2012•2013
FACULTY OF BUSINESS ECONOMICS
Master of Management: Management Information Systems

Masterproef
The influence of process contructs on process model understandability

Promotor :
Prof. dr. Benoit DEPAIRE

Ádám Kornél Nagy
Master Thesis nominated to obtain the degree of Master of Management , specialization Management Information Systems

Universiteit Hasselt | Campus Hasselt | Martelarenlaan 42 | BE-3500 Hasselt
Universiteit Hasselt | Campus Diepenbeek | Agoralaan Gebouw D | BE-3590 Diepenbeek

2012•2013

FACULTY OF BUSINESS ECONOMICS

Master of Management: Management Information Systems

Masterproef

The influence of process contructs on process model understandability

Promotor :
Prof. dr. Benoit DEPAIRE

Ádám Kornél Nagy

Master Thesis nominated to obtain the degree of Master of Management , specialization Management Information Systems

This master thesis is the result of a half year research on business process understandability and the conclusion of my one year study in the Master of Management programme of Hasselt University.

I have chosen the topic of business process model understandability as I find it very interesting and I think it is a very important topic that has implications on the operations of many companies.

I would like to take this opportunity to acknowledge the help and support that I received in the past year.

I very much enjoyed the lectures at UHasselt, I think I have gained knowledge and insight that will be very helpful later in my life. For that I am very thankful to all my professors. Special thank goes to Prof. Benoît Depaire, who was my promoter for this thesis. His guidance and his help in overcoming the obstacles I had encountered were crucial for my thesis.

I am also thankful to my fellow students, many of whom helped me with various things in the past year. I have met many great people during my studies at UHasselt. I would like to especially thank Abhishek Bakuli and Sinja Cimiotti for their help and suggestions that they provided for this thesis.

I trust that the findings in my thesis will prove to be useful and relevant. While working on the thesis I have gained a deeper understanding of the topic that I hope I can utilise later in my career.

Summary

The subject of this thesis is the influence of process constructs on process model understandability. It contains 5 chapters in which different aspects of the topic are investigated. This summary provides an overview of the content of the thesis.

The main research question of the thesis - as shown in the first chapter - is the following: *What factors influence the understandability of business process models?*

The literature review in the second chapter contains summaries of all relevant articles that have been written about the topic until now. It has been found that only a limited number of publications address the topic of business process model understandability (cognitive complexity) and most metrics have severe limitations or shortcomings.

The review of several cognitive complexity metrics has revealed that most of them are of little or no use when it comes to practical application. One promising and relatively new measure appears to be promising: the so called cognitive weight metric, which is explored in greater depth in the second part of the thesis.

The cognitive weight metric was first suggested to measure the complexity of software code by Shao and Wang in 2003, but it has been adapted to process models that are designed using the YAWL language by Gruhn and Laue in 2006. The main concept of the metric is that some constructs within the models are more difficult to understand than others and a value is assigned to each of them that represents their so called cognitive weight. In the thesis an adaptation of the metric from YAWL to the popular BPMN modelling language is suggested.

To see if whether the cognitive weight metric is viable and -more generally - if the number of various different constructs in a model indeed influence understandability differently, a survey was carried out. In the on-line survey respondents were asked to answer questions related to 4 different process models. The gender of the respondents and their previous experience with process models was also recorded.

The results of 30 respondents were then analysed using various statistical methods to see whether the different constructs have various effects on understandability. A multi-level analysis has revealed that the number of different constructs in a given model indeed have a significant effect on the understandability of that model. Different constructs appear to have different effects.

Considering these results, the cognitive weight metric proposed by Gruhn and Laue seems to be viable, although the exact cognitive weight values of the various constructs could not be validated due to the limited data available.

Based on the literature review and the survey conducted it can be said that several factors influence the understandability of business process models, therefore no single metric can capture it.

However, the cognitive weight metric appears to be very promising. Its viability is supported by this thesis and if further research can confirm the exact cognitive weight values for the various constructs then it can become a very useful metric for measuring the cognitive complexity (understandability) of business process models.

Table of contents

Summary 2

List of figures 5

List of tables 5

Chapter 1 – Introduction
1.1 General introduction 7
1.2 Research question 8
1.3 Research plan and structure 8

Chapter 2 – Literature review
2.1 Literature on process model complexity 11
2.2 Literature on understandability of process models 13
2.3 Summary of the Literature Review 17

Chapter 3 – BPMN and cognitive weights
3.1 Introduction to the elements of business process models 19
3.2 Cognitive weights 21
3.3 Adapting the cognitive weight metric to BPMN 23

Chapter 4 – Empirical research
4.1 Introduction 27
4.2 Methodology and survey format 28
4.3 Hypothesis 33
4.4 Survey results 34
4.5 General analysis 37
4.6 Multi-level analysis 39
4.7 Analysis results vs. hypothesis 43
4.8 Order of execution 44
4.9 Role of cognitive weight 46

Chapter 5 – Conclusion
5.1 Final conclusion 49

References 51

Appendices
Appendix 1 53
Appendix 2 54
Appendix 3 55
Appendix 4 56
Appendix 5 58

List of figures

Figure 3.1: Start event, message event, end event..20
Figure 3.2: Two different tasks..20
Figure 3.3: Sequence flow...20
Figure 3.4 Different gateways..21
Figure 3.5: Example process model containing some of the most common elements......21
Figure 3.6: Consecutive tasks, cognitive weight value: 1...24
Figure 3.7: Exclusive gateway, cognitive weight: 2 or 3...24
Figure 3.8: Parallel gateway, cognitive weight: 4...25
Figure 3.9: Inclusive gateway, cognitive weight: 7...25
Figure 4.1: Model A of the survey...29
Figure 4.2: Model B of the survey...30
Figure 4.3: Model C of the survey...31
Figure 4.4: Model D of the survey...32
Figure 4.5: Frequency of the different test scores shown on a histogram........................38
Figure 4.6: A part of Model A..44
Figure 4.7: A part of Model B..45
Figure 4.8: A part of Model D..45

List of tables

Table 2.1: Definition of BCSs and their equivalent cognitive weights................................15
Table 3.1: Cognitive weights of different workflow patterns...22
Table 3.2: Cognitive weights adapted to BPMN...25
Table 4.1: Sample data showing responses related to Model A in the survey...................36
Table 4.2: Test scores of the different models...37
Table 4.3: Frequency of the different test scores in the survey results.............................37
Table 4.4: Mean scores in the first and second wave of the survey..................................38
Table 4.5: Values related to score and subjective complexity of the multi-level analysis..40
Table 4.6: Results of the multi-level analysis on model, gender and experience..............41
Table 4.7: Results of the multi-level analysis on the model construct variables...............42

Chapter 1

Introduction

1.1 General introduction

According to the definition given by Geary A. Rummler and Alan P. Brache in their book *Improving Performance: How to Manage the White Space in the Organization Chart,* a business process is "the series of steps that a business executes to produce a product or service". [1] The larger an organization is, the more it relies on various processes for its activities. Complex activities are described by complex process models. These process models are used by all kinds of businesses in all sectors and their importance is constantly growing as the processes at companies keep becoming more and more complex and automated.

The purpose of the process models is to clearly document the processes of organizations and provide a better understanding of them. However, processes models often become overly complicated and include various flaws that hinder understanding and can make the processes inefficient. Different stakeholders at an organization might have different training and skills that can result in problems with understanding process models as well. While for the designer of the model it may seem perfectly understandable, other people might have problems understanding it or, which is probably even worse, misinterpret parts of it.

It is also very important to realize that while the complexity of a process model can be measured by different mathematical approaches, human understanding of the model does not necessarily correlate with the measured complexity, i.e. humans might have difficulties interpreting certain parts of a model even if it does not appear to be overly complicated in terms of mathematical complexity.

Gaining more insight in what exactly makes process models difficult to understand would allow the creation of better process models, which would lead to more effective operations within organizations, therefore any research related to this topic is definitely relevant and important.

1.2 Research question

The goal of this thesis is to find an answer to the following main research question:

- ***What factors influence the understandability of business process models?***

In order to be able to do that, several aspects of the topic have to be explored, as summarized by the questions below:

- *What study has been done in the field of business process model understandability until today?*

Knowing what research has been done before is crucial to see what is already known in the field and what requires further research. A full overview of both the history of the topic and the state-of-the-art is needed before anything else can be done.

- *What constructs within business process models contribute to their understandability?*

To see what factors influence the understandability of a model as a whole the best approach is most likely to see what elements within the model contribute to the understandability.

- *How much the various constructs contribute to understandability?*

Once it is known what constructs have an effect on the understandability, the next step should be to see how much they actually influence the understandability.

Finding the answers to the sub-questions above should lead to the answer to the main research question. The plan to find the answers is detailed in the following section.

1.3 Research plan and structure

First, a literature review is done to find out what studies have already been done in the field. The aim of that is to present high quality articles from reliable sources and explain why they are important and relevant to the topic of the thesis. Exploring the related literature provides an overview on the timeline of the various studies, ending with a review on the current state-of-the-art in the field. Since earlier studies were related to complexity of the models and their understandability was only studied more recently, the first part of the literature review is more about complexity, while its later parts concentrate more and more on understandability. Various Internet search engines and databases are used to find articles that are related to the complexity or understandability of business process models, including (but not limited to): AtoZ eJournals at Hasselt University, EBSCOhost and Google Scholar. The source of the articles is checked in each case to verify that it is reliable. Reputable scientific journals and authors are preferred over less known ones. The management of the various authors and articles is done using the Mendeley Desktop software.

The second part is a short introduction to how business process models are constructed and what basic elements are most often used. One of the several business process modelling languages (Business Process Model and Notation, BPMN) is introduced. This is required to provide a general understanding on how the models are constructed, which is crucial for the later parts of the research.

In the third part a promising approach to process model complexity, called *cognitive weights* is explained.

The fourth part of the thesis is an empirical research, testing the validity of cognitive weights along with other factors that might influence the understandability of process models. To accomplish this, a survey is performed amongst a group of student who are familiar with process models. The results of the survey are analysed using various statistical approaches.

In the end of the thesis all findings are summarised and conclusions are drawn.

Chapter 2

Literature review

2.1 Literature on process model complexity

The complexity of a process model is in many ways similar to the complexity of a computer program. Many early attempts at defining the complexity of process models derived the methods from software complexity metrics. Most approaches in earlier days and recently are related to graph theory.

One of the first measures introduced was the Coefficient of Network Complexity (CNC). Pascoe in 1966 [2] and Kaimann in 1974 [3] both discussed this, although their formulae differed slightly. Pascoe used the ratio of arcs to nodes, CNC = A/N, Kaimann argued that CNC = A^2/N is a better approach. According to this measure a model becomes more and more complex as the number of arcs increase in relation to the number of nodes. In many cases CNC is a good indication of a model's complexity, as more arcs mean more possible paths and thus more effort is needed to understand the model. However, in other cases more paths mean less complexity as a result of the nodes being better connected. Since neither CNC formula takes into account what kind of nodes are in the model and how exactly they are connected, the measure can provide a very inaccurate or even misleading idea of the model's complexity. Because of these shortcomings the CNC formulae are too primitive to be used for accurate measuring and are not widely used nowadays. Latva-Koivisto provides a more detailed explanation on the issues with CNC in *Finding a complexity measure for business process models* [4]. To demonstrate the problems with CNC he drew two different graphs with the same amount of arcs and nodes, but with very different complexity that is obvious at first sight. His graphs can be found in *Appendix 1* of this thesis.

Another paper related to the topic has been published in 1976 by Thomas McCabe who introduced the idea of measuring complexity through the number of control paths in a program. In his paper *A Complexity Measure* [5] McCabe uses graph theory and states that the complexity of a program can be expressed using the Cyclomatic Number, which corresponds to the number of linearly independent paths in the program. While originally designed for measuring the complexity of a computer program, it can be easily applied to process models. It is a more sophisticated approach than the Coefficient of Network Complexity as it does not only take the number of arcs and nodes of a graph into account, but the structure of the model as well. This approach has been in use ever since McCabe's paper has been published in 1976, however, it does not provide a perfect measure for complexity. While this metric gives a good general idea of it, a model's complexity depends on many other factors as well, that are not measured by the Cyclomatic Number.

In his paper *Finding a complexity measure for business process models* [4], published in 2001, Antti Latva-Koivisto does a good comparison on some of the measures mentioned earlier. He compares five graph complexity measures and analyses them according to different criteria. The compared complexity measures are Coefficient of Network Complexity (CNC), Cyclomatic Number (S), Complexity Index (CI), Restrictiveness Estimator (RT) and Number of Trees (T). CNC and S have been discussed earlier in this chapter. The CI (aka reduction complexity) is defined as the minimum number of node reductions required to reduce a graph to a single edge by Bein et al. in 1992. [6] RT is the number of feasible sequences in a graph, introduced by Thesen in 1977. [7] T is the number of distinct trees that a graph contains, as described by Temperley (1981). [8]

These three measures are less straightforward than CNC and S and their detailed calculation methods and review are not strictly relevant to this thesis. More details on them can be found in Latva-Koivisto's report or in the other respective referenced papers. Latva-Koivisto concludes that no single measure is clearly superior to the others, but CNC is inferior as it fails to capture the essence of complexity in models. CI is also found inferior, but mainly due to the difficulties of its implementation. The author suggests further research in implementing the algorithm to compute the CI.

Another paper that is similar in goal to that of Latva-Koivisto was published by Volker Gruhn and Ralf Laue in 2006 [9]. The authors argue that extensive research has been done on software complexity and they attempt to apply the same methods for business processes. A number of different software metrics are reviewed in the paper and their adaptability to process models is discussed. The first metric discussed is the Lines of Code (LOC), which measures the complexity of a program by counting either literally the lines in its code or - as more common in the case of modern programming languages - the number of executable statements. [10] According to the authors this can be applied to business process models by counting the number of activities in them. While that gives an idea of the model's size it does not take the structure into account and therefore can be misleading.

After the LOC the cyclomatic number (discussed earlier in this chapter) is also reviewed briefly by Gruhn and Laue, along with Control Flow Complexity (CFC), which is based on the cyclomatic number. CFC was defined by Cardoso in 2005 [11], it is based on the number of decisions in a model. Some other measures are also reviewed, including nesting depth, knot-count (number of handles), (anti) patterns, and fan-in / fan-out. These are either of little use on their own or are irrelevant to this thesis, further details on them can be found in [9] or in the articles referenced in that paper. There is one more metric discussed in the paper of Gruhn and Laue which is very relevant, but not explained here: cognitive weights. It will be reviewed later on.

To summarize [9]: in the opinion of the authors the cyclomatic number gives the best general idea of complexity and that a cognitive weight [12] metric (to be reviewed in detail later in this thesis) adapted to business process models could also be useful; however, such metric had not been available at the time of publication. Like Latva-Koivisto, Gruhn and Laue also conclude that no single metric can capture all aspects of a model's complexity. They suggest that different metrics should be used to capture different aspects of a model's complexity.

2.2 Literature on understandability of process models

Complexity of a business process is an important attribute, however, the goal of this thesis is to find factors that influence the *understandability*, which is while related to complexity is more complicated than that. Cognitive complexity distinguishes human factors from computational complexity.

In 2003 Jingqiu Shao and Yingxu Wang introduced the concept of cognitive weight in their paper *A new measure of software complexity based on cognitive weights.* [12] While the paper focuses on software complexity, the concept can be – and indeed has been – applied easily to business processes. By the definition of the authors “the cognitive weight of software is the degree of difficulty or relative time and effort required for comprehending a given piece of software modelled by a number of BCSs”. BCS in the definition refers to basic control structures in software, which correspond to constructs in a business process model, an overview of which is given in the next chapter of this thesis.

Shao and Wang describe how the cognitive weight of a piece of software can be calculated. The basic idea is that a cognitive weight (W_i, a natural number) is assigned to the different types of BCSs found in the piece of software measured and the total cognitive weight of the software component is the sum of those numbers. The authors’ definition of BCSs and their equivalent cognitive weights can be seen in Table 2.1 below:

Definition of BCSs and their equivalent cognitive weights (W_i)

Category	BCS	Structure	W_i	RTPA notation
Sequence	Sequence (SEQ)		1	$P \rightarrow Q$ Note: Consider only one sequential structure in a component
Branch	If-then-[else] (ITE)		2	$(?\exp BL = T) \rightarrow P$ $\mid (?\sim) \rightarrow Q$
	Case (CASE)		3	$?\exp RT =$ $0 \rightarrow P_0$ $\mid 1 \rightarrow P_1$ $\mid \ldots$ $\mid n-1 \rightarrow P_{n-1}$ $\mid \text{else} \rightarrow \varnothing$
Iteration	For-do (R_i)		3	$R_{i=1}^{n}(P(i))$
	Repeat-until (R_1)		3	$R_{\geq 1}^{\exp BL = T}(P)$
	While-do (R_0)		3	$R_{\geq 0}^{\exp BL = T}(P)$
Embedded component	Function call (FC)		2	$P \hookrightarrow F$ Note: Consider only user-defined functions
	Recursion (REC)		3	$P \circlearrowleft P$
Concurrency	Parallel (PAR)		4	$P \parallel Q$
	Interrupt (INT)		4	P $\parallel \odot (@eS \nearrow Q \searrow \odot)$

Table 2.1: Definition of BCSs and their equivalent cognitive weights (source: [12])

In their 2006 paper mentioned earlier ([9]) Gruhn and Laue argue that a cognitive weight metric that is well adapted for business process models could be useful in measuring the complexity of a model. Later in the same year they published *Adopting the Cognitive Complexity Measure for Business Process Models* [13], in which they explore the problem in detail. They point out the similarities and differences between program codes and business process models and then attempt to adopt the metric to the latter. First they define the cognitive weight of a business process model: “The cognitive weight of a BPM is the sum of the cognitive weights of its elements.” Then they assign weight values to different process model elements on a scale from 1 to 7. They argue that using their method the cognitive complexity of a process can be well measured, but they also note the limitations of the approach. The metric does not measure additional cognitive complexity resulting from the layout and from the descriptions which are written in a natural language. The authors also admit that their new metric cannot be used as a universal tool for measuring complexity and should be used alongside different metrics to capture all aspects of a process model’s complexity.

Jan Mendling of Wirtschaftsuniversität Wien is one of the very few researchers who have also done research in the field of business process understandability. He co-authored two papers that are very relevant to the topic of this one.

A recent study on process understandability is the *Influence Factors of Understanding Business Process Models* by Mendling and Mark Strembeck, published in 2008. [14] The two authors also note that surprisingly little research has been done in the field of process understandability. They conducted an experiment with the goal to see whether personal factors, model characteristics, textual content, modelling purpose, modelling languages and visual layout has any effects on human understandability of process models. They designed an online test and distributed it to students and professionals who were familiar with process modelling. The authors found that personal, model, and content related factors indeed influence understandability.

Another paper by Mendling, co-authored with Hajo A. Reijers is *A Study into the Factors that Influence the Understandability of Business Process Models* [15]. Published in 2011, this paper is similar to the other one (by Mendling and Strembeck). Similarly to the other paper, the authors had designed a questionnaire to test whether personal and model factors influence the understandability of the processes and then distributed it to 76 students. They concluded that while both factors play a role in understanding a model, personal factors are more important, an expert can understand even poorly designed diagrams. The authors suggest that perhaps it is a better choice for companies to provide good training to their employees rather than to put effort into restructuring complex models.

It is worth mentioning that Mendling and Reijers have published several other papers on process model understandability (together or with other co-authors), but those do not contain any important theories or findings that are not present in the papers that are reviewed in this thesis, therefore they are not included in the review.

2.3 Summary of the literature review

By reviewing the current literature on the understandability of process models it can be concluded that while there have been attempts to come up with a method to clearly describe the complexity of models, no universally applicable solutions have been found. Due to the nature of these models a universal metric that clearly measures the complexity is maybe impossible to find, but this is a topic for future research and will not be further discussed in this thesis. While considerable research has been done on complexity, interestingly the same cannot be said for understandability. Human understanding of business process models is arguably even more important than theoretic complexity. The literature review has revealed that the metric that appears to be the best at quantifiably measuring the understandability of a business process model is the cognitive weight metric proposed by Gruhn and Laue in [13].

Chapter 3

BPMN and cognitive weights

3.1 Introduction to the elements of business process models

There are several major business process modelling languages and tools that can be used to design process models, such as Business Process Model and Notation (BPMN), Event-driven process chain (EPC), Unified Modeling Language (UML), etc. Most of these share basic elements and are built in a similar way. This paper will not focus on the differences in the modelling languages, but on the process models in general. Due to its popularity, the Business Process Model and Notation (BPMN) language will be used for designing all models in this thesis.

Main elements

In this section a brief overview of the elements of business process models is given, in order to make the understanding of the rest of the paper easier for readers who are not familiar with these models. The elements described can be found in nearly all business process modelling languages, only their symbols or names might vary slightly. The names and symbols used here are taken from the BPMN 2.0 standard.

The models are based on events and activities.

An **event** is something that happens during a process (either at the beginning, during the process or at the end of it). Note that events *occur* rather than being done by someone and people inside the organization have no control over them. In BPMN it is represented by circles. Various symbols within the circle can be used to represent different kind of events. Figure 3.1 shows a start event, a message event and an end event.

Figure 3.1: Start event, message event, end event

An **activity** – unlike an event – is something that is done within the organization, either by a human or by a computer. In BPMN activities are represented by rounded rectangles. The most basic kind of activity is a **task**. In this thesis only tasks are used. Symbols in the upper left corner might be used to indicate the type of the task.

Figure 3.2: Two different tasks

To represent in what order events and activities follow each other **sequence flows** are used. These lines connect the different elements in the model and have an arrowhead to show their direction.

Figure 3.3: Sequence flow

The logical connections between the activities are shown by different **gateway** symbols. Gateways can act as **splits** or **joins**. Splits divide one flow arch into more than one, joins join multiple ones into one.

XOR splits represent a choice between possible flows, where only one of the possible flows can be followed. An XOR join joins flows. **OR** gateways are similar to XORs, but allow more than one possible choices. Zero choice is not acceptable in either case. If all flows must be taken simultaneously then an **AND** split is used. An AND join waits until all incoming flows are finished.

Figure 3.4: Different gateways

Figure 3.5 shows an example process with the most common elements. From left to right: start event, split gateway, two activities, join gateway, end event. The elements are connected via sequence flows.

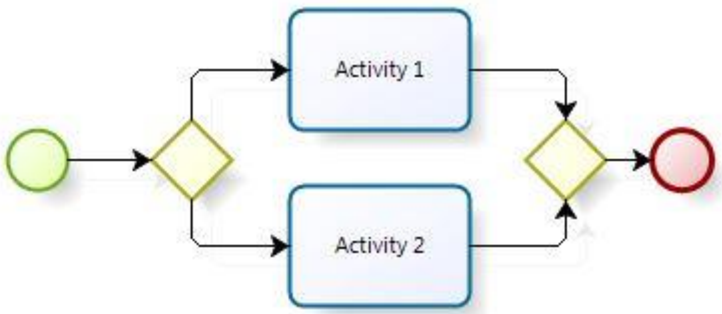
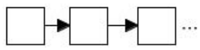
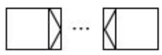
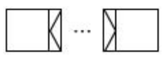
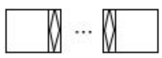


Figure 3.5: Example process model containing some of the most common elements

3.2 Cognitive weights

Since the publication of the proposed cognitive weight metric for business process models by Gruhn and Laue in 2006, the method has only been mentioned in a few scientific articles, but no further research has been done on the topic. Considering the limited number of publications on the topic of business process model understandability this is not surprising, however this approach appears to be very useful in determining the cognitive complexity of business process models.

Table 3.1 below is adapted from [13]. It shows the cognitive weights of different workflow patterns as proposed by Gruhn and Laue. Workflow patterns can be used to describe elements in both programming languages and business process models, especially the workflow language YAWL (Yet Another Workflow Language), which is based on them. The authors adapted the cognitive weights for YAWL, as seen in the table.

Workflow Pattern [16]	**BPM control structure**	**Corresponding software control structure**	**YAWL symbol**	**W**
Sequence	consecutive steps in a workflow	sequence		1
Exclusive Choice	XOR-split (exactly one of two branches is chosen) with corresponding XOR-join	branching with *if-then*		2
	XOR-split (exactly one of ≥ 3 branches is chosen) with corresponding XOR-join	branching with case (with an arbitrary number of selectable cases)		3
Parallel Split and Synchronization	An AND-split activates all outgoing links in parallel, a corresponding AND-join synchronizes the flows of control	execution of control flows in parallel		4
Multiple Choice and Synchronizing Merge	OR-split (a number of branches is chosen from 2 or more possible branches) with corresponding OR-join	branching with case, followed by parallel execution		7

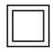
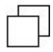
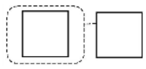
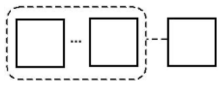
(none)	Composite task (subtask, can be used for decomposing a BPM into modules)	call of a user-defined function		2
Multiple Instances Patterns	Multiple Instance Activity (allows multiple instances of an activity to run concurrently)	branching, followed by parallel execution		6
Cancel Activity	Cancellation (by activating an activity one deactivates another one)			1
Cancel Case	Cancellation (by activating an activity one deactivates all elements within another part of the model)	comparable to a function call		2 or 3

Table 3.1: Cognitive weights of different workflow patterns (source: [13])

3.3 Adapting the cognitive weight metric to BPMN

Gruhn and Laue decided to adapt the cognitive weight metric to YAWL because they felt that its expressive power makes it the best choice for their paper. However, because of differences in business process modelling languages, the cognitive weights that have been defined for YAWL workflow patterns cannot be directly applied to other modelling languages. In this chapter an adaptation of the cognitive weights to the Business Process Model and Notation is proposed. The values are based on the ones defined by Gruhn and Laue for YAWL, taking the differences of the two languages into account. The cognitive weights for YAWL are derived from the weights of control structures in programming and can be found in greater detail in [12].

Sequence flow

The YAWL cognitive weight value for consecutive steps in a workflow is 1, making it the simplest pattern. Since the function and notation for this is practically the same in BPMN, the proposed value is also 1. The most common element in a sequence flow is a task, but in BPMN several different notations exist to symbolize things such as different intermediate events. BPMN also allows differentiation of tasks, such as user or service tasks, marked with different symbols in the corner of the task. Since the underlying structure is the same in all cases, the same value should be used whether the elements in the sequence flow are tasks or events.

Figure 3.6: Consecutive tasks, cognitive weight value: 1

Exclusive gateway

Also known as XOR split or join. One of multiple branches is chosen. Same function in YAWL and BPMN, but different notation. The difference in notation does not create difference in understandability, therefore the proposed value is the same as in YAWL: 2 for splits with two outgoing flows and 3 for three or more flows. The value is also 2 or 3 for XOR joins as well, based the on the number of incoming sequence flows.

Figure 3.7: Exclusive gateway, cognitive weight: 2 or 3

Parallel gateway

AND split or join, all connecting flows are followed in parallel. Same function as in YAWL, different notation, same complexity. The proposed cognitive weight for BPMN is the same as for YAWL: 4.

Figure 3.8: Parallel gateway, cognitive weight: 4

Inclusive gateway

One or more outgoing flows is chosen. Also known as OR split/join. Due to the multiple possible options this element can be relatively complicated, therefore it has a high cognitive weight for YAWL: 7. The same is true for its BPMN counterpart, therefore the suggested BPMN cognitive weight is also 7.

Figure 3.9: Inclusive gateway, cognitive weight: 7

An overview of the cognitive weights for the most basic BPMN elements (constructs) is provided in Table 3.2 below:

Element	BPM control structure	BPMN symbol	W
Sequence flow	consecutive tasks in a workflow		1
Exclusive gateway	XOR-split (exactly one of two branches is chosen) with corresponding XOR-join		2
	XOR-split (exactly one of ≥ 3 branches is chosen) with corresponding XOR-join		3

Parallel gateway	An AND-split activates all outgoing links in parallel, a corresponding AND-join synchronizes the flows of control		4
Inclusive gateway	OR-split (a number of branches is chosen from 2 or more possible branches) with corresponding OR-join		7

Table 3.2: Cognitive weights adapted to BPMN

While the most common constructs of BPMN models have been assigned a cognitive weight on the previous pages the standard has a much wider range of notations. However, assigning a cognitive weight to all of the elements and especially testing whether the proposed values indeed correlate with the effort required by people to understand it would not be possible, due to the limited extent of this thesis. Attempting to calculate the effects of additional characteristics of BPMN models, e.g. how pools complicate understanding would also require far more research. If however the cognitive weight values of the basic elements are confirmed to be correct and useful, then future research into the aforementioned areas might be suggested.

Chapter 4

Empirical research

4.1 Introduction

In order to test whether the different BPMN elements have different effects on people's understanding of process models, a survey has been conducted for this thesis. The main objective during the design process was that the analysis of the collected data should show the significance of the different elements on the understandability of a model. A regression analysis should provide coefficients for the different constructs used, which then can be compared with their cognitive weight values.

The survey was loosely based on the survey in [15] by Reijers and Mendling. Respondents were asked to provide some information like gender and familiarity with process models and they had to answer questions related to various process models. One of the similarities with the survey of Reijers and Mendling is that the size (and also the cognitive weight) was the same for each of the different process models in the survey. The reason behind this is that the size of a model is known to make understanding more difficult, as established by prior research and explained (amongst other sources) in [15] as well. The aim of this survey was to identify other influencing factors (especially certain constructs in the models) while controlling for the size effect of the model.

Of the basic BPMN constructs that had been assigned a cognitive weight in the previous section of the thesis, XOR gates with 3 or more branches were not included in any of the models. The reason for this was that they are very similar to their counterparts with 2 branches and to include enough of them in the models to be able to analyse their impact would have required more than 4 models (or more constructs in each model). Larger or more models would have made the survey much more complicated and time-consuming for the respondents, possibly causing a lower response rate and thereby influencing the explanatory power negatively.

4.2 Methodology and survey format

The data collection part of the survey was done online in early May 2013. The tool used to build and distribute the survey was Qualtrics (www.qualtrics.com), as it had all features required for the survey, including the randomization of question order, time limit on pages, easy result data exportation, etc. Qualtrics was chosen after reviewing the functionalities of several similar tools, including many well-known ones from such providers as Google and Survey Monkey. The Qualtrics tool appeared to be the best one for academic research such as this survey.

The survey started with asking for the name of the respondents. After that a short explanation on the survey design and on the notations was given, followed by an example model and questions so participants could familiarize themselves with how the models and questions will look like.

The second part of the survey included 4 process models that were designed according to the BPMN standard. The models included various gateways and tasks so that the understanding of each of them could be tested. There were 5 related questions to each of the 4 models and each question was related to 1 or 2 constructs in the model, so that it could only be answered correctly if the respondent understood the related construct. The order in which the models were showed, as well as the order of questions under each model was randomized.

The models used in the survey had been designed using only the basic BPMN elements that are described earlier in the thesis. This way the cognitive weight of each model can be calculated. The models were relatively simple, so that the importance of understanding each different construct is clear. If the models were more complex then it would not be clear what exactly makes their understanding difficult. Each model contained a different mix of constructs:

Model A:

sequence flow: 3, XOR: 0, AND: 1, OR: 1

Model B:

flow: 5, XOR: 1, AND: 0, OR: 1

Model C:

flow: 5, XOR: 1, AND: 2, OR: 0

Model D:

flow: 4, XOR: 2, AND: 0, OR: 1

The figures below show the business process models that were included in the survey, along with the questions that were asked from the participants in relation to the particular models.

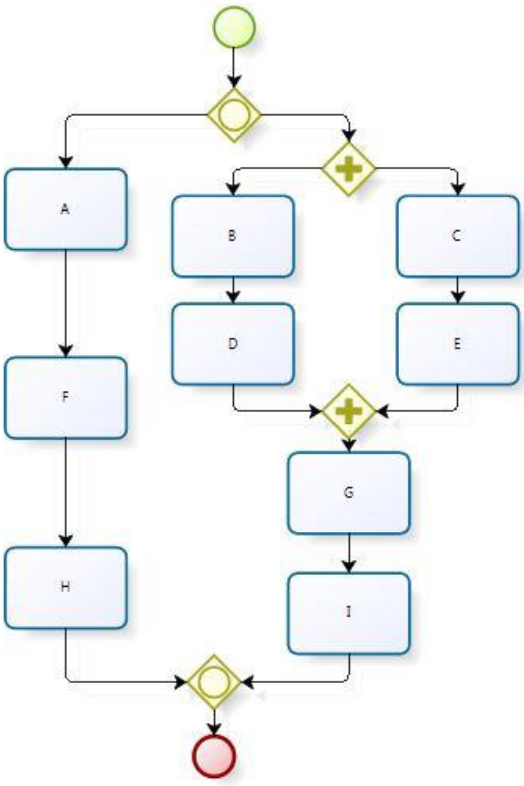


Figure 4.1: Model A of the survey

Question related to Model A:

- *Do B, C, D and E all have to be executed during the process?*
- *Can B be executed after C?*
- *Can all tasks except for A, F and H be executed during the process?*
- *Can E only be executed after B has been executed?*
- *Can H be executed without executing I as well?*

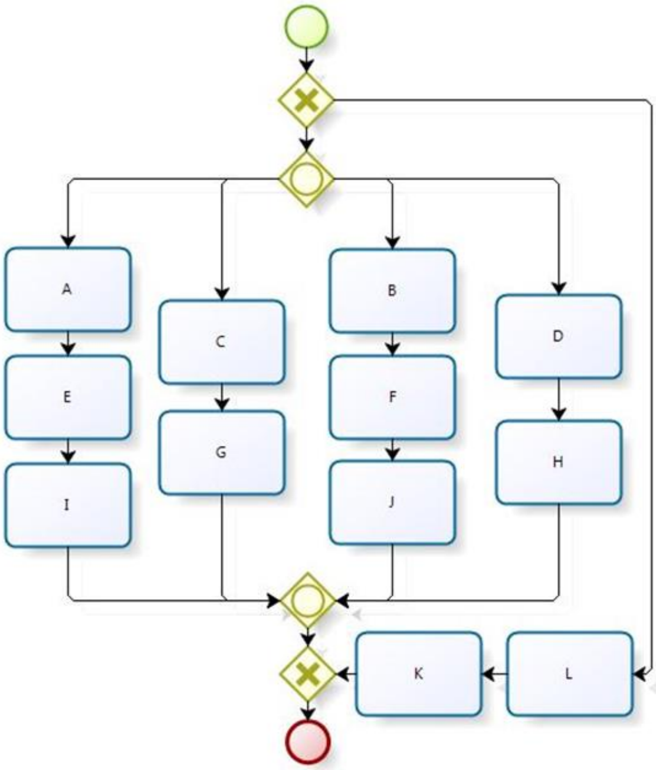


Figure 4.2: Model B of the survey

Questions related to Model B:

- *Can A, B and H be executed the same time?*
- *Can J only be executed if B has been executed before?*
- *Can the process end without K having been executed?*
- *Do A, B, C and D have to be all executed before the process can end?*
- *Can all tasks be executed during the process?*

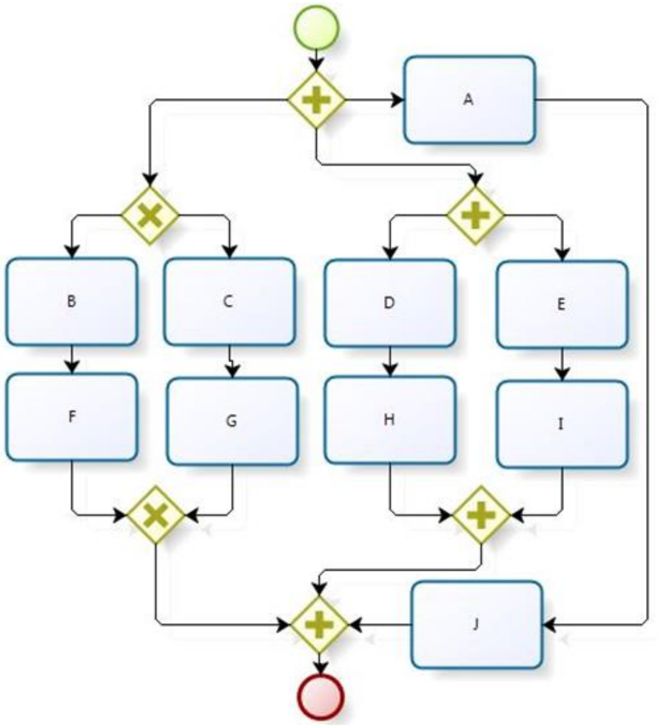


Figure 4.3: Model C of the survey

Questions related to Model C:

- *Are all tasks always executed during the process?*
- *Can C be executed after H?*
- *Are A and H always both executed?*
- *Can J be executed before A?*
- *Can the two final executed tasks in the process be A, followed by J?*

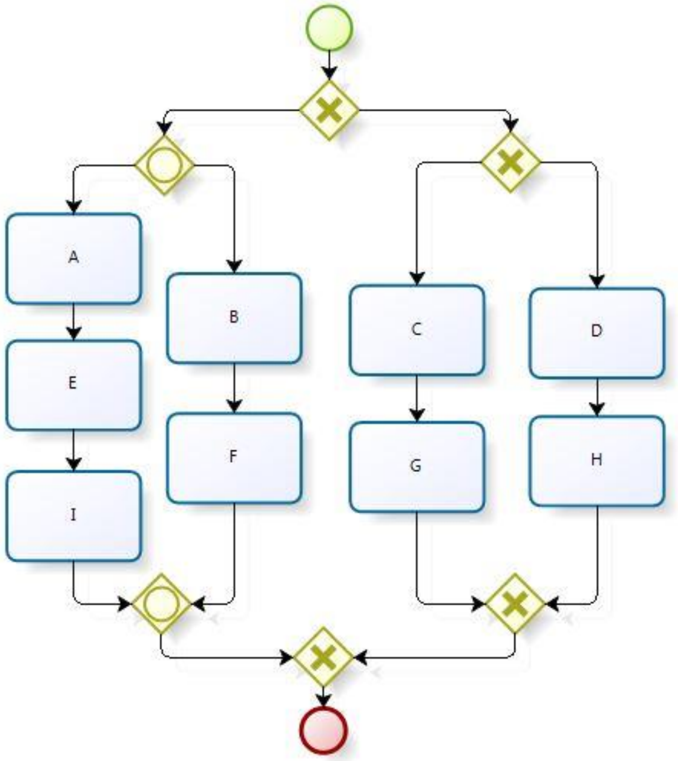


Figure 4.4: Model D of the survey

Questions related to Model D:

- *Can the process end with only B and F having been executed?*
- *Can E, F and H all be executed during the process?*
- *If A is executed does I also have to be executed later?*
- *Can I and F be executed at the same time?*
- *Can the process end with only G and C having been executed?*

In order to avoid respondents spending an overly long time at some questions and eventually figuring out the correct answer in an unrealistic timeframe, a time limit was added to the survey, allowing participants to only spend 60 seconds at a model and its 5 related questions. This was necessary because initial testing of the survey design showed that even people with no knowledge of process models whatsoever could answer most (if not all) questions correctly, since they had unlimited time to think about them and could look for help online. After some consideration and further testing a 60 second time limit was chosen. This timeframe seemed long enough to allow the participant to read and comprehend the 5 questions, but also short enough to force them to answer the questions without much thinking. After each model there was a page without time limit that allowed participants to relax for as long as they wanted before moving on to the next question.

In addition to the questions testing the participants' understanding of the models there were several other questions in the second half of the survey. The participants were asked to rate how difficult it is for them to understand the 4 models (and an additional one that was used as an example at the beginning of the survey) on a Likert scale with 7 options, ranging from very difficult to very easy. The aim of these questions was to be able to see how the ratings correlate with the ratio of correct answers in the previous part of the survey. While this is only a subjective understandability measure, compared to the more objective test questions, it was important to ask these questions, so that the results could be compared with the test scores. If the results of the two different measures correlate, then it can be concluded that the test questions indeed measure the understandability of the models.

The final part of the survey asked for the respondents' gender, whether they had been studying or working with process models before and there was also a field for free text comments on the models or questions.

After it had been tested with some people, the survey was sent to the main target group: students at Hasselt University who were taking the Business Process Modelling class in spring 2013. This target group was chosen for several reasons, but most importantly because it is controlled and all members are familiar with process models designed using BPMN.

4.3 Hypothesis

The research hypothesis is the following:

The various basic process model constructs have different influence on the understandability of the models.

The different constructs in the process models used in the survey are therefore expected to have an effect on the score of the participants on each model. Score in this case means the value between 0 and 5 that is calculated by adding together the number of correct answers to the questions related to the particular process model. The number of constructs that have high cognitive weights is expected to be negatively correlated with test scores for a model, i.e. more difficult constructs in the model will predict lower test scores.

In addition to the role of model constructs, other factors might also have an effect on test scores. The respondents' opinion about the difficulty of the model is assumed to be negatively correlated with their scores on the same model, i.e. if a person finds a model difficult their score will be lower. Previous work experience with process models is also assumed to be correlated with the test scores, so a person who has been working with process models in the past should have better scores on every model.

The respondents' gender and whether they have studied process models before is also recorded, but it is unknown if these will have an effect on the score. People who studied process models in earlier years would normally be expected to achieve higher scores, but everyone in the group of respondents have studied them in the months before the survey, so all participants have at least basic knowledge in the field. Considering this, the difference between people who studied process models in previous years as well and those who didn't will might not be significant.

4.4 Survey results

The survey was completed by 30 students in May 2013 in two waves. The initial invitation was sent to the participants on the 7th and a reminder was sent on the 15th to the people who had not filled out the survey after the first e-mail.

In the next part of the thesis the results are analysed and conclusions are made about the effects of different constructs on understandability.

Several things can be clearly seen by looking at the results. The time limit on the questions achieved its intended goal, i.e. people were forced to think quickly about the questions and had no time to look for help on the Internet or think about the correct answer for an overly long time. Many people used the total available time for answering the questions and did not proceed to the next question before the 60 second time limit was up. The number of unanswered questions and questions with incorrect answers in the final survey were significantly higher than in the early test versions of the survey without the time limit. In the free text field at the end of the survey many participants mentioned that they would have liked to have more time for answering, but this was expected.

Only one of the 30 participants indicated that they had worked with process models before, therefore the responses to that question are not included in the analysis.

During the survey participants could choose between 3 different answers to each main question (Yes, No, I don't know) and a fourth outcome was also possible (no answer). However, in the analysis a question is considered to have a binary result: it was either answered correctly or not. Doing analysis with all 4 possible outcomes would be tremendously more complicated and both the available time and the volume of this thesis are insufficient for that. Therefore, the results of the main part of the questionnaire (which is the 4 models and the 20 related questions) were converted as follows:

Correct answer to the question:	correct
Incorrect answer to the question:	incorrect
"I don't know" answer to the question:	incorrect
No answer to the question:	incorrect

The underlying logic of the conversion is that if someone did not answer a question then it can be reasonably assumed that the person was having difficulties determining the correct answer because certain constructs in the model were not easy to understand for them. Of course some of the incorrect answers of any kind were probably caused by the fact that the related question was displayed below others on the page and participants had little or no time to think about them after answering earlier questions, but since the order in which the questions were displayed was random this should not have an impact on the final data.

The data containing all 4 different outcomes is available for reference or possible further research, but was not used during the analysis.

The goal of the analysis was to see whether or not the hypothesis would hold. Several variables were used in the model, each of them was based on data from the survey: model, flow, XOR, AND, OR, respondent, score, opinion, gender, experience. Below is a short explanation of the variables:

- **model**: 1 – Model A, 2 – Model B, 3 – Model C, 4 – Model D
- **flow**: number of flow constructs (consecutive tasks without branching) in the model
- **XOR**: number of XOR constructs in the model
- **AND**: number of AND constructs in the mode
- **OR**: number of OR constructs in the model
- **respondent**: ID of the respondent (1-30)
- **score**: test score of the respondent on the given model (0-5)
- **opinion**: how difficult the respondent rated the given model (1-7, 1 – very difficult, 7 – very easy)
- **gender**: gender of the respondent (1 – male, 2 – female)
- **experience**: the respondent's experience with process models (0 – no experience, 1 – studied them before)

Table 4.1 shows the data related to the responses to Model A by the first 10 participant. The full data on which the analysis was performed can be found in *Appendix 5*. It includes the 120 main observations and the values of all related variables.

model	flow	XOR	AND	OR	resp. ID	score	opinion	gender	experience
1	3	0	1	1	1	2	4	2	0
1	3	0	1	1	2	4	6	1	0
1	3	0	1	1	3	5	5	1	0
1	3	0	1	1	4	5	3	1	0
1	3	0	1	1	5	3	5	1	0
1	3	0	1	1	6	2	6	1	0
1	3	0	1	1	7	4	6	1	0
1	3	0	1	1	8	3	5	1	1
1	3	0	1	1	9	2	4	1	0
1	3	0	1	1	10	3	6	2	1

Table 4.1: Sample data showing responses related to Model A in the survey

As it can be seen from the survey design and Table 4.1, the data is multi-level (hierarchical). With 4 process models and 30 survey participants, 120 test scores (observations) were collected. However, these observations are not independent from each other. Each individual respondent has 4 different test scores and it can be expected that these results are correlated, indicating association between the scores of a respondent. In this multi-level model test scores are the lower level of hierarchy and individuals (each of whom has 4 different scores) are the second level of hierarchy.

4.5 General analysis

65% of all answers were correct in the survey. The average of all 120 scores is 3.27, including several instances of all possible values from 0 to 5. The average scores for the models are as follows: 3.13 for Model A, 3.67 for Model B, 3.1 for Model C and 3.17 for Model D.

	Average score
Model A	3,13
Model B	3,67
Model C	3,1
Model D	3,17
Total	**3,27**

Table 4.2: Test scores of the different models

The frequency of the 6 possible different test scores (0-5) can be seen below:

Score	**Frequency**
0	5
1	10
2	22
3	25
4	27
5	31

Table 4.3: Frequency of the different test scores in the survey results

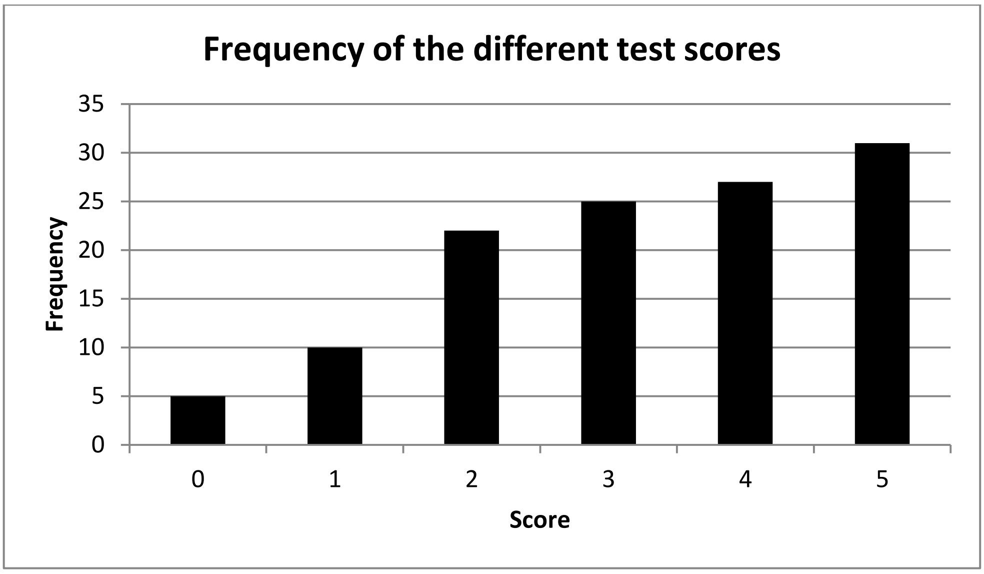


Figure 4.5: Frequency of the different test scores shown on a histogram

The standard deviation is 1.44, the variance is 2.08.

It is interesting to see that while the overall average of all scores is 3.27, there is a difference between the scores of those participants who completed the survey in the first wave and those who did it only in the second wave. The table below shows the mean values of the scores in first and second wave:

	1st wave	**2nd wave**	**Total**
Model A	3,33	2,67	3,13
Model B	3,57	3,89	3,67
Model C	3,14	3,00	3,1
Model D	3,24	3,00	3,17
Total	**3,32**	**3,14**	**3,27**

Table 4.4: Mean scores in the first and second wave of the survey

As it can be seen in the table, the mean value of all scores was 3.32 in the first wave and 3.14 in the second. A possible explanation for the more than 5% lower total scores in the second wave is that people who were less confident in their knowledge in the field were perhaps initially reluctant to take the survey.

An examination of the questions with the lowest scores yielded an interesting observation, it is detailed later on.

4.6 Multi-level analysis

For the analysis a Generalized Estimating Equations (GEE) multi-level model was used. The model allows analysis of a general linear model that has a possible unknown correlation, which in this case comes from the fact that the 120 test scores are not completely unrelated due to the previously explained structure of the model. The GEE model allows for the correction of the hierarchy present in the data.

The computer analysis of the data was done with the SAS 9.2 software using the *GENMOD* procedure. Another software that could have been used is R, the same results could be obtained by running a multi-level analysis using the *nlme* package.

For the analysis, the *score*, *opinion*, *gender* and *experience* variables were considered to be categorical. During the analysis they were always compared to a baseline value, which were the followings: at score the baseline was 0 (no correct answers), at opinion: 7 (very easy), at gender: 2 (female) and at experience: 1 (respondent has studied process models before). The values in the *Estimate* column in the tables show the chance of getting the value of the categorical variable in the corresponding row instead of the baseline value. This chance can be calculated by raising *e* (Euler's number) to the power of the *Estimate* value.

For the first analysis, the effect of the opinion, gender and experience variables were measured. *Opinion* turned out to be the only significant variable (at p = 10% level of significance). The results that belong to opinion can be seen in the next table. Since *opinion* shows how difficult the respondents found the particular process model, for easy interpretation, the opinion variable will be referred to as *subjective complexity* in the analysis.

Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Score = 1	-3,9172	0,7051	-5,2991	-2,5353	-5,56	<.0001
Score = 2	-2,691	0,7263	-4,1145	-1,2675	-3,71	0,0002
Score = 3	-1,4905	0,7002	-2,8628	-0,1182	-2,13	0,0333
Score = 4	-0,5478	0,692	-1,9041	0,8084	-0,79	0,4285
Score = 5	0,4924	0,7059	-0,8912	1,8759	0,7	0,4855
Subjective complexity = 1	-0,8832	0,6984	-2,252	0,4856	-1,26	0,206
Subjective complexity = 2	0,323	0,8312	-1,3062	1,9521	0,39	0,6976
Subjective complexity = 3	1,2852	0,7905	-0,2642	2,8346	1,63	**0,104**
Subjective complexity = 4	1,0399	0,7486	-0,4273	2,507	1,39	0,1648
Subjective complexity = 5	0,3792	0,7547	-1,1	1,8584	0,5	0,6154
Subjective complexity = 6	0,0681	0,689	-1,2823	1,4185	0,1	0,9213
Subjective complexity = 7	0	0	0	0	.	.

Table 4.5: Values related to score and subjective complexity of the multi-level analysis on the subjective complexity, gender and experience variables

In the survey participants had to rate the process models on a Likert scale ranging from 1 to 7, based on how difficult they think the model was. The value 3 (respondents assessing the model as “difficult”) is significant, therefore it can be said that that subjective complexity as a whole is significant. The results of the data analysis show that there is a negative correlation between the responses to this question and the results of the test questions related to the same model. If someone found a model more difficult there was a bigger chance that their total score on the test questions was lower.

Subjective complexity should not be considered to be an explanatory value however, as its nature is the same as that of the *score*: they are both linked to the participant’s understanding of the model. Therefore, the correlation between the two variables can be considered as a validation of the test.

A second analysis included the *model*, *gender* and *experience* variables. The subjective complexity variable was not included. The results can be seen in the following table.

Parameter	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Score = 1	-1.8765	0.6607	-3.1714	-0.5816	-2.84	0.0045
Score = 2	-0.6806	0.6722	-1.9981	0.6369	-1.01	0.3113
Score = 3	0.5048	0.6786	-0.8252	1.8349	0.74	0.4569
Score = 4	1.4487	0.6914	0.0937	2.8038	2.10	0.0361
Score = 5	2.5152	0.7153	1.1132	3.9172	3.52	0.0004
Model A	-0.0479	0.2692	-0.5755	0.4798	-0.18	0.8589
Model B	-0.8111	0.3021	-1.4033	-0.2190	-2.68	0.0073
Model C	-0.0610	0.3261	-0.7002	0.5782	-0.19	0.8516
Model D	0.0000	0.0000	0.0000	0.0000	.	.
Male	-0.8229	0.6231	-2.0442	0.3983	-1.32	0.1866
Female	0.0000	0.0000	0.0000	0.0000	.	.
Respondent does not have experience	-0.6788	0.5111	-1.6806	0.3230	-1.33	0.1842
Respondent has experience	0.0000	0.0000	0.0000	0.0000	.	.

Table 4.6: Results of the multi-level analysis on the model, gender and experience variables

The results show that Model B is very strongly correlated with higher test scores (at p = 0.0073), but this information is neither important, nor surprising, as Model B has the highest test scores of all models. Gender and experience are not significant (p = 0.1866 and 0.1842, respectively).

The estimates for *score* show the chance of getting the test score in the corresponding row instead of 0 (the baseline value) while the values of other variables are their baselines. It can be seen that the higher the score the higher the chance is to get it. This corresponds with the distribution of test scores illustrated in Figure 4.5.

To see the effect of the different model constructs (which was the main purpose of the survey), they were analysed separately from the other variables. The *gender* and *experience* control variables had already been established as not being significant, therefore they were not included in the next analysis.

However, after running the new analysis in SAS an unexpected problem arose. The sample size (the general limitations of which are mentioned in other parts of the thesis) did not allow the analysis of all 4 model constructs, the covariates did not have enough degrees of freedom.

Since the analysis worked if only 3 constructs were added, one of them had to be removed. Considering that sequence flow is different from the other 3 constructs (it is the only one that is not a gateway), it was chosen as the one to be omitted from the analysis.

The table below shows the results of the analysis. The 3 constructs (AND, OR and XOR) are not categorical, therefore their estimate values must be interpreted differently: they show how increasing the number of the given construct in a model by 1 (while the numbers of the other 2 constructs do not change) increases the chance of getting 0 on the test score. More generally, a higher estimate value increases the chance for a lower score, i.e. a higher value means that the construct is more difficult.

The estimates for *score* are not relevant in this case as they are calculated for models that have 0 of all constructs in them.

Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
AND	1.4397	0.8075	-0.1429	3.0222	1.78	**0.0746**
OR	2.1432	1.3913	-0.5836	4.8701	1.54	0.1234
XOR	0.7194	0.4638	-0.1897	1.6284	1.55	0.1209

Table 4.7: Results of the multi-level analysis on the model construct variables

First, the significance levels of the constructs should be checked. The p value for AND is 0.0746, therefore it can be said that the constructs are significant at p=10% level of significance.

The coefficient estimates for the 3 different model constructs are the most important values in the whole analysis, considering that the goal was to see what effect the constructs have on understandability. The significantly different values support the theory that the different constructs have different influence on understandability.

Several things must be taken into consideration before drawing conclusions from the multi-level model analysis. The data set used was rather small, with only 120 observations. Therefore the test has low variability and its power might not be enough to show certain effects. This became clear when the multi-level model analysis failed to return estimates for all 4 process constructs at the same time.

A larger data set (a few hundred respondents) could make the observation of more statistical significances possible. However, since the topic of the survey calls for respondents who have knowledge in a special field (i.e. business process models), it would be difficult to find a group that is large enough, yet also as controlled as the group whose responses were used for this analysis.

When looking at the estimate values for the 3 constructs it must be kept in mind that several other variables can have a role in the understanding, variables that were not controlled for due to the limitations of the survey and the analysis.

It must also be noted that the confidence limits of the constructs overlap, so further testing would be required to completely eliminate the possibility of errors.

Despite the aforementioned shortcomings of the survey, the results show clear correlation between the number of the various business process constructs and the test score participant obtained on the models and it can be concluded that the number of different constructs in the process models have significant effect on the understandability of the models.

4.7 Analysis results vs. hypothesis

The opinions of the respondents about the difficulty of each model has been proved to be correlated with their test scores, people who rated a model more difficult were more likely to have a lower score.

Gender and previous studies in the field of process models have not found to be correlated with the scores. This can be because of the previously discussed shortcomings of the survey, but it is also very possible that (as explained in the hypothesis) these are indeed not significant for understanding the models. Correlation was not expected in the hypothesis.

The main hypothesis was the following: *The various basic process model constructs have different influence on the understandability of the models*. This has been **confirmed**.

Moreover, the coefficient values for the different constructs relate to each other the same way as the cognitive weight values of the constructs. Higher values of either cognitive weight or coefficient in this analysis are both supposed to mean that the construct in question is more difficult to understand. OR has the highest value of both (coefficient estimate: 2.14, cognitive weight: 7), followed by AND (1.44, 4) and the least difficult is XOR (0.72, 2). This must be considered very cautiously though, as other influencing factors were not included in the analysis.

4.8 Order of execution

Examining the lowest test scores provides an interesting insight on what kind of questions were the most difficult to understand for the respondents. The second question on Model A has the lowest number of correct answers, only 13 out of the 30 respondents (43%) answered it correctly. The question with the next lowest score was the first one related to Model B, with 15 correct answers (50%). There are 4 questions with 17 correct answers (57%), out of those the fourth one related to Model D was similar to the ones with the two lowest scores. The 3 questions and the parts to which they are related in their respective processes are as follows:

2nd question on Model A: *Can B be executed after C?*

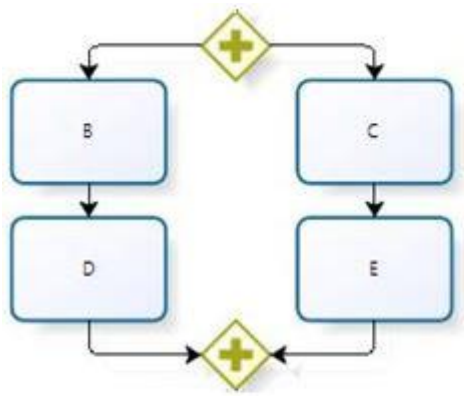


Figure 4.6: A part of Model A

1st question on Model B: *Can A, B and H be executed the same time?*

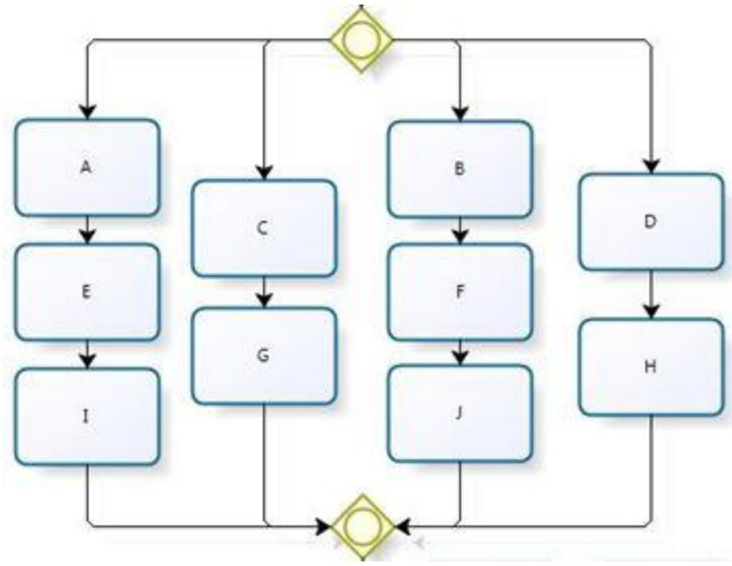


Figure 4.7: A part of Model B

4th question on Model D: *Can I and F be executed at the same time?*

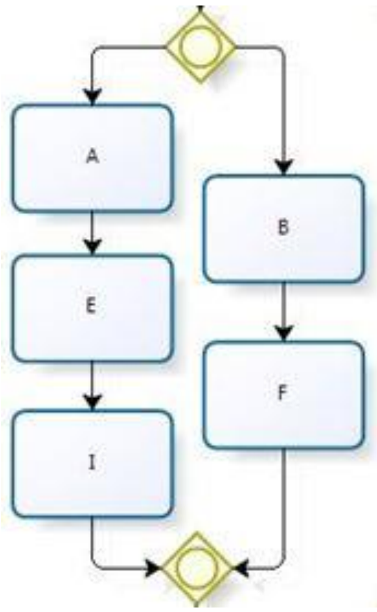


Figure 4.8: A part of Model D

As it can be seen these questions are all related to the order in which tasks can be executed after a gateway. Only 4 such questions were included in the questionnaire and 3 of them produced the lowest scores amongst all the 20 questions, therefore it can be assumed that many people have problems understanding in which order tasks are executed when multiple branches are followed after a gateway. Since the tasks can be executed in any order (including simultaneous execution) relative to the tasks on the other branches as long as the order within their own branch is respected, the correct answer to all 3 questions above is *yes*. Apparently this is not clear to many people, so it should be considered when designing business process models, even if in most cases it would probably not cause major problems. No research seems to have been done on this before, so confirming the existence of this problem and its possible effects would be an interesting topic for future research.

4.9 Role of cognitive weight

One of the main goals of the survey was to see whether the different constructs in process models have different and significant influence on the understandability of the models and thus find evidence that would support the viability of the cognitive weight metric.

Analysis of the survey results has shown that the different model constructs are indeed correlated with how well people understand the process models. The relative cognitive weight values of the 3 different constructs that were included in the analysis also seem to be correct, since the coefficients of the constructs in the multi-level analysis also relate to each other in the same way. However, the exact cognitive weight numbers can neither be confirmed nor rejected due to the limited available data.

Since Gruhn and Laue introduced the concept of cognitive weights for business process model elements in 2006 in their paper *Adopting the Cognitive Complexity Measure for Business Process Models* ([13]), no further research from other authors can be found on the topic. The original cognitive weight metric for measuring software complexity by Shao and Wang ([12]) has been used and researched further since 2003, but the same cannot be said for the process model metric that was derived from it by Gruhn and Laue.

This means that the cognitive weight metric has never been tested with actual people before, the values of the various elements were based on theory. The results of the survey that was carried out for this thesis suggest that the values might indeed be correct (at least approximately), therefore a metric based on cognitive weight might indeed be a viable and useful tool for measuring the cognitive complexity of process models. Of course, extensive further research should be carried out on the subject before wider application of the cognitive weight metric.

Chapter 5

Conclusions

5.1 Final conclusion

In this thesis different aspects of process model understandability have been explored and evaluated. At the beginning the introduction provides a brief explanation of business process models and explains their role and importance. After that the most basic elements of such models in the Business Process Model and Notation standard are introduced.

The literature review in the next section provides an overview of the most important research papers related to the topic. The available literature is not as extensive as it could be expected for a topic as important as the understandability of process models. The fact that there are lots of possibilities for further research was actually one of the main motivations to write this thesis, so that it might lead to new findings or confirm existing theories.

From the literature review it can be seen that most business process complexity metrics are derived from software code complexity metrics. Software complexity metrics exist since the 1970s and have been widely researched since that, but this is not the case with business model complexity, since only limited research has been done on that subject. Even less research has been conducted in the field of business process understandability, so it is still a topic where interesting new findings can be made.

The papers on process understandability in almost all cases end with the conclusion that no single metric can capture how difficult it is for people to understand a model. The cognitive weight metric appears to be one of the most promising of all metrics, however, further research is required to establish its validity and to confirm the values that were proposed by Gruhn and Laue for the different process model elements.

One of the goals of the thesis was to see if the difficulty of understanding of various constructs can be confirmed, to see whether the cognitive weight values of Gruhn and Laue are correct or not. The results of the survey that was carried out for this thesis support the theory of the authors. However, determining whether the exact cognitive weight values defined by Gruhn and Laue are correct or not is not possible due to the limited data that is available from this survey. The results are nonetheless promising, so further research on the subject is suggested.

The survey did yield an interesting, although less important result as well: many people have difficulties understanding in which order tasks can be performed after a gateway that allows for multiple outgoing branches to be taken. This finding should be confirmed by further tests though. However, if it can be confirmed then this is something that should be taken into consideration when designing business process models.

In conclusion it can be said that the understandability of business process models is an area in which only limited research has been done to date, and no reliable metric exists to capture it. A combination of different metrics that are reviewed in this thesis might be used to get an idea of the cognitive complexity of a given model, but a single reliable metric is yet to be developed, as the state-of-the-art methods have several shortcomings. The cognitive weight metric introduced by Gruhn and Laue is very promising. Further research must be done to check its usability and reliability, but this thesis (and its author) definitely support the concept.

References

1: Rummler, G. A., & Brache, A. P. (1995). Improving Performance: How to Manage the White Space in the Organization Chart (2nd ed.). Jossey-Bass.

2: Pascoe, T. L. (1966). Allocation of Resources – CPM. Revue Francaise de Recherche Opérationelle 38, pp. 31-38, 1966.

3: Kaimann, R.A. (1974). Coefficient of Network Complexity, Management Science Vol. 21, No. 2, pp. 172-177

4: Latva-Koivisto, A. M. (2001). Finding a complexity measure for business process models. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.25.2991&rep=rep1&type=pdf

5: McCabe, T. J. (1976). A Complexity Measure. IEEE Transactions on Software Engineering, SE-2(4), 308–320.

6: Bein, W.W., Kamburowski, J. and Stallmann, M.F.M. (1992). Optimal Reduction of Two-Terminal Directed Acyclic Graphs. SIAM Journal on Computing, Vol. 21, No.6, pp. 1112-1129, December 1992.

7: Thesen, A. (1977). Measures of the Restrictiveness of Project Networks. Networks 7, pp. 193-208.

8: Temperley, H.M.V (1981). Graph Theory and Applications. Ellis Horwood Ltd., England.

9: Laue, R., Gruhn, V. (2006). Complexity metrics for business process models. In Abramowicz, W., Mayr, H.C., eds.: BIS 2006, Proceedings. LNI 85. 1–12

10: Kan, S.H. (2002). Metrics and Models in Software Quality Engineering. Addison-Wesley Longman Publishing Co., Inc.

11: Cardoso, J. (2005). How to measure the control-flow complexity of web processes and workflows. In: The Workflow Handbook. 199–212

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

13: Gruhn, V., & Laue, R. (2006). Adopting the Cognitive Complexity Measure for Business Process Models. 2006 5th IEEE International Conference on Cognitive Informatics, 236–241.

14: Mendling, J., & Strembeck, M. (2008). Influence Factors of Understanding Business Process Models.

15: Reijers, H. A., & Mendling, J. (2011). A Study Into the Factors That Influence the Understandability of Business Process Models. IEEE Transactions on Systems Man and Cybernetics Part A Systems and Humans, 41(3), 449–462.

16: W. Aalst, A. Hofstede, B. Kiepuszewski, and A. Barros. (2003). Workflow patterns. Distributed and Parallel Databases, 14(3)

The tables and figures in the thesis are self-made, except when a source is indicated.

Process models were created using Bizagi Process Modeler. The survey was conducted using Qualtrics (www.qualtrics.com). Multi-level statistical analysis on the gathered data was done using the SAS (Statistical Analysis System) software.

Appendix 1

Figures 5 and 6 from [4]

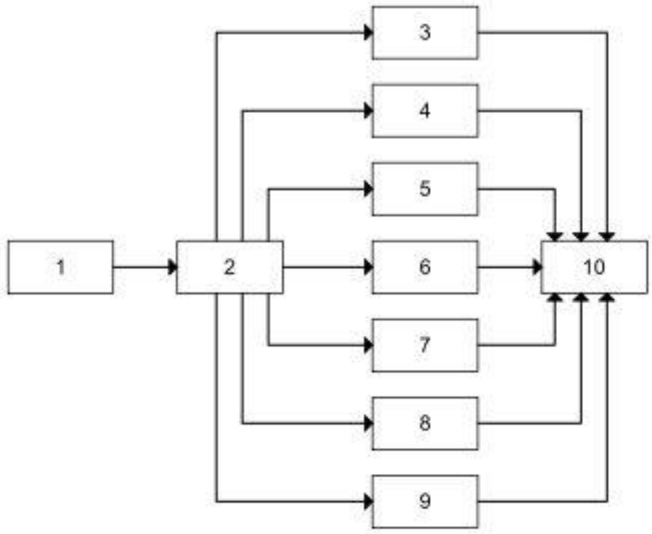


Figure 5. A graph with 10 nodes and 15 arcs.

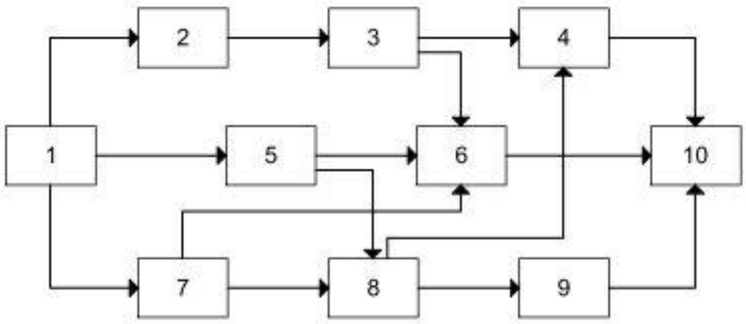
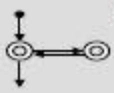


Figure 6. Another graph with 10 nodes and 15 arcs..

Appendix 2

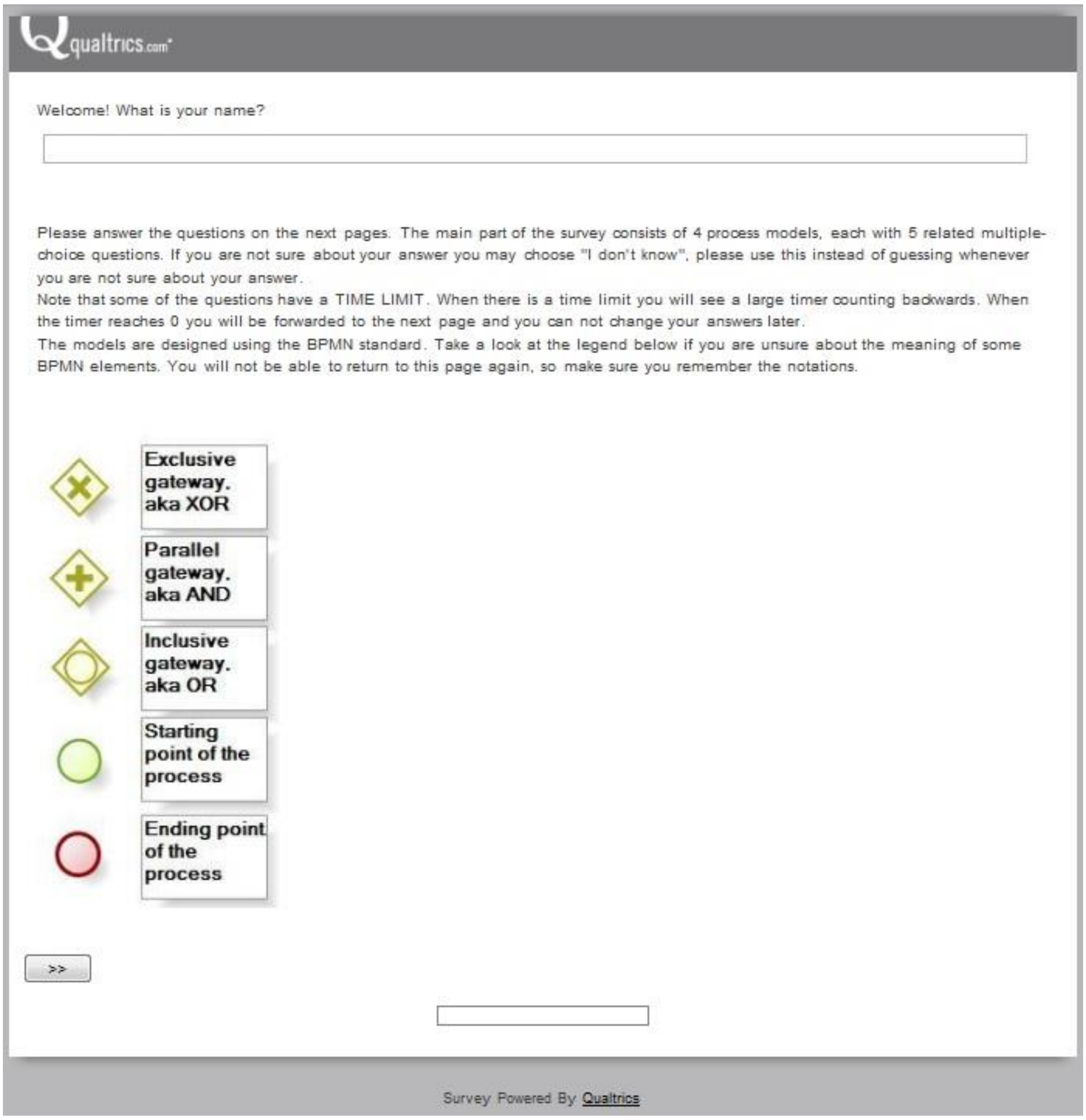
Table 1 from [12] (full)

Table 1
Definition of BCSs and their equivalent cognitive weights (W_i)

Category	BCS	Structure	W_i	RTPA notation
Sequence	Sequence (SEQ)		1	$P \rightarrow Q$ Note: Consider only one sequential structure in a component
Branch	If-then-[else] (ITE)		2	$(?\exp BL = T) \rightarrow P$ $\mid (?\sim) \rightarrow Q$
	Case (CASE)		3	$?\exp RT =$ $0 \rightarrow P_0$ $\mid 1 \rightarrow P_1$ $\mid \ldots$ $\mid n-1 \rightarrow P_{n-1}$ $\mid else \rightarrow \varnothing$
Iteration	For-do (R_i)		3	$R_{i=1}^{n}(P(i))$
	Repeat-until (R_1)		3	$R_{\geq 1}^{\exp BL=T}(P)$
	While-do (R_0)		3	$R_{\geq 0}^{\exp BL=T}(P)$
Embedded component	Function call (FC)		2	P↳ F Note: Consider only user-defined functions
	Recursion (REC)		3	P↺P
Concurrency	Parallel (PAR)		4	$P \parallel Q$
	Interrupt (INT)		4	P ‖⊙ (@eS ↗ Q ↘ ⊙)

Appendix 3

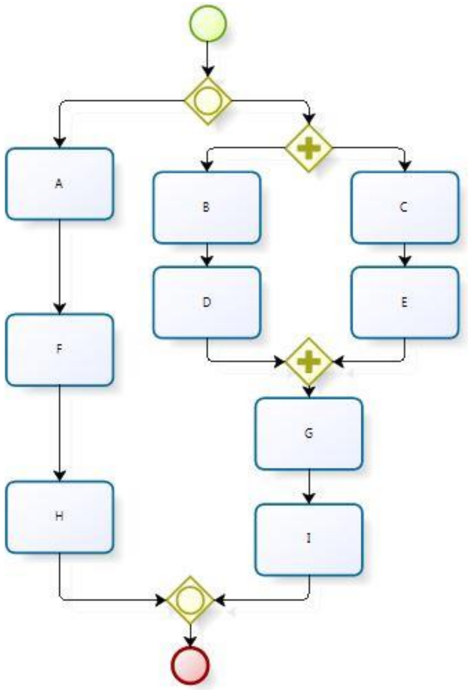
Welcome page of the survey, showing the introduction text and the legend.



Appendix 4

Models and their corresponding questions used in the survey

Model A



Do B, C, D and E all have to be executed during the process?

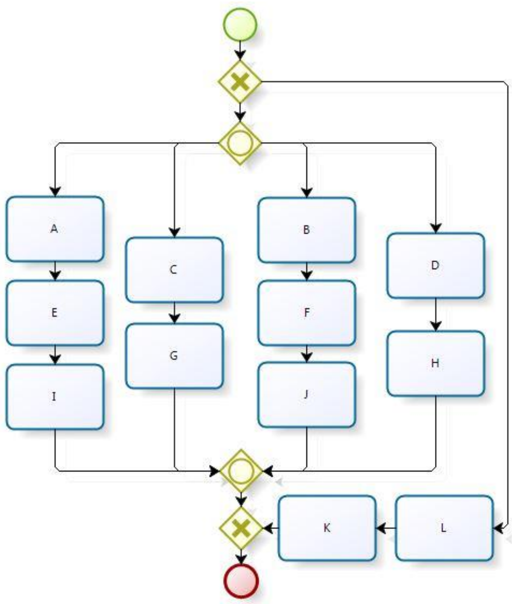
Can B be executed after C?

Can all tasks except for A, F and H be executed during the process?

Can E only be executed after B has been executed?

Can H be executed without executing I as well?

Model B



Can A, B and H be executed the same time?

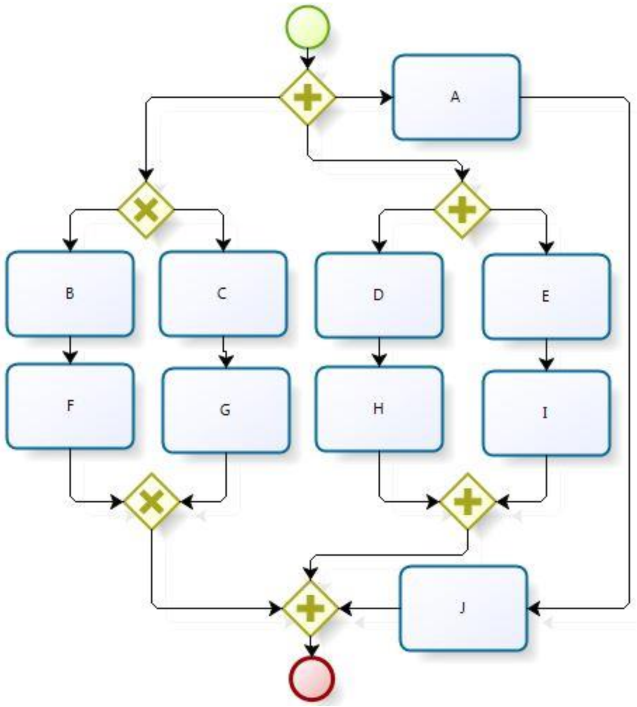
Can J only be executed if B has been executed before?

Can the process end without K having been executed?

Do A, B, C and D have to be all executed before the process can end?

Can all tasks be executed during the process?

Model C



Are all tasks always executed during the process?

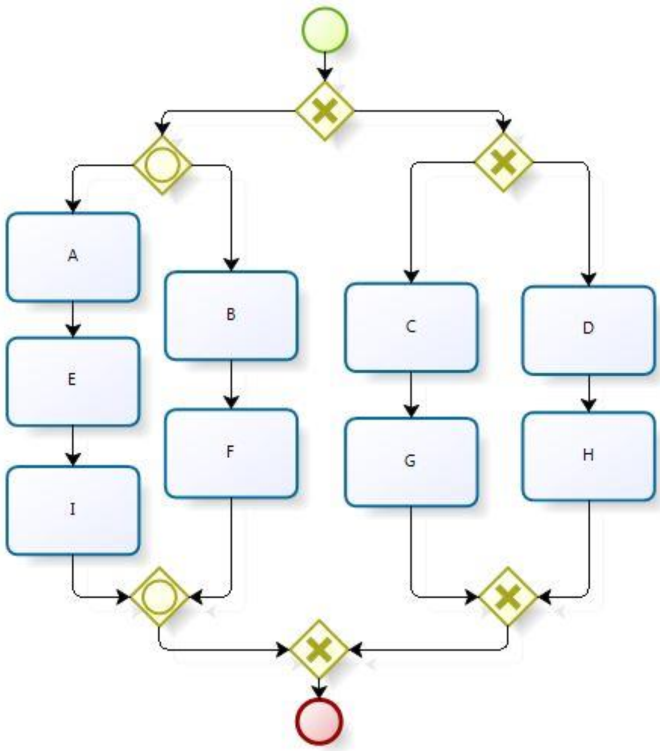
Can C be executed after H?

Are A and H always both executed?

Can J be executed before A?

Can the two final executed tasks in the process be A, followed by J?

Model D



Can the process end with only B and F having been executed?

Can E, F and H all be executed during the process?

If A is executed does I also have to be executed later?

Can I and F be executed at the same time?

Can the process end with only G and C having been executed?

Appendix 5

Data collected during the survey (full)

model: 1 – Model A, 2 – Model B, 3 – Model C, 4 – Model D
flow: number of flow constructs in the model
XOR: number of XOR constructs in the model
AND: number of AND constructs in the mode
OR: number of OR constructs in the model
respondent: ID of the respondent (1-30)
score: test score of the respondent on the given model (0-5)
opinion: how difficult the respondent rated the given model (1-7, 1 – very difficult, 7 – very easy)
gender: gender of the respondent (1 – male, 2 – female)
experience: the respondent's experience with process models (0 – no experience, 1 – studied them before)

model	flow	XOR	AND	OR	resp. ID	score	opinion	gender	experience
1	3	0	1	1	1	2	4	2	0
1	3	0	1	1	2	4	6	1	0
1	3	0	1	1	3	5	5	1	0
1	3	0	1	1	4	5	3	1	0
1	3	0	1	1	5	3	5	1	0
1	3	0	1	1	6	2	6	1	0
1	3	0	1	1	7	4	6	1	0
1	3	0	1	1	8	3	5	1	1
1	3	0	1	1	9	2	4	1	0
1	3	0	1	1	10	3	6	2	1
1	3	0	1	1	11	4	3	1	0
1	3	0	1	1	12	4	5	2	0
1	3	0	1	1	13	4	4	1	1
1	3	0	1	1	14	4	6	1	0
1	3	0	1	1	15	5	6	1	0
1	3	0	1	1	16	2	7	1	0
1	3	0	1	1	17	2	4	1	0
1	3	0	1	1	18	3	4	1	0
1	3	0	1	1	19	2	3	2	0
1	3	0	1	1	20	3	4	2	0

1	3	0	1	1	21	4	7	1	0
1	3	0	1	1	22	3	6	1	0
1	3	0	1	1	23	5	3	2	0
1	3	0	1	1	24	3	5	1	1
1	3	0	1	1	25	2	4	2	0
1	3	0	1	1	26	1	3	1	1
1	3	0	1	1	27	0	4	1	1
1	3	0	1	1	28	5	6	1	0
1	3	0	1	1	29	5	4	1	0
1	3	0	1	1	30	0	4	1	0
2	5	1	0	1	1	0	3	2	0
2	5	1	0	1	2	5	3	1	0
2	5	1	0	1	3	5	7	1	0
2	5	1	0	1	4	5	1	1	0
2	5	1	0	1	5	4	6	1	0
2	5	1	0	1	6	5	6	1	0
2	5	1	0	1	7	2	4	1	0
2	5	1	0	1	8	4	5	1	1
2	5	1	0	1	9	1	3	1	0
2	5	1	0	1	10	2	6	2	1
2	5	1	0	1	11	5	2	1	0
2	5	1	0	1	12	4	4	2	0
2	5	1	0	1	13	3	3	1	1
2	5	1	0	1	14	4	6	1	0
2	5	1	0	1	15	5	5	1	0
2	5	1	0	1	16	3	7	1	0
2	5	1	0	1	17	2	4	1	0
2	5	1	0	1	18	4	3	1	0
2	5	1	0	1	19	3	3	2	0
2	5	1	0	1	20	4	5	2	0
2	5	1	0	1	21	5	7	1	0
2	5	1	0	1	22	5	3	1	0
2	5	1	0	1	23	4	2	2	0
2	5	1	0	1	24	5	6	1	1
2	5	1	0	1	25	1	5	2	0
2	5	1	0	1	26	4	2	1	1
2	5	1	0	1	27	3	2	1	1
2	5	1	0	1	28	5	6	1	0
2	5	1	0	1	29	5	5	1	0
2	5	1	0	1	30	3	4	1	0
3	5	1	2	0	1	3	4	2	0

3	5	1	2	0	2	5	2	1	0
3	5	1	2	0	3	5	4	1	0
3	5	1	2	0	4	4	1	1	0
3	5	1	2	0	5	5	4	1	0
3	5	1	2	0	6	2	4	1	0
3	5	1	2	0	7	2	4	1	0
3	5	1	2	0	8	3	5	1	1
3	5	1	2	0	9	0	3	1	0
3	5	1	2	0	10	2	5	2	1
3	5	1	2	0	11	4	2	1	0
3	5	1	2	0	12	5	3	2	0
3	5	1	2	0	13	5	3	1	1
3	5	1	2	0	14	2	5	1	0
3	5	1	2	0	15	5	4	1	0
3	5	1	2	0	16	1	6	1	0
3	5	1	2	0	17	0	3	1	0
3	5	1	2	0	18	2	2	1	0
3	5	1	2	0	19	3	3	2	0
3	5	1	2	0	20	3	3	2	0
3	5	1	2	0	21	5	6	1	0
3	5	1	2	0	22	3	4	1	0
3	5	1	2	0	23	3	2	2	0
3	5	1	2	0	24	4	3	1	1
3	5	1	2	0	25	1	6	2	0
3	5	1	2	0	26	4	4	1	1
3	5	1	2	0	27	1	3	1	1
3	5	1	2	0	28	4	6	1	0
3	5	1	2	0	29	4	2	1	0
3	5	1	2	0	30	3	2	1	0
4	4	2	0	1	1	1	3	2	0
4	4	2	0	1	2	5	3	1	0
4	4	2	0	1	3	5	3	1	0
4	4	2	0	1	4	5	5	1	0
4	4	2	0	1	5	4	4	1	0
4	4	2	0	1	6	3	6	1	0
4	4	2	0	1	7	3	5	1	0
4	4	2	0	1	8	5	5	1	1
4	4	2	0	1	9	2	3	1	0
4	4	2	0	1	10	2	5	2	1
4	4	2	0	1	11	3	3	1	0
4	4	2	0	1	12	5	4	2	0

4	4	2	0	1	13	2	4	1	1
4	4	2	0	1	14	2	3	1	0
4	4	2	0	1	15	4	5	1	0
4	4	2	0	1	16	4	7	1	0
4	4	2	0	1	17	1	3	1	0
4	4	2	0	1	18	3	2	1	0
4	4	2	0	1	19	1	3	2	0
4	4	2	0	1	20	4	3	2	0
4	4	2	0	1	21	4	7	1	0
4	4	2	0	1	22	4	5	1	0
4	4	2	0	1	23	5	2	2	0
4	4	2	0	1	24	3	3	1	1
4	4	2	0	1	25	2	3	2	0
4	4	2	0	1	26	2	3	1	1
4	4	2	0	1	27	2	2	1	1
4	4	2	0	1	28	5	6	1	0
4	4	2	0	1	29	3	4	1	0
4	4	2	0	1	30	1	3	1	0

Auteursrechtelijke overeenkomst

Ik/wij verlenen het wereldwijde auteursrecht voor de ingediende eindverhandeling:
The influence of process constructs on process model understandability

Richting: **Master of Management-Management Information Systems**
Jaar: **2013**

in alle mogelijke mediaformaten, - bestaande en in de toekomst te ontwikkelen - , aan de Universiteit Hasselt.

Niet tegenstaand deze toekenning van het auteursrecht aan de Universiteit Hasselt behoud ik als auteur het recht om de eindverhandeling, - in zijn geheel of gedeeltelijk -, vrij te reproduceren, (her)publiceren of distribueren zonder de toelating te moeten verkrijgen van de Universiteit Hasselt.

Ik bevestig dat de eindverhandeling mijn origineel werk is, en dat ik het recht heb om de rechten te verlenen die in deze overeenkomst worden beschreven. Ik verklaar tevens dat de eindverhandeling, naar mijn weten, het auteursrecht van anderen niet overtreedt.

Ik verklaar tevens dat ik voor het materiaal in de eindverhandeling dat beschermd wordt door het auteursrecht, de nodige toelatingen heb verkregen zodat ik deze ook aan de Universiteit Hasselt kan overdragen en dat dit duidelijk in de tekst en inhoud van de eindverhandeling werd genotificeerd.

Universiteit Hasselt zal mij als auteur(s) van de eindverhandeling identificeren en zal geen wijzigingen aanbrengen aan de eindverhandeling, uitgezonderd deze toegelaten door deze overeenkomst.

Voor akkoord,

Nagy, Ádám Kornél

Datum: **8/06/2013**