Validating Structural Metrics for BPEL Process Models

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Abstract

Business process models tend to get more and more complex with age, which hurts the ease with which designers can understand and modify them. Few metrics have been proposed to measure this complexity, and even fewer have been tested in the Business Process Execution Language (BPEL) context. In this paper, we present three related experimental studies whose aim was to analyse the ability of four selected structural metrics to predict BPEL process model understandability and modifiability. We used Spearman's rho and regression analysis in all three experiments. All metrics passed the correlation tests meaning that they can serve as understandability and modifiability indicators. Further, four of the metrics passed the regression test for understanding time implying that they can serve as understandability predictors. Finally, only one metric passed the regression test for modification time implying that it can serve as a modifiability predictor.

Keywords: BPEL processes, business process models, web services, metrics validation, structural complexity, modifiability, understandability.

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1 Introduction

The Business Process Execution Language (BPEL) is a popular Web services composition language that has become very attractive among Web-based organizations in recent years. Web services created using the BPEL language are fully executable like any other software and are also called processes. BPEL as a language is limited in that it is not modular and not flexible, which means that it cannot guarantee quality for large processes [1]. These limitations are undesirable and have been addressed in the past using measurement-based approaches [2, 3, 4]. Metrics data indicate which processes are risky and hence helps designers to decide on corrective measures. Metrics enable designers to assess the software quality sub-characteristics, which sets the stage for improved product quality and decision-making during development [5, 17, 18].

Although the importance of metrics need not be overstated, only very few have been validated in the context of BPEL processes. For example, metrics validation studies found in [6, 7, 8] focused on Event-driven Process Chains (EPC) while those in [11, 12, 18] focused on models created using the Business Process Model and Notation (BPMN).

Other researchers studied characteristics that are slightly out of the scope of the work described in this paper. For instance, BPEL process re-usability is proposed in [4] while BPEL Process Usefulness Metric under Evolution is proposed in [13]. The study presented in this paper focuses on two quality characteristics, namely, understandability and modifiability. In an effort to operationalize these studied characteristics, we define understandability as the ease to understand a BPEL process. We also define modifiability as the ease to modify a BPEL process. The main purpose of this study, therefore, was to determine whether selected metrics are important BPEL process understandability and modifiability predictors.

The first step in our methodology was to select existing structural metrics. We then designed three related experiments to analyse the metrics. In each experiment, we conducted correlation tests to establish the significance of a relationship, followed by regression tests to further establish the predicting ability of our metrics.

The remaining part of this paper has the following organisation: Section 2 presents related work, Section 3 describes the selected metrics, Section 4 presents empirical studies, Section 5 gives the discussion, and Section 6 gives the conclusions.

2 Related Work

Several business process metrics that fall under the scope of structural complexity have been proposed [2, 6, 7, 8, 4, 18]. Despite the fact that some experimental studies have been undertaken to validate these metrics, these studies were not related to the understandability and modifiability of business process models.

Cardoso [2] proposed a metric called control-flow complexity (CFC). CFC was validated in a study consisting of two families of experiments, with each containing five related experiments [14]. In all these studies, the authors studied the relationship between BPMN model modifiability and understandability on one hand, and CFC on the other hand. Although CFC is a promising metric, more business process metrics that cover a wider scope of structural properties are needed.

In [8], Vanderfeesten et al. performed an experiment to validate their Cross-Connectivity (CC) metric. Results from the experiment show that the CC metric was correlated with error prediction but not with understandability of business process models. Although the CC metric was meant to be combined with other metrics before explaining understandability, there is little evidence to support this claim.

Similar experimental work has been done to investigate relationships between structural complexity metrics and the maintainability of software and data warehouse models [9]. Data warehouse metrics are however not applicable to BPEL process models which have numerous unique domain-specific features.

Other interesting metrics include the square metrics for measuring the complexity of business process models [18]. Despite the fact that these metrics are promising, they were designed to be used with BPMN models and not BPEL models.

3 Selected Metrics

We selected four metrics for empirical analysis from [3] and [10]. These metrics include the information flow for business process (IF4BP), the cognitive complexity for business process (CCBP), weighted structured activities and invokes (WSAI), and the structural complexity for business process (SCBP). Table 1 gives a description of these metrics.

Table 1 Metrics for BPEL process models

Metric	Definition
IF4BP	IF4BPm is the square of the product of incoming and outgoing activities i.e. $IF4BP = (NOIA * NOOA)^2$ Where m is a module in the model. IF4BP of the whole model is the sum of all IF4BPm in the model i.e. $IF4BP = \sum_{m-1}^{n} IF4BPm$
CCBP	The sum of incoming and outgoing activities multiplied by the sum of weight (Wc) of all control-flow constructs in a model i.e. $CCBP = (NOIA + NOOA) * Wc$ Where Wc is a weighted sum of all occurrences of sequence, selection, iteration and concurrent control-flow constructs which are assigned the weights of 1, 2, 3 and 4 respectively.
SCBP	The length of a control-flow unit in a model P multiplied by its average structural complexity i.e. $SCBP = l(P) * asc(P)$ Where l(P) is the length of P, and asc(P) is the average structural complexity of P. In this metric, weights of 1.1, 1.3, 1.5 and 1.7 are assigned to sequence, selection, iteration and concurrent control-flow constructs respectively.
WSAI	The total number of the weights of structured activities and invokes in a model i.e. $WSAI = \sum_{i=1}^{n} c_i$ Where n is the total control-flow constructs while c_i is a complexity associated to the i^{th} control-flow construct. Invokes are jumps that carry the same weight as selection. In this metric, weights of 1, 2, 3 and 4 are assigned to sequence, selection, iteration and concurrent control-flow constructs have respectively.

4 Empirical Studies

4.1 Overview

The related experiments presented in this paper followed the methodology for software engineering experiments [15]. We favoured this methodology because replication of experiments increases knowledge which in turn increases strength in the conclusions made [15].

Experiment Preparation. Based on the GQM template [16], the main aim of our experiments was to analyse the selected metrics for the purpose of evaluating their suitability as BPEL process modifiability and understandability predictors from the point of view of process designers.

Context Definition. Graduate computing students from Universiti Putra Malaysia served as context. We selected twenty software engineering students for the first experiment, eleven computer science students for the second experiment, and twenty computer science students for the third experiment. To ease generalization of results, all subjects in the second experiment had industrial experience in the area of software development.

Instrumentation. The objects that were used in all three experiments included 10 BPEL process models created using the OpenESB BPEL Designer. The metrics served as the independent variables. Table 2 shows the 10 models together with their corresponding metrics values. As can be seen, none of the metrics returns zero values, which is a positive characteristic.

Before proceeding with data analysis, we decided to explore the behaviour of our metrics using descriptive statistics. Table 3 shows summarized metrics values done using measures of central tendency and measures

Table 2 Metrics values

Model	IF4BP	CCBP	WSAI	SCBP
Model 1	1	6	3	6.1
Model 2	64	54	9	13.4
Model 3	16	4	3	6.6
Model 4	9	32	8	13.5
Model 5	16	25	9	12.6
Model 6	1	10	7	6.1
Model 7	1	2	3	3.3
Model 8	225	80	12	21.5
Model 9	9	20	7	8.5
Model 10	256	144	24	51.1

Table 3 Summary statistics

Metric	Min	Max	Range	Mean	STD
IF4BP	1.0	256.0	255.0	59.800	97.2817
CCBP	2.0	144.0	142.0	37.700	44.7761
WSAI	3.0	24.0	21.0	8.500	6.2227
SCBP	3.3	51.1	47.8	14.270	13.9794

Table 4 Correlations between the metrics

Metric	IF4BP	CCBP	SCBP	WSAI
IF4BP	1	0.796, p = 0.006	0.867, p = 0.001	0.811, p = 0.004
CCBP		1	0.948, p = 0.000	0.963, p = 0.000
SCBP			1	0.901, p = 0.000
WSAI				1

of dispersion. For instance, the IF4BP has the highest range and also carries the largest standard deviation (i.e. the most widely spread metrics values).

It is always good practice to check whether the independent variables are correlated with each other which could lead to multi-collinearity. Multi-collinearity is a problem where the independent variables are not really independent of each other, which could make that their effects to be confounding on each other. To address this, we used Spearman's rho (r_s) to correlate the metrics with each other. Results in Table 4 show that the metrics are strongly correlated at the 95% confidence level since all their 2-tailed p-values are less than 0.05. Following this finding, we decided to to investigate each metric separately in a simple quadratic regression rather than performing multiple regression. The aim was to eventually recommend the most resilient candidate(s) that proved strong in all the tests and drop the weaker ones.

4.2 The First Experiment

Definition. The experimental goal was to investigate the relationship between the metrics and BPEL model understandability.

Selection of Subjects. We selected a sample of twenty graduate software engineering students conveniently to participate in the experiment. All had taken courses in software modelling, software evaluation and empirical software engineering. A number of students had industrial experience.

Variables. Independent variables were the structural attributes while the dependent variable was the understandability of a model.

Hypotheses.

- *Null Hypothesis, H_0*. The selected metrics have no significant correlation with model understandability.
- *Alternative Hypothesis, H_1*. The selected metrics have significant correlation with model understandability.

Experimental Design. We implemented a within-subjects experimental design which meant that each subject executed all tests alone for one hour. We chose the design because it has high predictive power. Additionally, we favoured this design since we were testing only one dependent variable, meaning that carryover effects could not occur. We asked the subjects to rank the understandability characteristic based on a scale with five linguistic labels of – very difficult, a bit difficult, neither difficult nor easy, a bit easy, very easy.

Correlation Analysis. The returned questionnaires were complete and therefore adopted for analysis. Medians of subject ratings for each model were computed. We performed the Kolmogorov-Smirnov test and found out that our data was non normal. Thus, we employed the non-parametric Spearman's rho to test the hypotheses.

We controlled the probability of erroneously rejecting the null hypothesis with $\alpha = 0.05$, which represents type I error. Therefore, we set the following decision rule to reject the null hypothesis – for critical values of a two-tailed α test, reject H_0 if its p-value <0.05.

We found a strong correlation between the metrics and understandability at the 95% confidence level with all p-values being below 0.05 as shown in Table 5. This led us to reject the null hypothesis and accept the alternative hypothesis. The negative coefficients shown in Table 5 mean that complexity and understandability have an inverse relationship.

Regression Analysis. After exploring the behaviour of the data, it was decided to perform quadratic regression, which is a special kind of simple linear regression with a curvilinear form. A quadratic regression is a polynomial of the 2-order whose R squared (R^2) values are acceptable for determining significant predictor variables. In this section, regression tests that we discuss include the R^2 measure and the p-values. R^2 is an important measure because it shows the extent to which our metric can explain understandability and modifiability. Results from Table 6 show that all four metrics have high R^2 values and p-values that are below 0.05. We therefore rejected the null hypothesis and accepted the alternative hypothesis, meaning that the metrics

Table 5 Spearman Correlation Results

Metric	r_s	p-value
IF4BP	−0.877	0.001
CCBP	−0.957	0.000
SCBP	−0.972	0.000
WSAI	−0.965	0.000

Table 6 Regression results

Metric	R^2	p-value
IF4BP	0.726	0.011
CCBP	0.890	0.000
SCBP	0.945	0.000
WSAI	0.924	0.000

can be useful understandability predictors. Furthermore, the SCBP metric produced the highest R^2 values hence it is the strongest predictor candidate.

4.3 The Second Experiment (Replica of the First Experiment)

This section presents only those items that are different from the first experiment.

Selection of Subjects.
We selected a sample of eleven graduate Computer Science students. Most of the students were working professionals who were at the same time studying on a part-time basis. Other students were professionals who were studying on a full-time basis after having obtained study leaves from their employers. Students who had less than two years of work experience were not included in this group. Thus, all subjects in this experiment can be considered as moderate level professionals.

Correlation Analysis.
Spearman's correlation results indicate a strong correlation between the metrics and understandability at the 95% confidence level with all p-values being below 0.05. As was the case in the first experiment, we rejected the null hypothesis and accepted the alternative hypothesis. The negative coefficients shown in Table 7 mean that complexity and understandability have an inverse relationship such that when one increases, the other reduces.

Regression Analysis. Quadratic regression tests were done, and R^2 and p-values were computed. Results in Table 8 show that all four metrics have high R^2 values and p-values that are below 0.05. The null hypothesis was therefore rejected and the alternative hypothesis accepted, meaning that the metrics can be useful understandability predictors. In this experiment, the CCBP metric outperformed other metrics, which can be demonstrated by its higher R^2 value, though SCBP has a comparable value.

Table 7 Spearman correlation results

Metric	r_s	p-value
IF4BP	−0.861	0.001
CCBP	−0.953	0.000
SCBP	−0.924	0.000
WSAI	−0.939	0.000

Table 8 Regression results

Metric	R^2	p-value
IF4BP	0.778	0.005
CCBP	0.908	0.000
SCBP	0.905	0.000
WSAI	0.750	0.008

4.4 The Third Experiment

Definition. The experimental goal was to investigate the relationship between the metrics and BPEL model modification times and understanding times.

Selection of Subjects. We selected a sample of twenty graduate software engineering students conveniently to participate in the experiment. All had taken courses in software modelling, software evaluation and empirical software engineering. Some of the students had industrial experience in software development, and some had industrial experience.

Variables. Independent variables were the structural attributes while the dependent variables were the understanding time and modification time of a model.

Hypotheses.

- *Null Hypothesis,* H_{0UT}. The selected metrics have no significant correlation with model understanding time.
- *Alternative Hypothesis,* H_{1UT}. The selected metrics have significant correlation with model understanding time.
- *Null Hypothesis,* H_{0MT}. The selected metrics have no significant correlation with model modification time.
- *Alternative Hypothesis,* H_{1MT}. The selected metrics have significant correlation with model modification time.

Experimental Design. We chose a between-subject experimental design. In this design, we provided a model to each of the subjects, and then asked them to work separately for a period of one hour. To ensure that the design was balanced, we allocated a similar number of subjects to each model.

Correlation Analysis. After receiving the questionnaires from the subjects, the first task was to check for completeness. All 20 questionnaires were complete and therefore acceptable for data analysis. We set a 75% threshold for accurate answers below which a subject would have to be disqualified. No subject underperformed, hence all returned questionnaires were accepted as reliable for analysis.

Next, we computed the means of understanding times and modification times. After we were done with this exercise, we used Spearman Correlation (r_s) to test the stated hypotheses.

As in the first and second experiments, we controlled type I error with $\alpha = 0.05$. We then set the following decision rule to reject the understanding time null hypothesis: for critical values of a two-tailed α test, reject H_{0UT} if its p-value <0.05. We also set the following decision rule to reject the modification time null hypothesis: for critical values of a two-tailed α test, reject H_{1MT} if its p-value <0.05.

Results point to high correlation between the metrics and understanding and modification times since coefficients are high. In addition, results can be said to be significant because the p-values of all metrics are less than 0.05. Consequently, we rejected the null hypothesis H_{0UT} and accepted its corresponding alternative hypothesis. Similarly, the null hypothesis H_{1MT} was rejected and its corresponding alternative hypothesis accepted. Coefficients were also positive implying that whenever complexity increased, understanding and modification times also increased.

Although coefficients are generally lower than those of the subjective ratings, they are all significant since their p-values were less than 0.05 for both understanding time and modification time. Results of the third experiment are shown in Table 9.

Regression Analysis. We conducted regression analysis for the third experiment to establish the metrics prediction ability. As in the first two experiments, we performed quadratic regression tests and then computed R^2 and p-values.

Results in Table 10 show that the IF4BP metric failed the regression test for understanding time since it produced a low R^2 value and a p-value that was higher than 0.05. However, the remaining metrics attained significant

Table 9 Spearman correlation results

	Understanding Time		Modification Time	
Metric	r_s	p-value	r_s	p-value
IF4BP	0.636	0.048	0.647	0.043
CCBP	0.782	0.008	0.869	0.001
SCBP	0.845	0.002	0.838	0.002
WSAI	0.815	0.004	0.827	0.003

Table 10 Regression results

	Understanding Time		Modification Time	
Metric	R^2	p-value	R^2	p-value
IF4BP	0.326	0.251	0.236	0.390
CCBP	0.609	0.037	0.496	0.091
SCBP	0.685	0.017	0.607	0.038
WSAI	0.599	0.041	0.513	0.080

p-values for understanding time, meaning that they can be good predictors of the understandability of BPEL process models.

Further, modification time results in Table 10 show that only the SCBP metric passed the regression test since it achieved a p-value of 0.038, which is smaller than 0.05. Thus, we rejected the modification time null hypothesis and accepted its corresponding alternative hypothesis. Modification time results also show that the p-values for IF4BP, CCBP, and WSAI metrics were greater than 0.05, hence we therefore accepted their null hypotheses. From these results, SCBP is the only metric that can serve as a good modifiability predictor.

4.5 Validity Threats

This section presents an analysis of common threats that could potentially affect the validity of experimental results presented in this paper and the steps taken to mitigate them.

Threat to Construct Validity. The first two experiments were subjective since their dependent variable was measured using subjects' experience. To mitigate the risk that subjective data could cause to construct validity, we selected subjects with a level of knowledge in software development that could be considered as moderate. However, second experiment subjects were moderate level professionals, and this made their opinions to be more highly regarded than those of the first experiment. Moreover, the dependent variables of the third experiment were objective thus overcoming any potential subjectivity. Therefore, we can consider all our dependent variables as being constructively valid.

Threat to Internal Validity. We considered the different characteristics within our subjects such as industrial experience, motivation levels, among other factors, which normally affect internal validity. For instance, all subjects took a BPEL process modelling course.

Threat to External Validity. We considered subject characteristics that normally threaten generalizability of results, such as use of student subjects. We selected only those students who had taken software development courses. Furthermore, all students who participated in the second experiment had industrial experience. The careful selection of experimental subjects helped ease results generalization.

Threat to Conclusion Validity. Sample data sizes have been known to affect conclusion validity of a study if they are insufficient. We used the following sample data sizes: 10 models and 20 subjects resulting to 200 data values for the first experiment, 10 models and 11 subjects resulting to 110 data values for the second experiment, and 10 models and 20 subjects resulting to 200 data values for the third experiment. The size of these data values provided the predictive power that helped mitigate this type of threat to conclusion validity.

5 Discussion

Data from the experiments were analysed in two steps, that is, correlation analysis and regression analysis.

Correlation results were significant for all experiments. Correlation coefficients were also high, implying strong relationships. Since correlation tests can only indicate the existence and strength of a relationship, it can be argued that the studied metrics are valid understandability and modifiability indicators.

We conducted regression tests to find suitable candidates that can serve as understandability and modifiability predictors. This test was necessary because correlation alone cannot tell whether an independent variable can predict its corresponding dependent variable. All metrics passed the regression tests for the first and second experiments. In the third experiment, however, IF4BP metric failed the regression tests for understanding time and

Table 11 Summary of Global Results

	Understandability Ratings (Expt.1)		Understandability Ratings (Expt.2)		Understanding Time (Expt.3)		Modification Time (Expt.3)	
Metric	r_s	R^2	r_s	R^2	r_s	R^2	r_s	R^2
IF4BP	✓	✓	✓	✓	✓	×	✓	×
CCBP	✓	✓	✓	✓	✓	✓	✓	×
SCBP	✓	✓	✓	✓	✓	✓	✓	✓
WSAI	✓	✓	✓	✓	✓	✓	✓	×

Key: ✓ = metric validated; × = metric not validated

modification as its p-values were higher than 0.05 for both cases. Since this experiment involved objective data, we used it as a discrimination criteria such that a metric had to pass this test before qualifying as a predictor. For this reason, we dropped IF4BP from the list of predictor variables even though it passed the first two subjective experiments. The remaining CCBP, SCBP and WSAI metrics passed the regression tests for understanding time, hence they can serve as good predictors of understandability. Finally, SCBP metric passed the regression test for modification time since its p-value was lower than 0.05, while all other metrics failed the test. For this reason we consider SCBP as a valid both understandability and modifiability predictor for BPEL process models. Table 11 presents a summary of these global results.

6 Conclusions

The understandability and modifiability of business process models is very important to both designers and business process managers. Metrics that can predict these two characteristics are key to the development of the industry. We have presented three related experiments in this paper with the aim of finding good understandability and modifiability predictors. We collected subjective data from the first and second experiments since the subjects ranked each provided model's understandability. We then analysed the relationships between medians of subjects' ratings and the metrics. Although subjects from the second experiment had industrial experience, we did not observe any significant differences between their responses and those of subjects from the first experiment. The third experiment was objective where we analysed the relationships between means of understanding and modification times, and metrics. Analysis for each experiment involved both Spearman rho and regression analyses.

Correlation results from all experiments support a strong correlation between the metrics and modifiability and understandability. However, correlation coefficients for subjective experiments were negative while those from the objective experiment were positive. Negative values imply that whenever the predictor variables increased, the predicted variables decreased. Conversely, positive values indicate that whenever the predictor variables increased, the predicted variables also increased. Since the purpose of correlation is to establish a relationship, we can conclude our are metrics are good indicators of the understandability and modifiability of BPEL process models. Further, since regression is intended to predict or estimate the dependent variable, we can conclude that all metrics except IF4BP are good understandability predictors since they passed the regression test for both understandability and understanding time. Finally, we can conclude that only SCBP is a good modifiability predictor since it passed the regression test for modification time. An interesting observation is that the SCBP metric had very strong coefficients in all cases, and therefore, we recommend it as the overall predictor of both understandability and modifiability of BPEL process models.

In future, we plan to undertake more experimentation with the selected metrics, especially to further investigate the metrics that got mixed results.

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