Effects of Cognitive-Driven Development in the early stages of the software development life cycle

Victor Hugo Santiago C. Pinto[1,2][a] and Alberto Luiz Oliveira Tavares de Souza[2]
[1]*Federal University of Pará (UFPA) - Belém, PA. Brazil*
[2]*Zup Innovation - São Paulo, SP. Brazil*
victor.santiago@ufpa.br, alberto.tavares@zup.com.br

Keywords: Cognitive-driven development, Cognitive complexity metrics, Experimental study

Abstract: The main goal of software design is to continue slicing the code to fit the human mind. A likely reason for that is related to the fact that human work can be improved by a focus on a limited set of data. However, even with advanced practices to support software quality, complex codes continue to be produced, resulting in cognitive overload for the developers. Cognitive-Driven Development (CDD) is an inspiration from cognitive psychology that aims to support the developers in defining a cognitive complexity constraint for the source code. The main idea behind the CDD is keeping the implementation units under this constraint, even with the continuous expansion of software scale. This paper presents an experimental study for verifying the CDD effects in the early stages of development compared to conventional practices. Projects adopted for hiring developers in Java by important Brazilian software companies were chosen. 44 experienced software engineers from the same company attended this experiment and the CDD guided part of them. The projects were evaluated with the following metrics: CBO (Coupling between objects), WMC (Weight Method Class), RFC (Response for a Class), LCOM (Lack of Cohesion of Methods) and LOC (Lines of Code). The result suggests that CDD can guide the developers to achieve better quality levels for the software with lower dispersion for the values of such metrics.

1 Introduction

Separation of Concerns is one of the key principles of software engineering (Liskov and Zilles, 1974; Parnas, 1972) that a software engineer can apply in all software life-cycle. During analysis developers must subdivide the problem and adopt an architectural pattern in order to achieve proper modularity and cohesion.

Software complexity increases as new features are incorporated (Yi and Fang, 2020; Zuse, 2019; Fraser et al., 2007) impacting its maintainability, one of the most rewardful software quality attributes (ISO:ISO/IEC 25010, 2011). Therefore, the separation of component responsibility must consider not only the domain but also the cognitive complexity of software as it goes through an evolution (Wang, 2006).

Over the years, researchers continue to seek better and novel methods for handling complexity (Zuse, 2019; Clarke et al., 2016; Weyuker, 1988; Shepperd, 1988). Approaches have been adopted to support code design based on architectural styles and code quality metrics. Nevertheless, there is a lack of practical and clear strategies for changing the way that we develop software with regard to maintenance efforts efficiently.

Most research involving human cognition in software engineering focuses on evaluating programs and learning rather than on understanding how software development could be guided by this factor (Duran et al., 2018). Cognitive complexity departs from the standard practice of using strictly numeric values to assess software maintainability. It starts with the precedents set by cyclomatic complexity (CYC) (McCabe, 1976), but uses human judgment to determine how the code's structures should be interpreted. Shao and Wang proposed a set of object-oriented cognitive complexity metrics (Shao and Wang, 2003) and Misra et al. (Misra et al., 2018) suggested a relationship among basic control structures and corresponding weights. Although cognitive complexity measurements can help assessing the understandability of source code, studies exploring how this strategy can be used to reduce complexity in all stages of the de-

[a] https://orcid.org/0000-0001-8562-6384

velopment process are lacking.

In the cognitive psychology area, cognitive load refers to the amount of information that working memory resources can hold at one time. Cognitive Load Theory (CLT) (Sweller, 2010; Chandler and Sweller, 1991; Sweller, 1988) is generally discussed in relation to learning. Problems that require many items to be stored in short-term memory may contribute to an excessive cognitive load. According to Sweller (Sweller, 2010), some material is intrinsically difficult to understand and this is related to the number of elements that must be simultaneously processed in the working memory. Experimental studies performed by Miller (Miller, 1956) have suggested that humans are generally able to hold only seven plus or minus two units of information in short-term memory. Such limit for information units can be applied for software once the source code has an intrinsic complexity.

The developers are frequently affected by cognitive overload when they need to add a feature, fixing a bug, improve the design or optimize resource usage. Based on CLT and Miller's works involving cognitive complexity the principles for a method called Cognitive-Driven Development (CDD) were formulated (Souza and Pinto, 2020). The main idea of our proposed method is to try to standardize the way developers with different specialization degrees consider the complexity of the code. However, each developer can assume different intrinsically complex elements in the code. We suggest that such elements can be defined in common agreement between the members of the development team, considering basic control structures, code branches, project's nature and etc (Souza and Pinto, 2020). From these definitions, it is possible setting a feasible constraint for the cognitive software complexity.

This paper presents an experimental study for verifying the CDD effects in the early stages of development compared to development without a complexity constraint. This involved carrying out a static code analysis through object-oriented metrics. For this, we selected three real projects that Brazilian software companies adopt for hiring Java developers. 44 experienced software engineers from the same company attended this experiment, part of them were guided a complexity constraint, as suggested by the CDD. The resulting projects were evaluated with the following metrics: CBO (Coupling between objects), WMC (Weight Method Class), RFC (Response for a Class), LCOM (Lack of Cohesion of Methods) and LOC (Lines of Code). The result suggests that CDD can be useful in the early stages of software development and its principles can help developers to keep the software with lower dispersion for the values of such metrics.

2 Cognitive-Driven Development

Cognitive load represents the limit of what the working memory can process (Sweller, 2010). When you experience too much cognitive load, you cannot properly process code. A considerable part of the software development effort is focused on understanding code from other team members to apply changes later, add new features and fix faults. Human ability does not follow the same proportion of the continuous expansion of the software size, which makes this scenario even more challenging.

Suppose that we have a single feature to be developed and a team with distinct specialization levels. It is likely that different solutions will be delivered by each programmer. This would not be a problem if the intrinsic complexity degree for the source codes were not different. Regardless of the solution, how can we make all solutions remain at the same level of complexity? Usually, classes are simple and over time they become complex. How to standardize the people's perspective for the same code regarding the understanding? Each developer may have a different way of accounting for the elements that make it difficult to understand in the code. We assume that if the code can be understood, it can be evolved more easily. In this way, our attempt was to define a measure for the understanding degree based on the presence of basic control structures on the code. With this in mind, we were able to derive a complexity constraint and evolve the code keeping this rule.

These observations were fundamental for the investigations in cognitive psychology, specifically in CLT and in an important work known as *"Magical Number 7"* to propose a method for software development focusing on understanding called Cognitive-Driven Development (CDD). The main CDD principle is considering a reasonable limit for intrinsic complexity points (ICP) (Souza and Pinto, 2020) for reducing the cognitive load.

A satisfactory complexity constraint can be defined in discussions in the early stages of development and calibrated later, considering the project's nature and level of team expertise. Although our proposal is that the definition of this constraint includes code branches (*if-else*, *loops*, *when*, *switch/case*, *do-while*, *try-catch-finally* and etc.), *functions as an argument*, *conditionals*, *contextual coupling* - coupling with specific project classes and *inheritance of abstract or concrete class (extends)*, developers can include other elements as ICPs, such as SQL instructions and annotations. As a suggestion, specific features of programming languages and frameworks/libraries are not considered as ICPs, it is understood that such features are part of common knowledge and under the domain of the developers.

Figure 1 presents a piece of code from a Java class called *GenerateHistoryController*. This class was implemented for a project[1] called "complexity-tracker" which tries to provide indications of how complexity increases during the software evolution process. To clarify how ICPs are accounted, at the top of the figure is shown the number 6 corresponding to the total of ICPs: 4 points are related to contextual coupling (lines 17, 22, 26 and 37) and the remaining points refer to passing a function as an argument (lines 29 and 42).

3 Related work

A taxonomy of cognitive load in software engineering was provided by Gonçales et al. (Gonçales et al., 2019). Based on this classification, recent advances are related to programming tasks and machine learning techniques to identify the programmer's difficulty level and code-level comprehensibility. CDD can be applied as a complementary design to mitigate the increase in cognitive complexity regardless of the software size.

Duran et al. (Duran et al., 2018) proposed a framework for the Cognitive Complexity of Computer Programs (CCCP) that describes programs in terms of the demands they place on human cognition. CCCP is based on a model that recognizes factors when we are mentally manipulating a program. The contribution made by this work is to concentrate on the cognitive complexity present in program designs rather than on how the developers could be guided to generate source code reducing the cognitive load, as suggested by CDD.

Object-oriented cognitive complexity metrics were proposed in the work of Shao and Wang in (Shao and Wang, 2003) and extended by Misra et al. (Misra et al., 2018). Theoretical and empirical validation was carried out to evaluate the proposed metrics based on Weyuker's properties (Weyuker, 1988). The main CDD principle is not the proposition of new metrics but to provide an easy way to define a feasible complexity constraint for the creation (and evolution) of implementation units prioritizing the understanding. The development team can use any quality metric or, if they prefer, basic control structures in the code to support their classification. With this in mind, the directive suggested by CDD is to keep the complexity for implementation units under a feasible constraint to promote their readability, even with software complexity expansion.

[1] https://github.com/asouza/complexity-tracker

4 Experimental Methodology

The goal of this paper is to **verify the effects of employing the CDD in the early stages of development in comparison to the conventional practices**. For this, an experimental study was carried out in the industry context involving two groups of experienced developers who developed different projects from the same company. The first group focused on using CDD, i.e., coding without exceeding a cognitive complexity constraint, and the second was free to use conventional development practices. Both groups attended training about quality metrics and their importance for evaluating the code during development.

Resultant implementation units in this study were compared through object-oriented metrics to identify the differences among the samples individually. A complementary analysis was also carried out taking into account the distribution of complexity in the projects. Such investigation could promote discussions about the benefits of slicing the software to adjust it better in our human mind, reducing the cognitive load and improving quality metrics. To this end, we framed our research around the following Research Questions (RQs):

RQ1*: Is there a difference between the projects developed under a cognitive complexity constraint in comparison to those generated using conventional practices in terms of quality metrics?* In practice, a previous study (Pinto. et al., 2021) was carried out considering refactoring scenarios using known projects by the Java developer community. As a result, refactorings guided by cognitive complexity constraints were better evaluated in quality metrics. These results led us to question whether the same effect would be noticed in the early development stages since there are usually not so many changes at the beginning of a software project. To answer this question, all the units created by the subjects were evaluated using the same metrics

RQ2*: Do the implementation units from the projects developed with the CDD have a distribution closer to the quality metrics than in projects that followed the non-CDD methods?* In addition to the analysis of the implementation units in an individual way, we believe that a high-level view for all projects

```java
...
@Controller
public class GenerateHistoryController {

    // Contextual Coupling
    @Autowired
    private GenerateComplexyHistory generateComplexyHistory;

    @PostMapping(value = "/generate-history")
    // Contextual Coupling
    @ResponseBody
    public ResponseEntity<?> generate(@Valid GenerateHistoryRequest request,
            UriComponentsBuilder uriComponent) {

        // Contextual Coupling
        InMemoryComplexityHistoryWriter inMemoryWriter = new InMemoryComplexityHistoryWriter();

        // Function as an argument
        new RepoDriller().start(() -> {
            request.toMining(inMemoryWriter).mine();
        });
    }

    @PostMapping(value = "/generate-history-class")
    // Contextual Coupling
    @ResponseBody
    public ResponseEntity<?> generatePerClass(@Valid GenerateHistoryPerClassRequest request,
            UriComponentsBuilder uriComponent) {

        InMemoryComplexityHistoryWriter inMemoryWriter = new InMemoryComplexityHistoryWriter();
        // Function as an argument
        new RepoDriller().start(() -> {
            request.toMining(inMemoryWriter).mine();
        });

        generateComplexyHistory.execute(request,inMemoryWriter.getHistory());

        URI complexityHistoryGroupedReportUri = uriComponent.path(
                "/reports/pages/complexity-by-class?projectId={projectId}")
                .buildAndExpand(request.getProjectId()).toUri();
        return ResponseEntity.created(complexityHistoryGroupedReportUri)
                .build();
     }
 }
```

Figure 1: Class GenerateHistoryController

can support the discussions about the effects produced when using a complexity constraint in favor of the development. The distribution degree for metrics values could indicate how much complexity has been sliced among the implementation units. With this in mind, we would like to identify the effects of adopting a complexity limit in code quality and if this element had some influence on the developers in the separation of concerns and complexity distribution.

4.1 Project Selection

Three real projects used for the technical evaluation and hiring of software engineers by important Brazilian software companies were chosen: (i) Lend of literary works (Virtual Library), (ii) Real Estate Financing and (iii) Payment Service Provider. This choice was motivated by the need to use real projects, the challenges of which could prove the difficulty in dealing with complexity even in the early stages of software development. It should be noticed that such projects do not require knowledge about frameworks, specific libraries, and APIs, the developers only need to concentrate on using Java language. When starting the experiment, the subjects received one of the projects with the required classes to develop a complete flow, i.e., a minimal project and its corresponding requirements document.

Book lend and returns flow should be implemented for **Virtual library**. In general, users request a loan for a certain number of days and a particular type of book. There are copies with unrestricted or restricted circulation and two types of users: standard and research users. The first user profile can only access exemplars of free circulation, while the second can request access to any copies. A complete flow for Virtual Library starts from book loans until its returns. More detailed specifications and constraints were provided to the developers.

The requirements document for **Real Estate Financing** describes that several messaging systems are employed to integrate different microservices. A list of events containing data on loan proposals, real estate guarantees and proponents was provided to the subjects. Based on the validation rules, developers need to return valid proposals after processing all events. Note that a proposal is a template that contains the loan information, including multiple proponents, who are the people involved in the loan agreement.

The main idea of the **Payment Service Provider** is that transactions related to purchases of products from shopkeepers are received and then they can make their withdrawals on top of the available balance (receivables). The project provided contains pieces of code responsible for sending the necessary data to implement a complete flow of generation of receivables.

There were also test scripts to verify the resulting code covering different execution scenarios in these projects. A class called "*solution*" was provided; more specifically, its method "*run*" is the main entry point of the solution for these projects. Therefore, all tests are performed from this method and the classes available in the package called "*ready*" could not be modified during the experiment.

4.2 Planning

The planning followed the *Goal Question Metric (GQM)* (Van Solingen et al., 2002) model for defining the goals and evaluation methods. The principles formulated by Wohlin et al. (Wohlin et al., 2012) were also adopted for the experimentation process. The characterization of this study can be formally summarized as follows:

Analyzing *the effects of the CDD in comparison to conventional practices focusing on early-stage of software development* ***with the aim*** *of comparing the quality of resulting implementation units through object-oriented metrics,* ***regarding the*** *distribution degree to such metrics from the* ***standpoint*** *of software engineers* ***in the context*** *of the industry.*

The hypotheses and objectives for the experimental study are described in detail as follows. It should be noticed that the single difference when using CDD here is determining the ICPs and imposing a feasible limit to guide the development, assuming that it helps reduce the cognitive load on the code.

We suggested a complexity constraint of 7 ICPs (maximum value) for the group that used the CDD as a design rule for the code to be produced. The planning phase has six parts described in the following subsections.

4.2.1 Context selection

The experiment was conducted involving full and senior developers from the same company and it was performed in a controlled way.

4.2.2 Formulation of the Hypothesis

The RQ_1 was formalized into two hypotheses. **Null hypothesis (**H_0**)**: There is no difference between the conventional practices (Non-CDD) and the adoption of a complexity constraint, suggested by CDD, in the early stages of software development when comparing the quality metrics adopted in this study.

Alternative Hypothesis (H_1**)**: There is a difference between the conventional practices and the adoption of a complexity constraint, in the early stages of software development under the perspective of the quality metrics adopted in this study. These hypotheses can be formalized by Equations 1 and 2:

$$H_0 : (\mu Non-CDD^{metrics} = \mu CDD^{metrics}) \quad (1)$$

$$H_1 : (\mu Non-CDD^{metrics} \neq \mu CDD^{metrics}) \quad (2)$$

Similarly, the RQ_2 was formalized into two hypotheses. **Null hypothesis (**H_0**)**: There is no significant difference between the conventional practices (Non-CDD) and the adoption of a complexity constraint, suggested by CDD, considering distribution degree for the quality metrics adopted in this study, since they are equivalent.

Alternative hypothesis (H_1**)**: There is a difference between the conventional practices and the adoption of a complexity constraint, taking into account the distribution degree for the quality metrics adopted in this study. The hypotheses for the *RQ2* can be formalized by Equations 3 and 4:

$$H_0 : (\mu Non-CDD^{distribution} = \mu CDD^{distribution}) \quad (3)$$

$$H_1 : (\mu Non-CDD^{distribution} \neq \mu CDD^{distribution}) \quad (4)$$

4.2.3 Variable Selection

The dependent variables are: **"the values from static analysis for object-oriented metrics (CBO, WMC, RFC, LCOM and LOC)"**. CBO (*Coupling between objects*): this counts the number of dependencies for a certain class, such as field declaration, method return types, variable declarations, etc. For this experiment, dependencies to Java itself were ignored. WMC (*Weight Method Class*), so-called McCabe's complexity (McCabe, 1976), this counts the number of branch instructions in a class. RFC (*Response for a Class*) counts the number of unique method invocations in a class. LCOM (*Lack of Cohesion of Methods*) calculates the LCOM metric. Finally, LOC (*Lines of code*) counts the lines of code, when ignoring empty lines and comments. Note that these metrics were selected because they are considered important according to the code quality concerns of the company.

The independent variables are the projects adopted in this study: **Virtual library**, **Real Estate Financing** and **Payment Service Provider**.

4.2.4 Selection of Subjects

The subjects were selected according to convenience sampling (Wohlin et al., 2012). 44 software engineers who took part in the experiment were working on the development of web projects and they had a degree of knowledge of the Java language.

4.2.5 Experimental Design

The experimental principle of assembling subjects in homogeneous blocks (Wohlin et al., 2012) was adopted to increase the accuracy of this experiment. We looked for ways to mitigate interference from the subjects' experience in the treatment outcomes. One pilot experiment were carried out with a restricted number of subjects. It should be noted that they were not included in the real experiment and the gathered data were helpful in select proper projects and features to be developed as a challenge. In addition, this process enabled the groups to be rearranged for the real experiment.

When separating the subjects into balanced groups, we first asked them to fill out a *Categorization Form* with questions about their experience in areas related to the experiment, a self-evaluation. Based on the data that was obtained, we divided them into two blocks with the same number of subjects. However, not all developers were invited and filled the categorization form accepting the participation in the date defined attended the experiment. We had almost a hundred developers who attended the training about software quality metrics and how this could guide software development. The main CDD principles were taught for half of them. Finally, more than 60 subjects attended the experiment but only 44 projects were considered valid, i.e., the solution was completely developed and verified using the test scripts provided in the study. From this set, one group with 26 developers had to apply conventional development practices focusing on quality and the metrics explained during the training. In contrast, the second group with 18 subjects attended a planned training session about the CDD principles to generate high-quality code without exceeding the complexity constraint for each software artifact.

The *Categorization Form* included questions regarding knowledge about: (i) Object-oriented programming, Java, the number of books read about software development (e.g., Java, *Clean Code*, *Clean Architecture*, *Domain-Driven Design*, etc.) and the number of real (corporate) projects with active participation; (ii) professional experience in Java (More than 3 years, 2 to 3 year or only 1 year); (iii) known software metrics by them and that can eventually be used to improve code cohesion and the separation of concerns; (iv) programming practices and code design that they employ daily; Finally, (v) testing activities and tools.

Figure 2 describes the results of the application of this form in a grouped bar chart. The subjects *"S27-S15"* (Part A) belong to the group that applied CDD principles ("CDD group") in their projects and the subjects *"S25-S80"* (Part B) followed conventional practices without a cognitive complexity constraint ("Non-CDD group"). This chart takes account of numeric values (number of books, courses and real/corporate projects) for each subject. The main reason to use these elements is that the "time experience" is a relative measurement. For instance, likely, a programmer with little time for development but who has attended a higher number of projects can perform better than a person with more time experience and attended a low number of projects. Nevertheless, data related to professional experience were gathered in terms of years of Java development. More than 3 years: 11 (CDD group) and 14 (Non-CDD group); Only 1 year: 2 (CDD group) and 5 (Non-CDD group). Finally, Between 2 to 3 years: 5 (CDD group) and 7 (Non-CDD group).

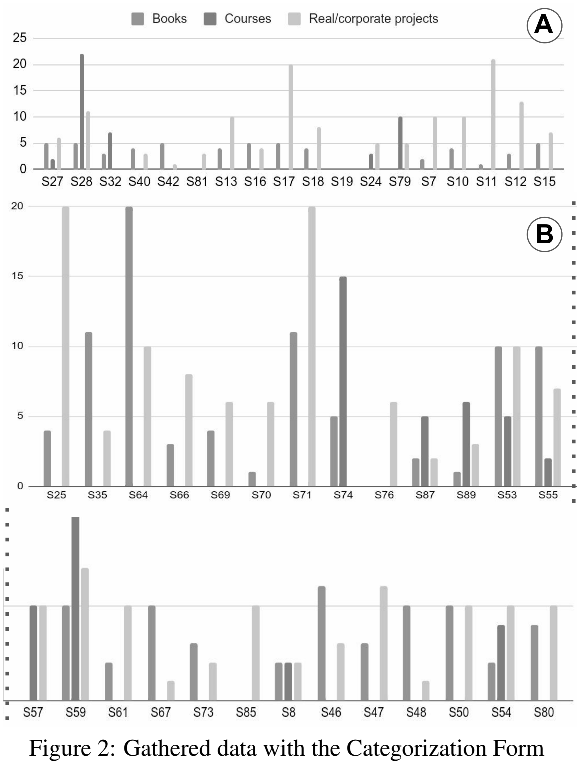

Figure 2: Gathered data with the Categorization Form

Additional information was also obtained to define this separation which can be described as follows, including corresponding percentages of answers. Such answers were also crucial in determining which subjects should develop which projects.

With regard to **software metrics**, we asked the participants which one they use to generate code thinking about readability, cohesion and separation of concerns. The choices/answers where as follows: *Fan-in/Fan-out* (9.09 %), *Cyclomatic Complexity* (27.27 %), *KLOC* (29.55 %), *Number of root classes* (9.09 %), *Coupling between objects* (72.73 %), *LCOM* (47.73 %), *Class size* (47.73 %), *Coupling factor* (43.18 %) or *Software Maturity Index* (SMI) value (11.36 %).

As regards the **programming practices and code design**, most subjects underlined the importance of following principles from: *Clean Architecture* (52.27 %), *SOLID* (79.55 %), *Domain Driven Design (DDD)* (38.64 %), *(Test Driven Development (TDD)* (45.45 %), *General responsibility assignment software patterns (GRASP)* (6.82 %) and *Conventional practices for code cohesion* (47.73 %). Finally, for **testing techniques** they were as follows: *functional testing techniques* (56.82 %), *structural testing techniques* (31.82 %) and some subjects reported that they do not perform testing activities in a systematic way (11.36 %).

4.2.6 Instrumentation

A document was provided to the subjects that described constraints and guidelines to assist them in both the development and the data submission process, as follows:

- The initial package structure had to be kept;
- Automated tests must be kept working completely without any changes;
- It is not allowed to modify the classes available in an specific package (called "*pronto*").

Concerning the guidelines, our suggestion was to fork the corresponding repository from GitHub and import it into IDEs. Each subject was assigned to develop just one of the three projects; the researchers made this definition considering the balance of groups concerning projects. After the development, the subjects were requested to submit the URLs of their remote repositories using a web form.

4.3 Operation

Once the experiment had been defined and planned, it was undertaken through the following stages: preparation, operation and validation of the collected data.

4.3.1 Preparation

At this stage, the subjects were committed to experimenting and were made aware of its purpose. They accepted the confidentiality terms regarding the provided data, which would be only used for research purposes, and were granted their freedom to withdraw by signing a *Consent Form*. In addition, other objects were provided:

- *Characterization Form*: A questionnaire in which the subjects assessed their knowledge of the technologies and concepts used in the experiment;
- *Instructions*: A document describing all the stages, including the instructions about the submission process of the forked repository and classes provided for each project;
- *Data Collection Form*: Document to be filled in by the participants with the information about the projects and their suggestions to improve future experimental studies..

The platform adopted had Java as its implementation language and Eclipse or IntelliJ IDEA as development environments. The groups attended 1-hour training in a web meeting format separately (one for Non-CDD and the other for CDD group). In addition, the meetings were recorded and shared to clarify the main goal for our study: producing source code using excellent practices focusing on readability. Complementary materials were provided and a webchat was created for settling doubts before the experiment, which lasted one week.

For the CDD group, a class from a real-world project was selected to illustrate the identification process of ICPs and define a complexity constraint to keep a feasible understanding degree for all developers in a supposed team. The CDD fundamentals were explained by highlighting the importance of defining a cognitive complexity constraint to guide the development (Souza and Pinto, 2020).

The maximum time to be spent for all subjects during the development activity was defined as four and a half hours. This includes the time to understand the project specifications, create new classes, include and fix features and finally, execute the test scripts. This time interval was defined based on the average time in a pilot study.

4.4 Data Analysis

This section examines our findings. The analysis is divided into two areas: (i) descriptive statistics and (ii) hypotheses testing.

4.4.1 Descriptive Statistics

The quality of the input data (Wohlin et al., 2012) was verified before the statistical methods were applied. There is a risk that incorrect data sets can be obtained due to some error or the presence of outliers, which are data values much higher or much lower than the remaining data.

The metrics adopted in this study have different scales and when taking note of the "resulting implementation units" we decided to be conservative and analyze all the gathered data, in an individual way per metric. When clarifying descriptive statistics and making comparisons, it is essential to explain that the raw data for the metrics were analyzed. We also applied the standard deviations to measure the amount of variation or dispersion of a set of values.

Standard deviations were calculated for each project per subject, considering the implementation units created during our study. Table 1 includes these kinds of data, respectively. The data were separated considering the projects, subjects from CDD or Non-CDD group and finally, the SD(s) that is the standard deviation of the sample standard deviations (s) for values of the metrics. For instance, in the left part of the Table, a version of "Payment Service Provider" was developed by $S40$ and the standard deviations for the values collected for the metrics: CBO, WMC, RFC, LCOM and LOC were: 1.41, 1.87, 2.59, 1.52 and 8.88, respectively. From another perspective, the standard deviations for CDD group (SD(s)) were 0.84, 1.13, 3.86, 1.30 and 15.90.

Although it is difficult to have a generalizable result, in most cases the standards deviations (SD(s)) for the projects delivered by Non-CDD group are more than the values for SD(s) considering the projects developed by CDD group. This fact can raise several discussions since all the projects were started in this experiment, i.e., it was not expected to have a difference between the dispersion of the metrics for the projects developed by the two groups in the early stages of software development. We assume that adopting a cognitive complexity constraint, as suggested by the CDD, enhances the possibility of slicing the features. This contributes to achieving better values for the metrics adopted in this study.

Figure 3 presents a summarized view for the SD(s), taking into account all versions created by subjects from CDD and Non-CDD group. This chart is helpful to observe that the subjects that followed a complexity constraint were implicitly guided to improve the code quality. This behavior of the subjects could be expected but the existence of a restriction forced the results.

For Virtual library (A) and Real Estate Financing (B) it is clear that versions implemented by Non-CDD group had dispersion measures higher than the versions created by CDD group. Nonetheless, for the versions of the Payment Service Provider (C) this perception is not the same because the dispersion measures between the groups were very close. This effect can be justified because this project is less complex than the others in terms of features/business rules to be implemented. Thus, we can not observe a very distant dispersion measure between the values of the metrics for the implementation units.

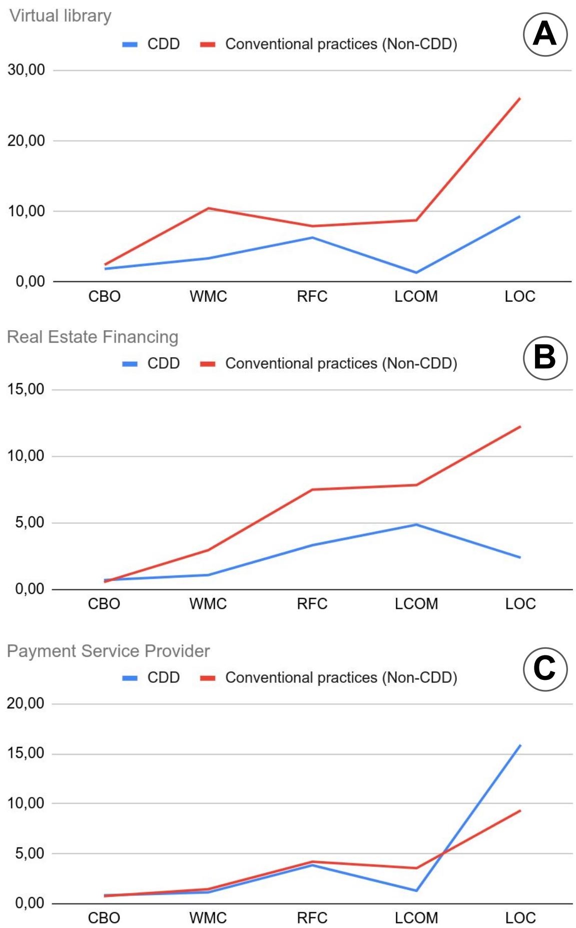

Figure 3: Standard deviations considering all projects (SD(s))

4.4.2 Hypotheses Testing

Metrics - Since some statistical tests only apply if the population follows a normal distribution, before choosing a statistical test, we examined whether our gathered data departed from linearity. This involved conducting the Shapiro-Wilk normality test to check if the samples had a normal (ND) or non-normal distribution (NND).

Table 1: Standard deviations for the metrics considering all versions of projects per subject

Payment Service Provider

CDD group

	CBO	WMC	RFC	LCOM	LOC
S27	2.15	1.46	3.48	3.68	4.24
S28	0.00	4.00	13.00	0.00	46.00
S32	1.64	3.65	3.54	2.05	14.72
S40	1.41	1.87	2.59	1.52	8.88
S42	2.00	2.22	4.20	0.58	10.02
S81	2.30	1.35	5.71	2.23	3.82
SD(s)	**0.84**	1.13	3.86	1.30	**15.90**

Non-CDD group

	CBO	WMC	RFC	LCOM	LOC
S25	1.90	3.49	7.89	5.65	9.33
S35	1.15	1.15	1.00	0.00	1.00
S64	2.01	1.05	2.15	1.32	4.32
S66	3.16	4.62	6.31	11.05	15.83
S69	2.00	1.00	1.53	0.58	3.46
S70	1.77	4.03	6.29	5.55	15.84
S71	0.89	3.13	2.88	7.28	14.34
S74	0.58	1.53	6.11	3.21	11.55
S76	1.72	0.90	3.05	0.49	5.77
S87	0.71	3.54	9.90	0.00	25.46
S89	1.00	4.00	15.00	3.00	31.00
SD(s)	0.76	**1.45**	**4.21**	**3.57**	9.34

Real Estate Financing

CDD group

	CBO	WMC	RFC	LCOM	LOC
S13	0.93	3.23	1.13	4.0	10.27
S16	1.42	4.11	4.16	8.45	13.57
S17	2.73	3.06	3.62	7.84	12.16
S18	1.96	3.59	11.82	14.09	11.82
S19	1.59	5.20	4.61	0.33	12.89
S24	1.10	2.39	4.34	0.45	8.22
S79	0.60	1.92	3.48	5.0	7.25
SD(s)	**0.71**	1.09	3.33	4.87	2.40

Non-CDD group

	CBO	WMC	RFC	LCOM	LOC
S53	1.82	4.24	6.01	9.08	15.29
S55	2.01	4.36	3.18	21.26	14.85
S57	1.00	12.00	12.00	6.00	44.00
S59	2.42	3.32	4.70	10.76	10.65
S61	1.92	2.77	13.86	29.47	15.82
S67	0.74	5.45	3.52	16.99	11.26
S73	1.29	6.55	11.53	15.93	27.98
S85	1.91	7.27	25.50	22.90	34.30
SD(s)	0.57	**2.95**	**7.50**	**7.84**	**12.24**

Virtual library

CDD group

	CBO	WMC	RFC	LCOM	LOC
S7	3.76	1.57	3.58	0	5.44
S10	7.00	9.00	13.00	3	26.00
S11	2.31	1.53	0.58	0	4.04
S12	3.87	1.91	4.36	1.5	10.47
S15	6.00	6.00	15.00	0	19.00
SD(s)	1.88	3.37	6.31	1.34	9.34

Non-CDD group

	CBO	WMC	RFC	LCOM	LOC
S8	2.94	1.71	2.38	0.00	3.77
S46	3.35	3.95	4.22	0.00	15.62
S47	7.00	18.00	20.00	21.00	61.00
S48	7.00	29.00	8.00	15.00	66.00
S50	2.36	1.73	1.91	0.00	5.25
S54	7.00	5.00	20.00	1.00	29.00
S80	1.53	3.51	4.73	1.15	10.69
SD(s)	**2.45**	**10.48**	**7.93**	**8.76**	**26.10**

Table 2 shows the results of the normality tests for all samples, i.e., averages of the values for the metrics in relation to the versions implemented by the subjects. For instance, considering all metrics adopted in this study for versions of "Payment Service Provider" developed by Non-CDD and CDD groups we do not reject the hypothesis that the data are from a normally distributed population. This is different when considering the metric LCOM for "Real State Financing" because both Non-CDD and for CDD group we do not reject the hypothesis that the data are from a non-normal distribution.

Variance testing was performed for all metrics considering the solutions produced by Non-CDD and CDD groups for "Payment Service Provider". The *p-values* were 0.235, 0.5766, 0.8666, 0.1007 and 0.02448 for CBO, WMC, RFC, LCOM and LOC (based on $\alpha = 0.05$, respectively). Unpaired Two-Samples T-test (or unpaired t-test) can be used to compare the means of two unrelated groups of samples. This kind of statistical testing was conducted and the results for *p-values* were 0.5386, 0.8331, 0.9524, 0.2708 and 0.6592 for CBO, WMC, RFC, LCOM and LOC, respectively. Therefore, we can not reject the null hypothesis for the difference between the versions implemented by Non-CDD and CDD groups, in terms of the metrics (on averages) adopted in this study.

The same testing was carried out for the solutions of "Real State Financing" considering the following metrics: CBO, WMC, RFC and LOC. The *p-values* were 0.1959, 0.00376, 0.2256 and 0.004085. With this in mind, Unpaired Two-Samples T-test was verified and the *p-values* were 0.5753, 0.04231, 0.2091 and 0.03565. Therefore, it is possible to reject the null hypothesis for WMC and LOC, considering $\alpha = 0.05$.

Similarly, variance testing was performed for the implementations of "Virtual library" considering just CBO and LOC due to the values from the Shapiro-Wilk normality test, as aforementioned. The *p-values* were 0.7245 and 0.01444. Unpaired Two-Samples T-test ware also verified and as a result, the *p-values* were 0.8603 and 0.2184. Finally, we can not reject the null hypothesis for CBO and LOC considering the versions produced by Non-CDD and CDD groups.

The Mann-Whitney U Test is a nonparametric test that can be used when one of the samples does not follow a normal distribution. We applied this kind of testing for LCOM considering the solutions for "Real State Financing" and for WMC, RFC and LCOM for "Virtual library". Summarizing the results, the value for *p-value* with respect to the LCOM samples was 0.005905. Thus, there is a difference between the versions for "Real State Financing" produced by Non-CDD and CDD groups, i.e., it is possible to reject the null hypothesis for LCOM is this project. On the other hand, we can not reject the null hypothesis for WMC, RFC and LCOM for "Virtual library", the values for *p-values* were 0.8763, 0.8705 and 0.6647, respectively.

Hypothesis Testing - Standard deviations: Similarly, we applied statistical tests to determine if there is a difference between the standard deviations for the values of the metrics.

Table 2: Shapiro-Wilk normality tests for metrics samples (averages)

Metric	Samples		Results
Payment Service Provider			
CBO	*Non-CDD*	*p-value = 0.1604*	ND
	CDD	*p-value = 0.6543*	
WMC	*Non-CDD*	*p-value = 0.241*	ND
	CDD	*p-value = 0.8814*	
RFC	*Non-CDD*	*p-value = 0.1015*	ND
	CDD	*p-value = 0.242*	
LCOM	*Non-CDD*	*p-value = 0.2942*	ND
	CDD	*p-value = 0.4326*	
LOC	*Non-CDD*	*p-value = 0.06566*	ND
	CDD	*p-value = 0.06413*	
Real State Financing			
CBO	*Non-CDD*	*p-value = 0.5138*	ND
	CDD	*p-value = 0.6742*	
WMC	*Non-CDD*	*p-value = 0.1902*	ND
	CDD	*p-value = 0.2505*	
RFC	*Non-CDD*	*p-value = 0.6314*	ND
	CDD	*p-value = 0.7724*	
LCOM	*Non-CDD*	***p-value = 0.01147***	NND
	CDD	***p-value = 0.006358***	
LOC	*Non-CDD*	*p-value = 0.1637*	ND
	CDD	*p-value = 0.575*	
Virtual library			
CBO	*Non-CDD*	*p-value = 0.1153*	ND
	CDD	*p-value = 0.6922*	
WMC	*Non-CDD*	***p-value = 0.005702***	NND
	CDD	*p-value = 0.3644*	
RFC	*Non-CDD*	***p-value = 0.03518***	NND
	CDD	*p-value = 0.2551*	
LCOM	*Non-CDD*	***p-value = 0.002211***	NND
	CDD	*p-value = 0.04824*	
LOC	*Non-CDD*	*p-value = 0.0508*	
	CDD	*p-value = 0.6462*	ND

Variance testing was performed for CBO and LCOM samples considering the solutions produced by Non-CDD and CDD groups for "Payment Service Provider". The *p-values* were 0.724 and 0.03802. Unpaired Two-Samples T-test ware also verified and as results, the *p-values* were 0.9062 and 0.1571. Therefore, it is not possible to reject the null hypothesis for the measures of the dispersion of the set of values refer to such metrics.

Similarly, we carried out the variance testing for CBO, WMC, LCOM and LOC for "Real State Financing" and the results for *p-values* were 0.63, 0.06206, 0.007702 and 0.04069. Therefore, it is possible to reject the null hypothesis only for the LCOM and LOC samples. Finally, for "Virtual library" the variance testing was applied only for LOC sample, resulting in 0.2719 as *p-value*. This indicates that we can not reject the null hypothesis for such metric in this project.

Mann-Whitney U Test was applied for the WMC, RFC and LOC samples with respect to the solutions produced for "Payment Service Provider" and the *p-values* were 0.9199, 1 and 0.8836, respectively. Thus, it is not possible to reject the null hypothesis for such WMC, RFC and LOC samples in this project. This same test was carried out for RFC sample taking into account the "Real State Financing" and the *p-value* was 0.1206. Finally, CBO, WMC, RFC and LCOM samples obtained for "Virtual library" were evaluated using Mann-Whitney U Test and as *p-values* the results were: 0.9341, 0.4318, 0.7449 and 0.6647. Finally, both for "Real State Financing" and "Virtual library", it is not possible to reject the null hypothesis concerning the difference between the dispersion in the values for such metrics.

4.5 Threats to Validity

Internal Validity. *Level of Experience of Subjects*: One can argue that the heterogeneous knowledge of the subjects could have affected the collected data. To overcome this threat, the participants were divided into two-balanced blocks that accounted for their level of experience.

During the training, the subjects that had to apply the cognitive complexity constraint attended a training session on how to use this limit to guide the development process. Thus, they adopted conventional practices during programming like the other group but following such limit;

Productivity under evaluation: the results may have been affected because the subjects often tend to think they are being evaluated during an experiment. We attempted to overcome this problem by explaining to the subjects that no one was being evaluated and their participation would be treated as anonymous;

Validity by Construction. *Hypothesis expectations*: the subjects already knew the researchers, a point which is reflected in one of our hypotheses. This issue could have affected the collected data and caused the experiment to be less impartial. Impartiality was kept by insisting that the participants had to keep a steady pace throughout the study. The main challenge for the researchers was to perform this experiment completely using a web meeting room due to the restrictions of social isolation and the pandemic caused by COVID-19.

External Validity. *Interaction between configu-*

Table 3: Shapiro-Wilk normality tests for standard deviations samples

Metric	Samples		Results
Payment Service Provider			
CBO	*Non-CDD*	*p-value = 0.3137*	ND
	CDD	*p-value = 0.1119*	
WMC	*Non-CDD*	***p-value = 0.04006***	NND
	CDD	*p-value = 0.1895*	
RFC	*Non-CDD*	*p-value = 0.1956*	
	CDD	***p-value = 0.01326***	NND
LCOM	*Non-CDD*	*p-value = 0.1196*	ND
	CDD	*p-value = 0.9022*	
LOC	*Non-CDD*	*p-value = 0.4079*	
	CDD	***p-value = 0.01003***	NND
Real State Financing			
CBO	*Non-CDD*	*p-value = 0.4938*	ND
	CDD	*p-value = 0.8474*	
WMC	*Non-CDD*	*p-value = 0.1584*	ND
	CDD	*p-value = 0.9514*	
RFC	*Non-CDD*	*p-value = 0.1098*	
	CDD	***p-value = 0.01573***	NND
LCOM	*Non-CDD*	*p-value = 0.921*	ND
	CDD	*p-value = 0.6014*	
LOC	*Non-CDD*	*p-value = 0.08716*	ND
	CDD	*p-value = 0.4502*	
Virtual library			
CBO	*Non-CDD*	***p-value = 0.04983***	NND
	CDD	*p-value = 0.6808*	
WMC	*Non-CDD*	***p-value = 0.01113***	NND
	CDD	*p-value = 0.08483*	
RFC	*Non-CDD*	***p-value = 0.02475***	NND
	CDD	*p-value = 0.3184*	
LCOM	*Non-CDD*	***p-value = 0.002712***	NND
	CDD	***p-value = 0.04595***	
LOC	*Non-CDD*	*p-value = 0.08004*	ND
	CDD	*p-value = 0.4999*	

ration and treatment: it is possible that the exercises carried out in the experiment are not accurate for every Java web application. To mitigate this threat, different projects were selected based on the real-world criterion, i.e., the complexity of the applications and the fact that the researchers have contact with real-world projects of the company.

Conclusion Validity. *Measure reliability*: this refers to the metrics used to measure the development effort. To mitigate this threat, we only used the time spent, which was captured in forms filled in by the subjects. This was useful only to observe the Productivity of the developers;

Low statistical power: a statistical test can reveal reliable data. Unpaired Two-Samples T-test and Mann-Whitney U Test were adopted to analyze the metrics for all the delivered versions statistically.

5 Conclusion

Human factors in software engineering impose several challenges. The maintenance can consume more resources than all the effort spent in the creation of new software (Lenberg et al., 2015). Cognitive Load Theory is a framework for investigating the effects of human cognition on task performance and learning (Sweller, 1988; Sweller, 2010). Cognition is constrained by a bottleneck created by working memory, in which we humans can only hold a handful of elements at a time for active processing; to the best of our knowledge, the cognitive complexity constraint has not been applied previously to guide software development. Thus, we proposed a method called Cognitive-driven development (CDD) (Souza and Pinto, 2020) in which a pre-defined cognitive complexity for application code can be used to limit the number of intrinsic complexity points and tackling the growing problem of software complexity, by reducing the cognitive overload.

The main focus of this work was to assess the effects of adopting a complexity constraint in the early stages of software development. Software Development Companies in Brazil use the projects chosen for this study for hiring new software engineers. 44 experienced developers attended our experiment, divided into Non-CDD and CDD groups. Both groups were aware of the importance of quality metrics and the need to produce high-quality code for other developers to understand. The CDD group received different training that included practices guided by a cognitive complexity limit, including our suggestions for elements to set a constraint.

The main findings of our experiment showed that in terms of quality metrics (on average) there was no statistically significant difference between samples of CBO, WMC, RFC, LCOM and LOC, with or without complexity constraint, i.e., projects developed by Non-CDD and CDD groups. However, this is not true for WMC, LOC, and LCOM samples regarding the "Real State Financing" because the projects delivered by the CDD group were better evaluated considering such metrics. Regarding the standard deviations for the samples, only LCOM and LOC for "Real State Financing" had differences when employing a complexity constraint. In addition, it was possible to note a lower dispersion for the values of the metrics samples gathered when analyzing the projects implemented by the CDD group. Such results can be considered positive since all projects were evaluated in the early stages of development. A package containing the tools, materials and more details about the experimental stages is available at *https://bit.ly/3xUdsuo*.

As future investigations, we intend to explore the following factors: (i) defining an automated refactoring strategy employing search-based refactoring and cognitive complexity constraints and (ii) carrying out new empirical-based studies to evaluate restructured projects with CDD principles, by exploring the number of faults and understanding development in the medium and long term.

Acknowledgement

This study was financed in part by the PROPESP and PROINTER/UFPA.

REFERENCES

Chandler, P. and Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and instruction*, 8(4):293–332.

Clarke, P., O'Connor, R. V., and Leavy, B. (2016). A complexity theory viewpoint on the software development process and situational context. In *Proceedings of the International Conference on Software and Systems Process*, pages 86–90.

Duran, R., Sorva, J., and Leite, S. (2018). Towards an analysis of program complexity from a cognitive perspective. In *Proceedings of the 2018 ACM Conference on International Computing Education Research*, pages 21–30.

Fraser, S. D., Brooks, F. P., Fowler, M., Lopez, R., Namioka, A., Northrop, L., Parnas, D. L., and Thomas, D. (2007). "No Silver Bullet" Reloaded: Retrospective on "Essence and Accidents of Software Engineering". In *Companion to the 22nd ACM SIGPLAN Conference on Object-Oriented Programming Systems and Applications Companion*, OOPSLA '07, page 1026–1030, New York, NY, USA. Association for Computing Machinery.

Gonçales, L., Farias, K., da Silva, B., and Fessler, J. (2019). Measuring the cognitive load of software developers: a systematic mapping study. In *2019 IEEE/ACM 27th International Conference on Program Comprehension (ICPC)*, pages 42–52. IEEE.

ISO:ISO/IEC 25010 (2011). Systems and software engineering – Systems and software Quality Requirements and Evaluation (SQuaRE), System and software quality models. International Organization for Standardization ISO.

Lenberg, P., Feldt, R., and Wallgren, L. G. (2015). Human factors related challenges in software engineering–an industrial perspective. In *2015 ieee/acm 8th international workshop on cooperative and human aspects of software engineering*, pages 43–49. IEEE.

Liskov, B. and Zilles, S. (1974). Programming with abstract data types. *ACM Sigplan Notices*, 9(4):50–59.

McCabe, T. J. (1976). A complexity measure. *IEEE Transactions on software Engineering*, (4):308–320.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological review*, 63(2):81.

Misra, S., Adewumi, A., Fernandez-Sanz, L., and Damasevicius, R. (2018). A suite of object oriented cognitive complexity metrics. *IEEE Access*, 6:8782–8796.

Parnas, D. L. (1972). On the criteria to be used in decomposing systems into modules. In *Pioneers and Their Contributions to Software Engineering*, pages 479–498. Springer.

Pinto., V., Tavares de Souza., A., Barboza de Oliveira., Y., and Ribeiro., D. (2021). Cognitive-driven development: Preliminary results on software refactorings. In *Proceedings of the 16th International Conference on Evaluation of Novel Approaches to Software Engineering - Volume 1: ENASE,*, pages 92–102. INSTICC, SciTePress.

Shao, J. and Wang, Y. (2003). A new measure of software complexity based on cognitive weights. *Canadian Journal of Electrical and Computer Engineering*, 28(2):69–74.

Shepperd, M. (1988). A critique of cyclomatic complexity as a software metric. *Software Engineering Journal*, 3(2):30–36.

Souza, A. L. O. T. d. and Pinto, V. H. S. C. (2020). Toward a definition of cognitive-driven development. In *Proceedings of 36th IEEE International Conference on Software Maintenance and Evolution (ICSME)*, pages 776–778.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive science*, 12(2):257–285.

Sweller, J. (2010). Cognitive load theory: Recent theoretical advances.

Van Solingen, R., Basili, V., Caldiera, G., and Rombach, H. D. (2002). Goal question metric (gqm) approach. *Encyclopedia of software engineering*.

Wang, Y. (2006). Cognitive complexity of software and its measurement. In *2006 5th IEEE International Conference on Cognitive Informatics*, volume 1, pages 226–235. IEEE.

Weyuker, E. J. (1988). Evaluating software complexity measures. *IEEE transactions on Software Engineering*, 14(9):1357–1365.

Wohlin, C., Runeson, P., Höst, M., Ohlsson, M. C., Regnell, B., and Wesslén, A. (2012). *Experimentation in Software Engineering*. Springer Berlin Heidelberg.

Yi, T. and Fang, C. (2020). A complexity metric for object-oriented software. *International Journal of Computers and Applications*, 42(6):544–549.

Zuse, H. (2019). *Software complexity: measures and methods*, volume 4. Walter de Gruyter GmbH & Co KG.