be further subdivided into *agreement, missing aspects, accurate description, mistakes*, and *satisfaction*. It is rated by each subject on a 5-point Likert scale, i.e., between 0 (strongly disagree) and 4 (strongly agree), after finishing the modeling task. *Agreement* expresses to which degree the process model matches with the real-world business process. *Missing aspects* rates whether significant aspects are missing in the resulting process model. In turn, *accurate description* expresses how accurate the process model matches the real-world process. *Mistakes* corresponds to the subject rate indicating whether there are serious mistakes in the resulting process model. Finally, *satisfaction* expresses the degree of satisfaction a subject has with the process model created by him or her. *Process granularity* is measured through the complexity of the resulting process models, i.e., *number of activities, edges, gateways*, and *execution paths*. Fig. 2 summarizes the variables considered in a research model.

3.4 Experimental Design

We apply guidelines for designing experiments as described in [35] and conduct a *randomized balanced single factor experiment*. The experiment is *randomized* since subjects are assigned to groups randomly. Further, only a *single factor* varies, i.e., the level of construal. Fig. 3 illustrates the setup. **Instrumentation and data collection procedure.** To precisely measure response variables in a non-intrusive manner, we use the *Cheetah Experimental Platform (CEP)* [9]. CEP provides a BPMN modeling environment that records all modeling steps and their attributes (i.e., timestamp, type
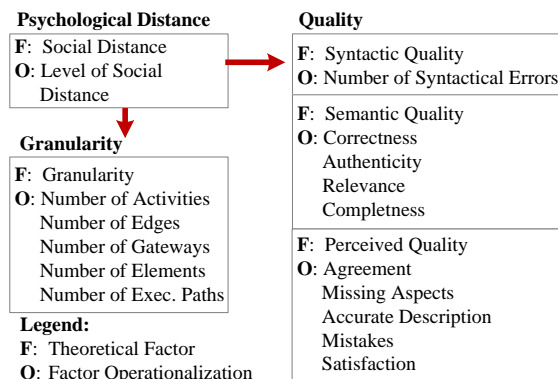
Psychological Distance

F: Social Distance
O: Level of Social Distance

Granularity

F: Granularity
O: Number of Activities
Number of Edges
Number of Gateways
Number of Elements
Number of Exec. Paths

Legend:
F: Theoretical Factor
O: Factor Operationalization

Quality

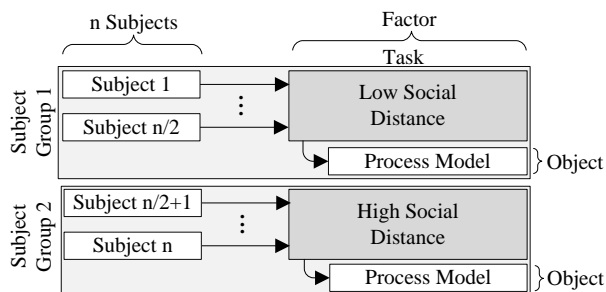| |
|---|
| **F**: Syntactic Quality |
| **O**: Number of Syntactical Errors |
| **F**: Semantic Quality |
| **O**: Correctness |
| Authenticity |
| Relevance |
| Completness |
| **F**: Perceived Quality |
| **O**: Agreement |
| Missing Aspects |
| Accurate Description |
| Mistakes |
| Satisfaction |

Figure 2: Research Model

Figure 3: Experiment Design

of modeling action). Further, resulting process models are stored. Finally, demographic data and qualitative feedback is gathered from subjects based on questionnaires.

3.5 Risk Analysis

Generally, any experiment bears risks that might affect its results. Thus, its validity or—more precisely—its levels of validity need to be checked: *internal validity* ("Are effects caused by independent response variables?") and *external validity* ("May results be generalized?").

Risks to *internal validity*. Risks that might influence the modeling outcome include process modeling experience of subjects involved and uneven distributions of subjects over two groups. Furthermore, post data validation ensures that in both groups subjects are at least moderately familiar with process modeling (cf. Sect. 4.3). It is assured that both groups show about the same familiarity level (i.e., median is 5.0 and 4.5 for groups). The chosen modeling task constitutes another risk to internal validity. To ensure familiarity of subjects and to guarantee that differences in quality and granularity are due to social distance, we choose a scenario all subjects know well (i.e., the campus has only one canteen, which is used by all subjects). Particularly, this prevents faulty models due to lack of domain knowledge. To further ensure that subjects are not negatively influenced by tiredness, boredom, or hunger, the experiment is conducted at a time of the day for which the mentioned frame of mind can be excluded. Finally, expected duration of modeling tasks is 15 min. This should prevent faulty models due to lack of motivation. Subjects are recruited on a voluntary basis.

Risks to *external validity*. The subjects have academic background (i.e., students and research staff), which might limit generalizability of results. However, the subjects rather have profound knowledge in process modeling (cf. Sect. 4.3). Hence, we may consider them as proxies for professionals who have obtained basic training so far. As another risk for external validity, process model quality may depend on the appropriateness of the chosen modeling languages and tools. To mitigate this risk, both groups use an easy-to-use process modeling tool as well as an established process modeling language. Finally, a potential risk for external validity is that we measure social distance with one modeling task. To mitigate this and to improve generalizability, experiments in different environments or conditions one may conduct.

4. EXPERIMENT OPERATION

Based on the provided experiment definition, Sect. 4.1 summarizes the experiment preparation. Sect. 4.2 describes the execution of the experiment, while Sect. 4.3 introduces the validation of the data collected during the experiment.

4.1 Experiment Preparation

Students and research staff familiar with process modeling are invited to join the experiment. Subjects are not informed about aspects intended to investigate. However, they know the experiment takes place in the context of a thesis. For all subjects, anonymity is guaranteed. Before conducting the experiment, a pilot study is performed whose results are used, to eliminate ambiguities and misunderstandings as well as to improve the description of the modeling task. Additionally, it is checked whether social distance between the tasks is sufficiently large. Finally, an evaluation sheet is created to assess the level of construal by analyzing quality and granularity of resulting process models.

4.2 Experiment Execution

The experiment is executed in a computer lab at Ulm University. All in all 44 students and research staff participate. Due to spatial constraints, up to 12 subjects may participate at the same time and several sessions within a period of four weeks are offered. Each session lasts about 15 minutes and runs as follows: The procedure of the experiment is explained and worksheets with task description are handed out. Thereby, subjects are randomly assigned to one of the subject groups (cf. Sect. 3.4). Then, subjects fill out an initial questionnaire capturing their actual modeling experience. This information is used to test whether the subjects are familiar with process modeling. Finally, subjects model the process based on the textual description from the worksheets. After finishing the task, subjects provide their rating for *perceived quality* (cf. Sect. 3.3). At the end, they may give feedback. All results are stored in the CEP database.

4.3 Data Validation

In total, data is collected from 44 subjects. Two of them are excluded due to invalidity of the process models obtained; i.e., one contains only one start node and the other one differs substantially from the postulated task description. Finally, 42 subjects are considered for data analysis; i.e., 32 subjects are students and 10 are research staff; 5 subjects are female. In addition, we screened the subjects for familiarity with BPMN (process modeling language we use in our models), since our research setup requires subjects to be familiar with BPMN. On a Likert scale from 0 to 6 the

median value for *familiarity* with BPMN is 5.0 (i.e., above average). For confidence in *understanding* BPMN process models, a median value of 5.0 is obtained. Perceived competence in *creating* BPMN models has a median value of 4.0. Prior to the experiment, subjects analyzed 38 process models and created 18 in average. Since all values range above average and subjects are familiar with process modeling, we may conclude that the participating subjects fit to the targeted profile. The full data set can be found in [36].

5. DATA ANALYSIS & INTERPRETATION

Sect. 5.1 presents descriptive statistics for data gathered during the experiment. Sect. 5.2 discusses whether a data set reduction is needed. Sect. 5.3 tests hypotheses from Sect. 3.2.

5.1 Data Analysis and Descriptive Statistics

Figure 4 shows box plots (i.e., median, min, and max values as well as 1st and 3rd quartiles) of all measures related to granularity of process models, i.e., number of *activities*, *edges*, *gateways*, *total process elements*, and *possible paths*.
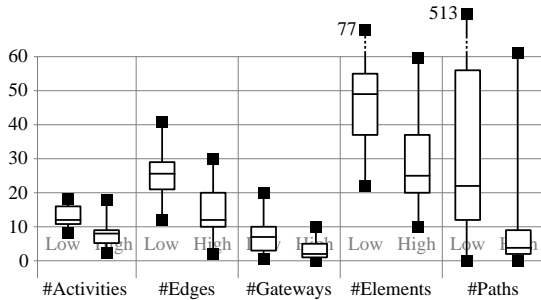
Figure 4: Measurements for Granularity

Figure 4 shows, all measured values are higher in the context of low social distance. In particular, differences in the numbers of possible paths are especially large. Note that low social distance results have a median of 21 possible paths, while high distance only leads to 3.50 possible paths.

Next, Figure 5a displays box plots of measurements for *syntactic* and *semantic quality*.

As shown in Figure 5a, process models with low social distance seem to give a better account of the domain; however, subjects make more syntactical errors (median of 3 for low, 2 for high). Further, Figure 5b gives an overview of measures regarding *perceived quality* of subjects. It shows that subjects with low social distance believe that the description of their designed process models matches the real-world process more accurately (median of 3 for low, 2 for high). It is noteworthy that in conjunction with low distance, satisfaction leads to a median of 1, while high distance leads to a median of 2. Our observations are merely based on descriptive statistics. For a more rigid investigation, hypotheses will be tested for statistical significance in Sect. 5.3.

5.2 Data Set Reduction

Generally, results of any statistical analysis depend on the quality of its input data, i.e., faulty data might contribute to incorrect conclusions. Therefore, it is important to identify outliers and evaluate whether they shall be excluded, i.e., a
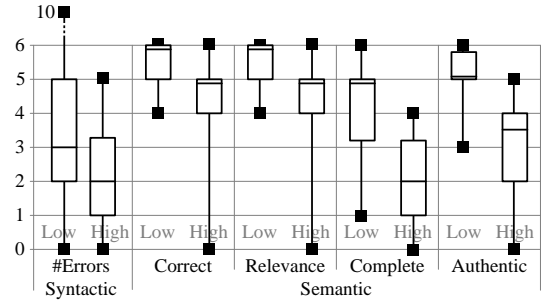
(a) Measurements for Syntactic and Semantic Quality
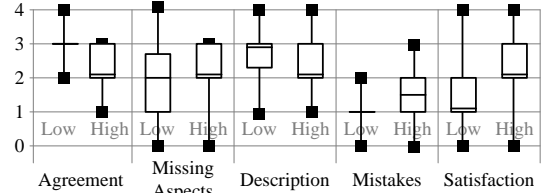
(b) Measurements for Perceived Quality

Figure 5: Measurements for Quality Metrics

data set reduction might become necessary. Note that the latter might be also critical due to potential loss of information. In our experiment, several outliers can be identified. We decided not to remove them since we consider them as correct, i.e., they are not a result of wrong modeling. One subject modeled a process model with 513 possible execution paths. Another subject modeled a task with 10 syntactical errors. Removing them would bias results obtained. Furthermore, we do not have to remove results from any subject due to missing process modeling knowledge—since all subjects are familiar with process modeling (cf. Sect. 4.3).

5.3 Hypothesis Testing

Sect. 5.1 indicates differences regarding low and high social distance. In the following, we test whether observed differences are statistically significant. We test our response variables based on a *non-parametric two-sample u-test* [37]. A successful u-test (with $p < p_0$ at risk level $\alpha = 0,05$) will reject a null hypothesis. Table 2 shows results of hypothesis testing (cf. Sect. 3.2).

In summary, hypotheses $H_{1,1}$ and $H_{1,3}$ can be accepted. In turn, hypothesis $H_{1,4}$ is only partially supported and thus it cannot be accepted. Further, hypothesis $H_{1,2}$ must be rejected. From this, we can conclude that low social distance has a positive impact on the *granularity* ($H_{1,1}$) and *semantic quality* ($H_{1,3}$) of resulting process models. We may also assume that low social distance has a positive impact on the *perceived quality* ($H_{1,4}$); however, since it is partially supported, it cannot be generalized. Regarding *syntactic quality* ($H_{1,2}$), no statistically significant difference is observed.

6. RELATED WORK

This paper investigates the impact of social distance on the quality and granularity of process models. Hence, it is related to existing research regarding the quality and granularity of process models. There are different frameworks and guidelines in respect to process model quality. Among

Level of Granularity $H_{1,1}$		
Response Variable	**p-value**	**Significant?**
Number of activities	0.001 (< 0.05)	Yes
Number of edges	0.001 (< 0.05)	Yes
Number of gateways	0.001 (< 0.05)	Yes
Number of elements	0.001 (< 0.05)	Yes
Number of paths	0.001 (< 0.05)	Yes
Syntactic Quality $H_{1,2}$		
Response Variable	**p-value**	**Significant?**
Number of syn. errors	0.087 (> 0.05)	No
Semantic Quality $H_{1,3}$		
Response Variable	**p-value**	**Significant?**
Correctness	0.006 (< 0.05)	Yes
Relevance	0.001 (< 0.05)	Yes
Completeness	0.001 (< 0.05)	Yes
Authenticity	0.001 (< 0.05)	Yes
Perceived Quality $H_{1,4}$		
Response Variable	**p-value**	**Significant?**
Agreement	0.017 (< 0.05)	Yes
Missing aspects	0.347 (> 0.05)	No
Description	0.034 (< 0.05)	Yes
Mistakes	0.038 (< 0.05)	Yes
Satisfaction	0.084 (> 0.05)	No

Table 2: Results of Hypothesis Testing

others, the SEQUAL framework uses semiotic theory for identifying various aspects of process model quality [26], whereas GoM (Guidelines of Process Modeling) describes quality considerations for process models [7] and 7PMG (Seven Process Modeling Guidelines) characterize desirable properties of a process model [8]. Moreover, significant research on factors affecting process model comprehensibility and maintainability exists. The influence of model complexity on process model comprehensibility is investigated in [5]. In turn, [38] analyzes the effect of modularity on process understanding. The influence of grammatical styles for labeling activities on model understanding is discussed in [39], and an experiment investigating the impact of secondary notations is presented in [40]. The impact of different quality metrics on error probability is discussed in [41].

[42] provides prediction models for true usability and maintainability of process models. Effects of how and at which level of granularity a designer models a particular process is described in [27]. Regardless, in the context of process modeling there exists little work taking cognitive aspects into account. [29] presents the effects of reducing cognitive load on end user understanding of conceptual models. Understanding complex models quickly reaches cognitive limits. [11] describes the cognitive difficulty of understanding different relations between model elements.

Common to all these works is the focus on the resulting process model (i.e., the product of process modeling), while little attention has been paid on the process of the process modeling itself. The Nautilus project complements these works by investigating the process of process modeling for tracing model quality back to different modeling strategies resulting in process models of different quality [43, 44].

7. DISCUSSION AND CONCLUSION

This paper investigates whether social distance affects process modeling and quality as well as granularity of the resulting process models. In particular, an experiment is conducted showing that for social distance there is a significant

difference depending on whether a process designer has a low or high social distance to the modeled domain. For enterprises, our results indicate that process designers showing a high social distance to a particular business process tend to create a more coarse-grained and abstract process model. In addition, process models, whose designers show a high social distance, reflect a lower semantic model quality. In particular, these models tend to be more incomplete and less correct with respect to the domain to be modeled. Further, process designers with low social distance are more self-confident about the process models they create. In the context of an enterprise, it is thus recommended to involve process designers being more confident with corresponding business processes; e.g., to achieve a high process model quality.

Based on our results, in general, one can assume that lower social distance leads to more precise and fine-grained process models. However, while results look promising, their generalization needs to be confirmed by additional experiments; i.e., in order to obtain more accurate results allowing such a generalization, additional studies are needed either through replication or similar studies in other environments to investigate the influence of social distance on the *process of process modeling*.

Furthermore, our experiments related to other psychological distances (i.e., spatial, temporal and hypothetical distance) will be subject of future papers. Combining experiment results for all psychological distances enables us to extract guidelines on how modeling teams in enterprises should be put together and optimal process models can be achieved. Finally, experiments with practitioners are planned to validate results in a real-world setting.

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